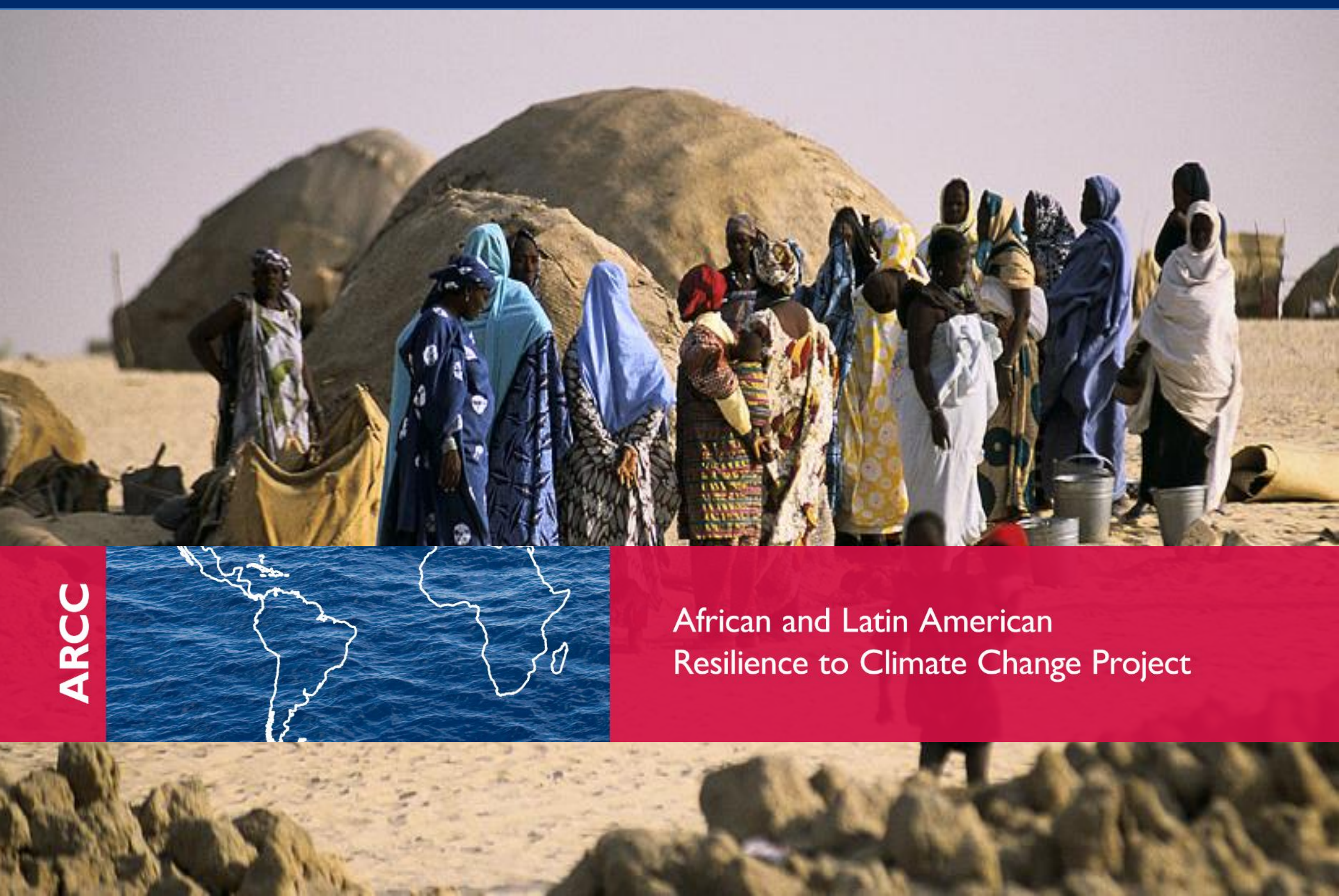
USAID
FROM THE AMERICAN PEOPLE

SPATIAL CLIMATE CHANGE VULNERABILITY ASSESSMENTS: A REVIEW OF DATA, METHODS, AND ISSUES

AUGUST 2014



ARCC

African and Latin American Resilience to Climate Change Project

This report was prepared by Alex de Sherbinin, Center for International Earth Science Information Network (CIESIN), Earth Institute at Columbia University, through a subcontract with Tetra Tech ARD.

The author wishes to acknowledge the contributions of Sandra Baptista to the development of the outline, literature review, and compilation of Annex 2. The author would also like to thank the following reviewers for their valuable comments and suggestions: David Abson, Alexander Fekete, Vladimir Gil, Stefan Kienberger, and Benjamin Preston. In addition, Emilie Schnarr provided assistance with compiling the bibliography and contacting publishers for permissions.

Cover Photo: Mali, World Bank, 2008

This publication was produced for the United States Agency for International Development by Tetra Tech ARD, through a Task Order under the Prosperity, Livelihoods, and Conserving Ecosystems (PLACE) Indefinite Quantity Contract Core Task Order (USAID Contract No. AID-EPP-I-00-06-00008, Order Number AID-OAA-TO-11-00064).

Tetra Tech ARD Contacts:

Patricia Caffrey
Chief of Party
African and Latin American Resilience to Climate Change (ARCC)
Burlington, Vermont
Tel.: 802.658.3890
Patricia.Caffrey@tetratech.com

Anna Farmer
Project Manager
Burlington, Vermont
Tel.: 802-658-3890
Anna.Farmer@tetratech.com

SPATIAL CLIMATE CHANGE VULNERABILITY ASSESSMENTS: A REVIEW OF DATA, METHODS, AND ISSUES

AFRICAN AND LATIN AMERICAN RESILIENCE TO CLIMATE CHANGE (ARCC)

AUGUST 2014

TABLE OF CONTENTS

ACRONYMS AND ABBREVIATIONS

ARCC	African and Latin America Resilience to Climate Change
BMZ	German Federal Ministry for Economic Cooperation and Development
CABI	Centre for Agricultural Bioscience International
CaNaSTA	Crop Niche Selection for Tropical Agriculture
CHRR	Center for Hazards and Risks Research
CIESIN	Center for International Earth Science Information Network at Columbia University
DEM	Digital Elevation Model
DFID	United Kingdom's Department for International Development
DHS	Demographic and Health Survey
DRR	Disaster Risk Reduction
DSSAT	Decision Support for Agro-technology Transfer
ECMWF	European Centre for Medium-Range Weather Forecasts
GCM	General Circulation Model (or Global Climate Model)
GDP	Gross Domestic Product
GIM	Global Impact Model
GIS	Geographic Information System
GPS	Geographic Positioning System
IMR	Infant Mortality Rate
IPCC	Intergovernmental Panel on Climate Change
ISI-MIP	Inter-Sectoral Impact Model Intercomparison Project
LISEM	Limburg Soil Erosion Model
MAUP	Modifiable Area Unit Problem
MAXENT	Maximum Entropy
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NDVI	Normalized Difference Vegetation Index
NGO	Nongovernmental Organizations
OECD	Organization for Economic Cooperation and Development

OLS	Ordinary Least Squares
PC	Principal Component
PCA	Principal Components Analysis
PRA	Participatory Rural Appraisal
PROVIA	UNEP Programme of Research on Climate Change Vulnerability, Impacts and Adaptation
SADC	Southern African Development Cooperation
SLR	Sea-Level Rise
SoVI	Social Vulnerability Index
SRES	IPCC Special Report on Emissions Scenarios
SREX	IPCC Special Report on Climate Extremes
SSI	Social Susceptibility Index
SSP	Shared Socioeconomic Pathway
SRTM	NASA Shuttle Radar Topography Mission
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme
UNISDR	United Nations Internationals Strategy for Disaster Risk Reduction
USAID	United States Agency for International Development
VA	Vulnerability Assessment
YCELP	Yale Center for Environmental Law and Policy

EXECUTIVE SUMMARY

Spatial vulnerability assessments and allied methods such as spatial impact assessment are useful tools for understanding patterns of vulnerability and risk to climate change at multiple scales, from local to global. The demand for vulnerability maps among development agencies and governments is increasing as greater emphasis is placed on scientifically sound methods for targeting adaptation assistance. This report provides a review of current practices in vulnerability mapping at different spatial scales across multiple sectors and systems, with a special emphasis on Africa and Latin America and the Caribbean. It critically assesses the approaches used in spatial vulnerability assessment, identifies accepted practices, and develops recommendations for practitioners. The report is intended to inform the work of the U.S. Agency for International Development (USAID) and its development partners, as well as climate and development researchers and practitioners more broadly.

Mapping is useful because climate variability and extremes, the sensitivity of populations and systems to climatic stressors, and adaptive/coping capacities are all spatially differentiated. The interplay of these factors produces different patterns of vulnerability. Typically spatial vulnerability assessment involves data integration in which geo-referenced socio-economic and biophysical data are combined with climate data to understand patterns of vulnerability and, in turn, inform where adaptation may be required. Maps have proven to be useful boundary objects in multi-stakeholder discussions, providing a common basis for discussion and for deliberations over adaptation planning. Maps can help to ground discussions on a solid evidence base, especially in developing country contexts where geographic information may not be easily accessible for all stakeholders.

That said, vulnerability mapping also has its shortcomings. While maps may identify *where* to target adaptation assistance, more detailed field research and consultation with stakeholders are necessary in order to determine *what* is needed for adaptation programming and *how* to develop local resilience. In other words, spatial vulnerability assessment may be a useful entry point for adaptation priority setting, but it is not a replacement for rigorous field-based vulnerability assessments that deepen understanding of current and future impacts on key economic sectors, environmental systems, or people groups. The power of spatial assessment is that it presents a large amount of information in a simplified and visually attractive manner. Yet this strength is also a weakness, insofar as uncertainties in the data and important analytical assumptions may be hidden from the user. A key recommendation of this technical report is that the data and methods used in spatial vulnerability assessment be clearly documented, and that map and other information on uncertainties and assumptions be included as part of any vulnerability mapping report. Methodologies should be clearly documented, and technical annexes should provide detailed information on each map layer to ensure transparency and replicability

1.0 INTRODUCTION

Spatial data integration and spatial analysis have become standard tools in the toolkit of climate change vulnerability assessments. The United Nations Environment Programme (UNEP) Programme of Research on Climate Change Vulnerability, Impacts and Adaptation (PROVIA) Research Priorities on Vulnerability, Impacts and Adaptation (PROVIA, 2013a) highlights "measuring and mapping vulnerability" as a first priority for supporting adaptation decision-making. In many cases "vulnerability assessment" (VA) is synonymous with spatial vulnerability assessment (henceforth "spatial VA"), owing in part to an understanding that vulnerability and its constituent components exhibit high degrees of spatial and temporal heterogeneity (Preston et al., 2011). The purposes vary according to the specific study, but spatial VAs are generally intended to identify areas at potentially high risk of climate impacts — so-called climate change "hotspots" (de Sherbinin, 2013) — and to better understand the determinants of vulnerability in order to identify planning and capacity building needs, or to better target funding and adaptation programs. There is as yet no consensus on what constitutes "best practice" in spatial VA. As the number of spatial VAs increases, and the conceptualizations, methods, and data used to assess vulnerability multiply, this is an opportune time to assess the strengths and weaknesses of commonly used methodologies; identify the most useful approaches; and to summarize data, methods, and results in a number of different thematic areas.

While vulnerability mapping has become commonplace in recent years, there are still important issues that need to be addressed. By summarizing and synthesizing information in ways that are meant to be useful to policy (Abson et al., 2012), vulnerability maps are often developed with the goal of guiding resource allocations and influencing policy decisions. Yet there are impediments in terms of data availability and accuracy, methodological issues, and other issues that arise in any assessment process that need to be critically examined. Preston et al. (2011: 178) cite many of the benefits of vulnerability mapping, but also caution that there is "evidence that the power of maps has cultivated a bias regarding their inherent utility." They suggest that this assumption should be examined critically since, given the limitations, maps could just as easily obfuscate an issue as provide clarity. These issues are discussed in greater detail in Section 5.0.

For this report, we conducted a broad search for published literature on spatial VA, climate vulnerability mapping, and geographic information system (GIS) approaches using the Thomson Reuters Web of Knowledge. We searched well known climate vulnerability and adaptation web portals such as Linking Climate Adaptation, Centre for Agricultural Bioscience International (CABI), AdaptNet, and Climate Front Lines. In addition, recognizing that much of the work is conducted by consulting groups or researchers under contract, and many times this never makes it into the peer-reviewed literature, we sent messages to relevant web fora and email discussion lists to identify gray literature (e.g., reports or working papers). The ratio of peer-reviewed literature (journal articles and book chapters) to gray literature cited in this report is roughly three-to-one.

This paper is divided into several sections. Section 2.0 addresses the conceptualization of vulnerability and identifies the most common frameworks used in spatial VA. Section 3.0 provides an overview on data needs for spatial VAs, and Section 4.0 addresses common methods. Examples are given from multiple sectors, including cropping systems, livestock systems, water resources, fisheries, natural hazards, human health, poverty and food security, and urban vulnerability and critical infrastructure. The focus is on the developing world, with regional priority given to examples from Africa and Latin America and the Caribbean. Finally, Section 5.0 focuses on common issues related to spatial and temporal scale, uncertainty, and cartographic representation, and Section 6.0 provides key recommendations. Annex 1 provides a representative list of indicators used in spatial VAs and Annex 2 provides sample results for a number of spatial vulnerability assessments related to water resources.

2.0 DEFINITIONS AND FRAMEWORKS FOR VULNERABILITY ASSESSMENTS

This section defines vulnerability and describes some of the major conceptual frameworks utilized in vulnerability mapping: the Intergovernmental Panel on Climate Change (IPCC) framework (Parry et al. 2007), extended vulnerability frameworks (Turner et al., 2003; Birkmann, 2006), and the livelihood framework (Carney, 1998a and b). Beyond vulnerability frameworks, we also consider the IPCC's Special Report on Climate Extremes (SREX) risk management framework, which focuses on the probabilities of extremes of different magnitudes (IPCC, 2012).

Vulnerability can be defined as the degree to which a system or unit is likely to experience harm due to exposure to perturbations or stress (Turner et al., 2003). The concept of vulnerability originated in research communities examining risks and hazards and entitlements (Adger, 2006). In the risk and hazards community, the vulnerability concept emerged out of the recognition by these research communities that a focus on stressors alone (e.g., floods or earthquakes) was insufficient for understanding responses of, and impacts on, systems exposed to such stressors. With the concept of vulnerability, it became clear that the ability of a system — whether an economy, an economic sector, a population group, or an ecosystem — to attenuate stresses or cope with consequences through various strategies or mechanisms constituted a key determinant of impacts on that system and system response.

In the last decade, the terminology of vulnerability has been refined as researchers and policy makers have focused increasingly on vulnerability to climate change impacts. There are essentially two major conceptualizations of vulnerability (O'Brien et al., 2007; Füssel, 2009). The first is *contextual vulnerability*, which focuses on factors that determine a system's ability to withstand and recover from shocks. This approach comes out of political economy, and focuses on the intrinsic characteristics of a population (e.g., age, sex, socioeconomic status, ethnicity, livelihood strategies, etc.) and other factors (e.g., institutions, entitlements, historical inequalities, market forces) that may influence a population's (or system's) ability to withstand stressors. There is often a strong emphasis on differential vulnerabilities across social strata, and a concern for poor or marginal groups.

The second conceptualization is *outcome vulnerability* (Füssel 2009: 5), which "represents an integrated vulnerability concept that combines information on potential climate impacts and on the socio-economic capacity to cope and adapt." The IPCC framework builds on this, in that vulnerability is considered to be a function of *exposure* to climate impacts, including variability and extremes, and the *sensitivity* and *adaptive capacity* of the system being exposed (Parry et al., 2007). The three components can be expanded on as follows:

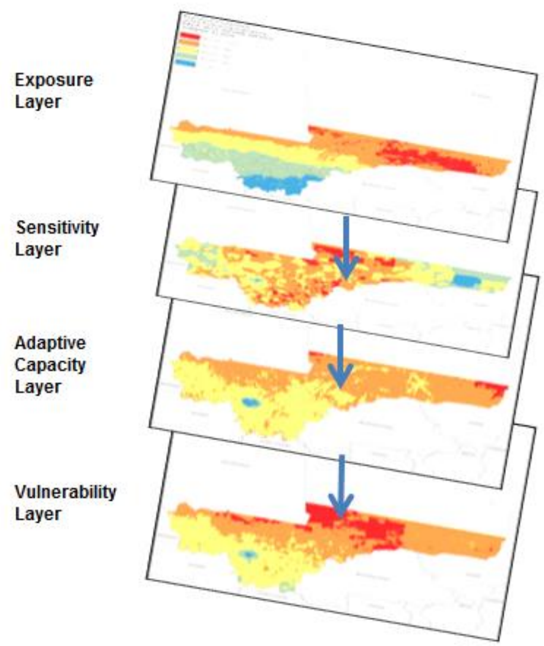
- E = exposure — size of the area and/or system, sector or group affected (i.e., does the event occur there or might it occur there under climate change?), and the magnitude of the stressor.

- S = sensitivity — the characteristics of a system or population and the governance/market structures that influence the degree to which it is affected by stressors.1
- A = adaptive capacity — capacities of the system, sector or group to resist impacts, cope with losses, and/or regain functions.

The IPCC definition suggests that the most vulnerable individuals, groups, classes, and regions or places are those that (1) experience the most exposure to perturbations or stresses, (2) are the most sensitive to perturbations or stresses (i.e., most likely to suffer from exposure), and (3) have the weakest capacity to respond and ability to recover (Schiller et al., 2001). In Section 3.0, we discuss further some of the conceptual issues underlying the IPCC definition, and provide examples of indicators that are frequently used to measure these components.

The IPCC framework is the most commonly used framework for vulnerability mapping (de Sherbinin, 2013; UNDP 2010). In this approach, composite spatial indices of vulnerability are developed based on spatial data layers representing the different components of vulnerability. These may be produced based on averaging/adding normalized indicators (i.e., variables whose value ranges have been standardized in order to make them comparable to one another) representing each component, or via principal components or cluster analysis. In a strict sense, this is what is meant by a vulnerability map. Often the individual components will be shown as separate maps or map insets. Figure 1 is a rendering of a vulnerability mapping for the southern part of Mali, including a combination of data layers rolled up into an overall vulnerability map. Areas of high vulnerability may be termed "hotspots."

FIGURE 1. SCHEMATIC DIAGRAM OF DATA LAYERS REPRESENTING ASPECTS OF VULNERABILITY



Source: de Sherbinin et al., 2014

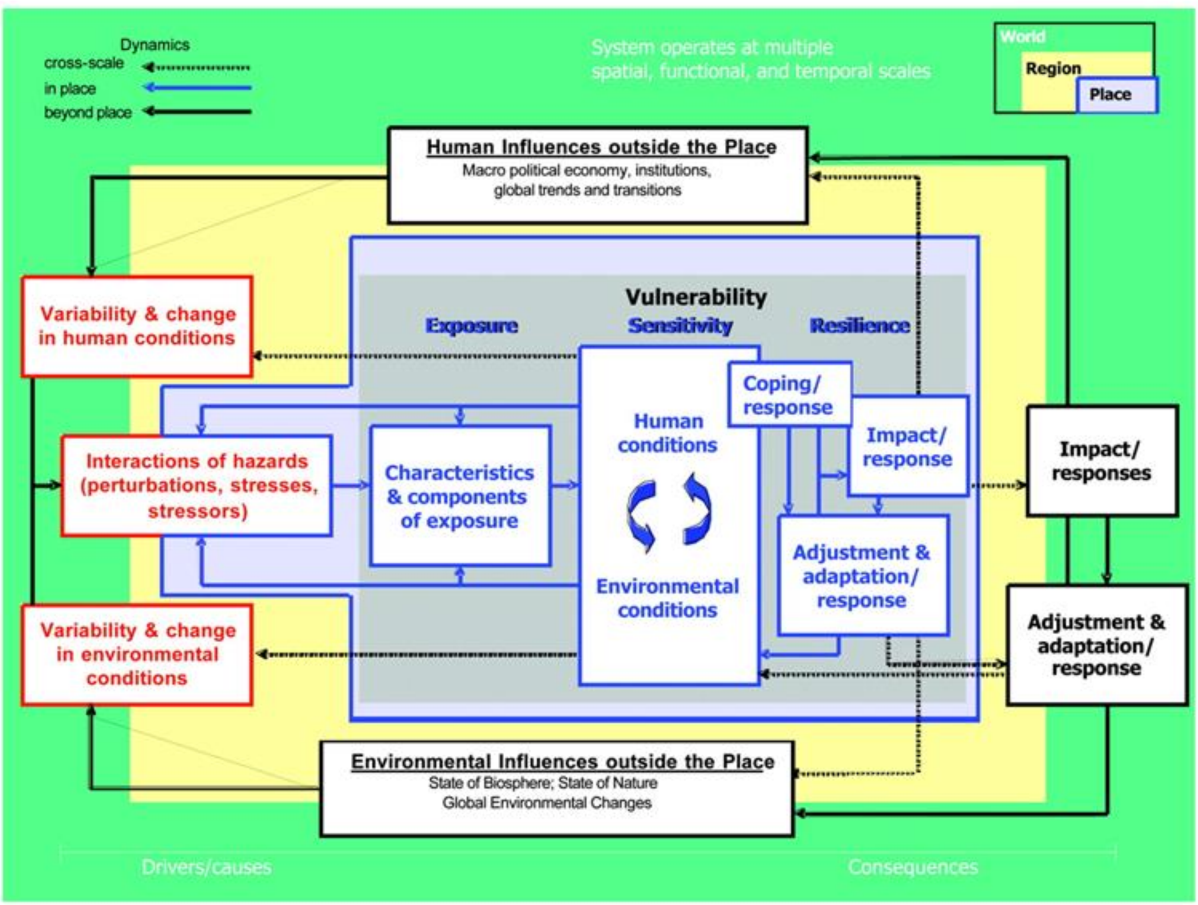
This report also describes a number of efforts based on process-based modeling (e.g., crop and hydrological models) in which climate scenario data are one input into models predicting future crop yields or water resource constraints. Although these are more properly identified as *impact* maps and not vulnerability maps, since they may or may not include sensitivity and adaptive capacity (some crop models make assumptions about improved seeds or soil water management), the results may be an input to a broader spatial VA. Similarly, there are what might be termed impact assessments (exposure mapping) in which only current and future climate impacts are considered. This kind of information can be considered in conjunction with sensitivity and adaptive capacity indicators to understand patterns of vulnerability, or in the context of risk management.

---

1 In modeling approaches, sensitivity can represent the dose-response function (e.g., the impact on crop yields or water stress of an X° rise in temperature or Y percent change in precipitation).

Extended vulnerability frameworks, such as those described in Birkmann et al. (2013), Birkmann (2006), and Turner et al. (2003) (Figure 2), generally seek to expand on elements of the IPCC framework by including a broader array of place-based contextual factors and conceptualizing the feedbacks among elements. They recognize that as the system changes, it may in turn have impacts on the stressors, which is the essence of the "coupled socio-ecological system" (Holling, 2001). In vulnerability mapping, these frameworks are primarily useful for "opening up the box" of vulnerability and helping analysts to identify a broader array of factors that may affect vulnerability, and to better understand proximal and distal drivers of vulnerability.[2] However, data and model limitations render it difficult to implement these frameworks, which are characterized by complex spatio-temporal dimensions and scales. In Preston et al.'s (2011) review of 45 vulnerability mapping studies, only 9 percent of the studies employed expanded frameworks. There is a sense in which the theoretical and conceptual sophistication of the framing of vulnerability has outrun the utility of such frameworks for assessment purposes (Levy, 2012; Preston, *personal communication*).

FIGURE 2. THE EXTENDED VULNERABILITY FRAMEWORK

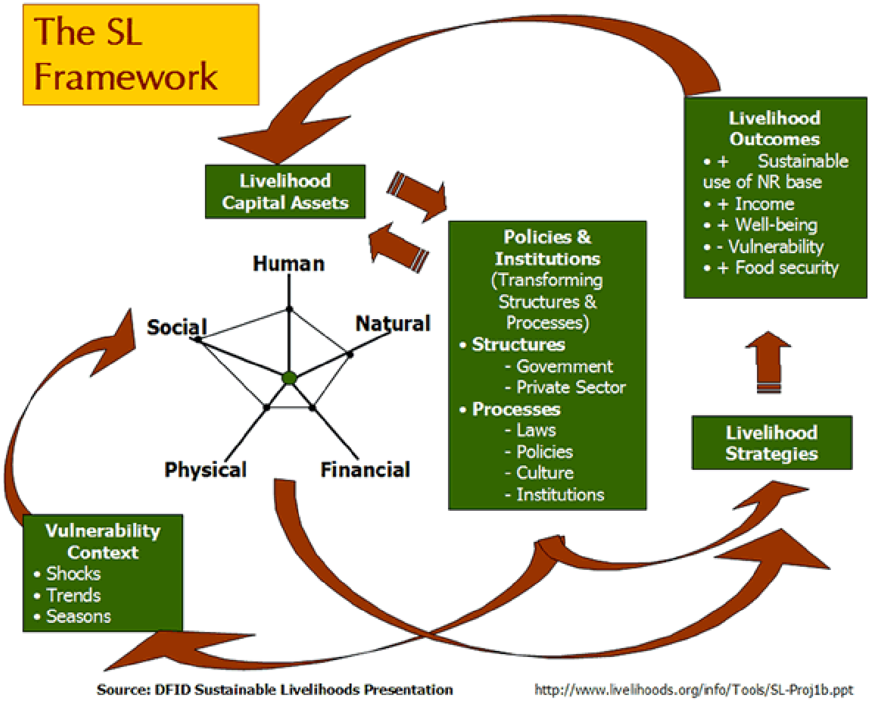


Source: Turner et al., 2003

[2] According to Abson (2013, *personal communication*), "lack of income might be a proximal cause of food insecurity, while lack of education is the ultimate drivers that determines the proximal cause. More consideration of the relations between such distal/proximal drivers are required in climate vulnerability studies."

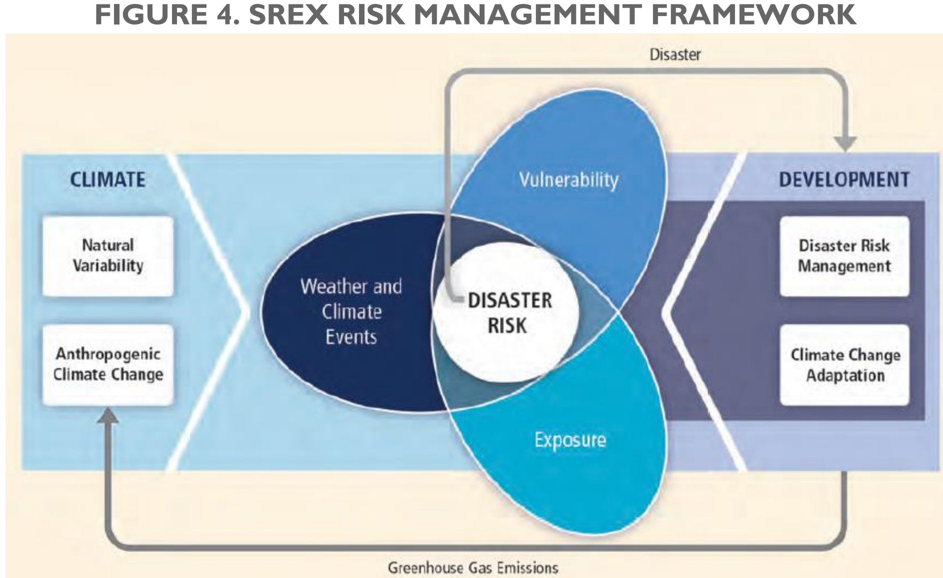
The United Kingdom's Department for International Development (DFID) sustainable livelihood framework (Carney, 1998a and b) has been employed in some vulnerability mapping efforts in least developed countries (Figure 3). The framework described five capitals deployed by natural-resource dependent households: natural capital (e.g., assets such as water, soil, timber, and non-timber forest products), social capital (e.g., interpersonal networks, membership in groups, and access to wider institutions of society), human capital (e.g., formal and informal education, local ecological knowledge, the ability to work, and good health), physical capital (e.g., land, tools, oxen, roads, and markets), and financial capital (e.g., cash savings, supplies of credit, and regular remittances and pensions) (de Sherbinin et al., 2008). At coarse scales, these capitals are not easy to map; at local scales, it may be possible to map them using participatory techniques. However, some mapping efforts (e.g., Warner et al., 2009, below) have broadly used livelihood security, sometimes in combination with ecosystem services (Reid et al., 2005), as an analytical framework for mapping livelihood assets that may be impacted by climatic changes.

FIGURE 3. THE DFID SUSTAINABLE LIVELIHOODS FRAMEWORK



The IPCC SREX (2012) introduced the SREX framework, which separates out exposure and includes vulnerability as a separate component that combines the sensitivity and adaptive capacity elements of the IPCC framework (Figure 4). Vulnerability in this case is analogous to contextual vulnerability. Some have found that this is more practical in a risk management

FIGURE 4. SREX RISK MANAGEMENT FRAMEWORK



Source: IPCC, 2012

framework, since it more clearly separates out the climatological elements from the system being exposed. Risk management focuses on understanding the probability distributions of weather and climate events of certain magnitudes, which is vital for disaster preparedness and infrastructure construction, whereas vulnerability assessments tend to emphasize underlying societal vulnerabilities and factors that put people and infrastructure at risk. Thus, a major focus is examining the "long tail" of extremes, such as floods and droughts, and their changing distributions and potential impacts on infrastructure or cropping systems (i.e., disaster risk). However, risk management frameworks tend to give second-order importance to longer-term trends in average rainfall or temperature, which can also have major livelihood implications.

While the range of frameworks and interpretations of vulnerability and resilience can be bewildering, for spatial VA it is generally sufficient to be explicit about the framework used and the reason for choosing it. Whatever one's choice, the framework needs to be "fit for purpose," in terms of illuminating the features of interest in the complex coupled human-environment system. However, at a minimum, any quantitative vulnerability assessment requires definition of the *system* of analysis (what is vulnerable?), the *valued attributes* of concern (why is it important?), the *external hazard* (to what is the system vulnerable?), and a *temporal reference* (when?) (Füssel, 2007). Preston et al. (2009) also note that when vulnerability mappers engage with stakeholders, who may include decision-makers, the framing must take into account the needs and understanding of those decision-makers, an issue we return to in Section 4.2.

We turn next to issues with the measurement of vulnerability.

3.0 MEASURING VULNERABILITY

This section assumes some familiarity with climate vulnerability assessment in general and spatial VA in particular. Readers with less familiarity may wish to read the examples describing climate change impacts on the water sector found in Annex 2. Also, the topic of vulnerability indicators, which is closely related, is addressed in the USAID Africa and Latin America Resilience to Climate Change Project (ARCC) technical report on composite indicators (Baptista, 2013).

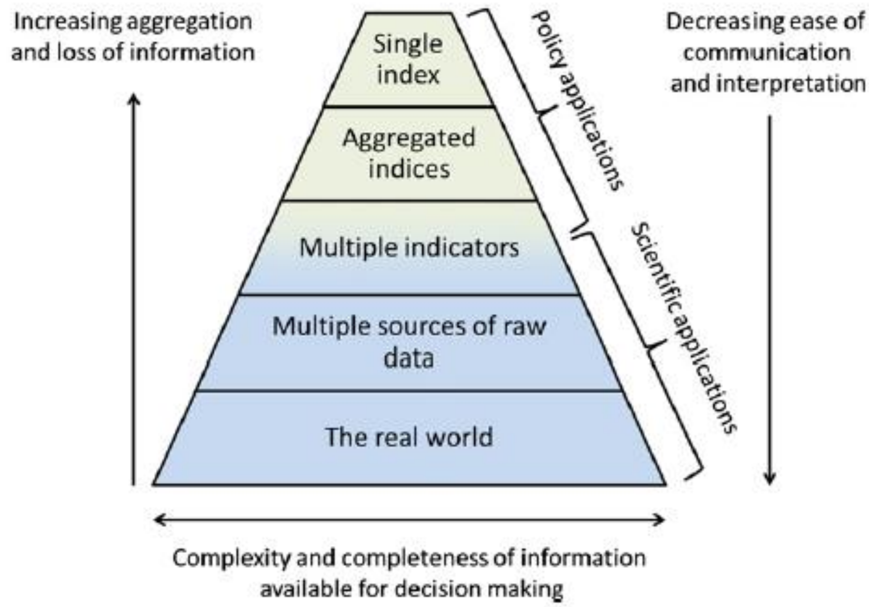
There are a number of conceptual challenges in vulnerability mapping that need to be addressed before turning to the question of data and indicators. Hence we address those first, and then proceed to a more specific discussion of data sources and limitations for the "exposed elements" (the systems, economic sectors, or groups that define the "what" of the VA) and the climate stressors (the external hazard of the VA).

3.1 CONCEPTUAL ISSUES

The topic of data and indicators, or "measurement" more broadly, is fundamental to the process of developing spatial indices of vulnerability. As Abson (2012: 516) states, indices have the advantage of reducing "the amount and complexity of the information that must be communicated while simultaneously providing an indication of the interaction of multiple, spatially homogenous indicators through a single aggregated vulnerability 'score.'" There is an inherent trade off, however, between the richness of information and the complexity of real world, and the communicability and utility of that information for policymaking (Abson, 2012) (Figure 5). Furthermore, because vulnerability cannot be measured directly,[3] it involves a process of identifying "indicating variables," which point to the construct of vulnerability, and aggregating them (Hinkel, 2011). Thus for the sensitivity part of the IPCC framework, it is common to use indicating variables such as poverty levels and infant mortality rates (IMR). For factors such as coping or adaptive capacity, measures might include education, institutional capacity, funding levels for disaster risk reduction (DRR), or insurance coverage. Even where adequate data are available, these are often less-than-adequate proxies for intrinsic vulnerability. As Kasperson et al. (2005: 149) write, "Political and social marginalization, gendered relationships, and physiological differences are commonly identified variables influencing vulnerability, but incorporating this conceptual understanding in global mapping remains a challenge."

[3] Vulnerability has been termed an "emergent phenomena," in that it *emerges* from the stresses on the system, and therefore cannot easily be measured directly. Generally, a stressor, such as a major storm or flood, is said to reveal the underlying vulnerabilities of the coupled human-environment system. Two recent examples include the earthquake that struck Haiti in January 2010 and the one that struck Chile in February 2010, which was 500 times stronger (though at some distance from populated areas). The Haiti earthquake was far more devastating, and revealed underlying fragility in buildings and infrastructure, endemic poverty, and failures of governance that contributed to far higher casualties (Kurczy et al., 2010).

FIGURE 5. TRADE-OFFS BETWEEN COMMUNICABILITY AND INFORMATION RICHNESS



Source: Abson et al., 2012, reproduced with permission

Differentiating between indicators that measure sensitivity (or susceptibility) versus adaptive capacity may be challenging (Fekete, 2012). For example, illiteracy or low education levels could be measures indicating high sensitivity and low adaptive capacity. According to Lucas and Hilderink (2004), determinants of coping/adaptive capacity are awareness, ability, and action. The ability to cope in the face of a climate stressor, or to take action with regard to restoring and rebuilding, are heavily influenced by insurance markets, emergency services, and broader institutions and governance structures that can be difficult to measure (Chen et al., 2011). As an example, an assessment of climate vulnerability in southern Africa by Midgley et al. (2011) provides a comprehensive list of indicators by IPCC category, including 16 exposure indicators, 23 sensitivity indicators, and 12 adaptive capacity indicators (Annex 1). Yet the rationale for including a given indicator in the sensitivity or adaptive capacity categories can seem somewhat arbitrary (e.g., percent land under irrigation is a sensitivity indicator but could arguably be seen as an adaptive mechanism for rainfall deficits). This could be seen as an argument in favor of collapsing sensitivity and adaptive capacity into an overall "social vulnerability" term similar to the SREX framework, were it not for the fact that addressing them in policy contexts may imply a different set of interventions.

Adger and Vincent (2005) and Preston et al. (2011) argue that indicators should only be selected on the basis of theoretical linkages, and with some understanding of the relative contributions of exposure versus sensitivity and adaptive capacity to overall vulnerability. The reality is, however, that the precise contributions are difficult to quantify. Uncertainties in underlying data layers and insufficient understanding regarding the relative importance of the different components and the functional form of relationships among them makes spatial VA challenging, especially when covering larger regions at coarser spatial scales, an issue we take up again in Section 5.2. While recognizing the many conceptual ambiguities in adequately capturing vulnerability in quantitative metrics, spatial VA is still the only approach available for providing some degree of spatial precision in targeting interventions and identifying the spatial dynamics of vulnerability. Most of its shortcomings are inherent in any effort to model a complex world.

3.2 MEASURING THE EXPOSED ELEMENTS

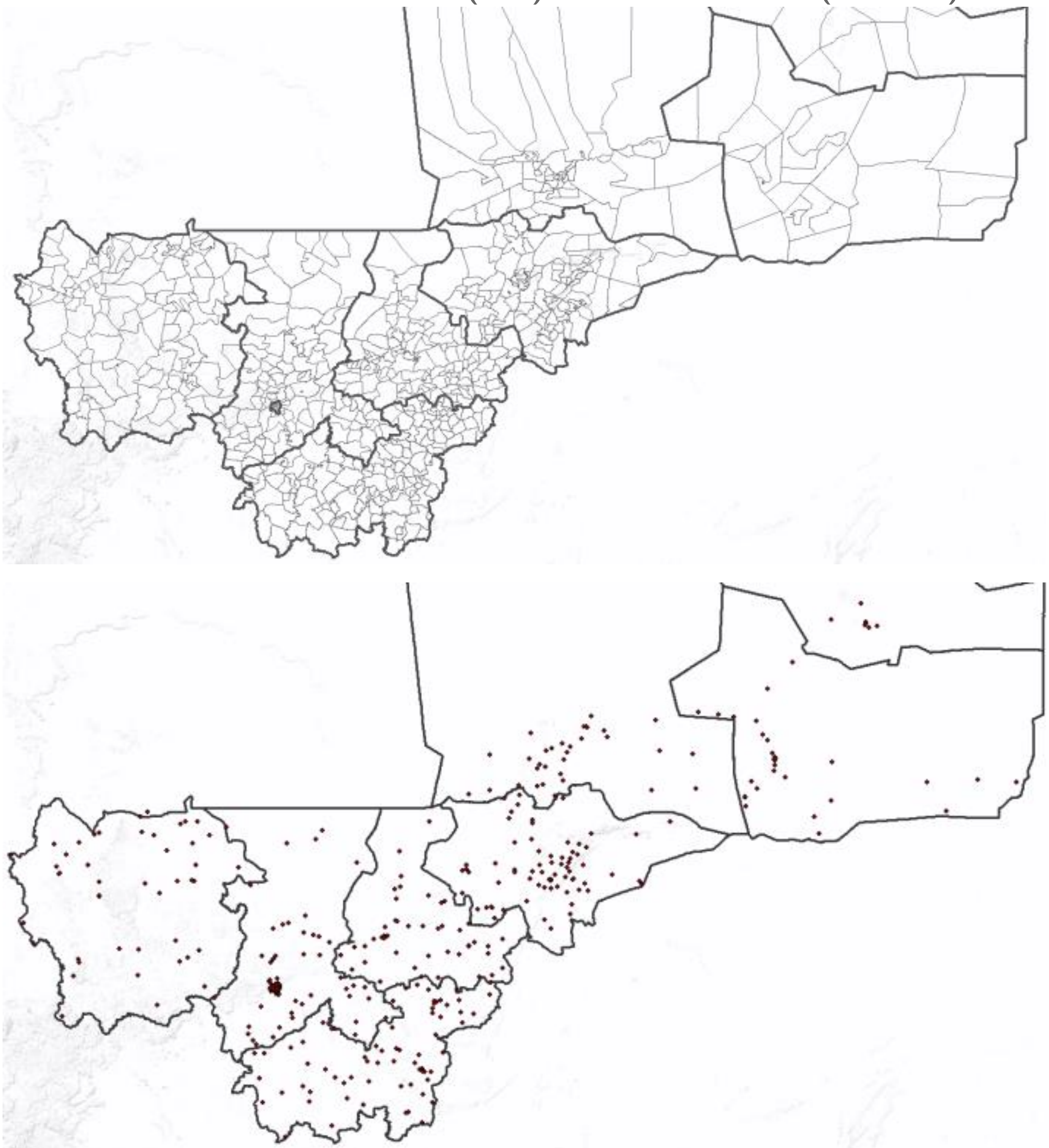
In this section, we address the majority of spatial VA approaches that rely on available data, rather than participatory mapping approaches (Section 4.2) that generate their own data. Measurement of the exposed elements entails cataloging of available data, and evaluating them in terms of their conceptual proximity to the component being measured, their spatial resolution, how up-to-date they are, and their reliability and validity. It may be possible to set up a scoring system across these axes in order to communicate the confidence that the developers have in each data set underlying the assessment (e.g., see Appendix A, Table A.6, of Yale Center for Environmental Law and Policy [YCELP] et al., 2005). At a minimum, it is recommended for developers of spatial VAs to provide ample metadata on each data layer, including an assessment of data limitations.

We addressed some of the issues surrounding the conceptual proximity of indicators to the component being measured above. Two measures may purport to address the same thing, but one may be conceptually and methodologically closer than the other. For example, an ideal sensitivity measure might be household wealth as measured by material assets through a Demographic and Health Survey (DHS), or small area estimates of poverty on a census tract basis. These may be available for a national assessment, if the statistical infrastructure is fairly robust, but they are less likely to be available for an international assessment. So measures have been developed such as "infrastructure poverty" (Midgley et al., 2011; Abson et al., 2012), which measures the population count relative to satellite observed night-time lights, and identifies areas that are poor on the basis of lower brightness per population in a given area. This, however, relies on certain assumptions concerning the luminosity of an area and the degree to which a population is under-served by electricity, and also is subject to compounding uncertainties such as the spatial location of populations (census units are often too coarse) or the effects of dense vegetation on luminosity in relatively affluent areas. Thus, this might be termed a proxy measure of less validity than direct measurements of poverty or affluence. In other words, the direct measures of household wealth or poverty are closer in proximity to the sensitivity category than the infrastructure poverty measure, even if the latter may be resolved at a higher spatial resolution.

Consideration of the spatial resolution of input variables is important for any vulnerability assessment. The next section will address the spatial resolution of climate indicators, which in the absence of downscaling can be quite coarse (grid cells on the order of 50s to 100s of km on a side). Here we focus on variables representing social vulnerability or other systems of interest. Figure 6 shows the relative input unit size for a variety of measures in a spatial VA for Mali. At left are depicted the communes nested in cercles (equivalent to provinces), and at right the DHS cluster centroids, which represent the approximate locations of surveys responses from 10 households. Data at the commune level would generally be considered adequate, but data at the cercle level would be too coarse to adequately identify spatial patterns at the subnational level. The DHS centroids tend to be denser in more populated areas, and hence spatial interpolations between the cluster points are more robust in those areas and less robust in the sparsely populated north of the country.[4] Note that the data reporting units will have an impact on statistical properties, since the larger or more populated the unit the more averaging that occurs. Indicator values in smaller units will typically exhibit greater variance than in larger units (see Section 5.1.3 on the modifiable areal unit problem).

[4] Bayesian spatial interpolation between cluster points is recommended because it provides a spatial error map along with the interpolated surface.

FIGURE 6. INPUT UNITS FOR MALI SPATIAL VA: COMMUNES AND CERCLES (TOP) AND DHS CLUSTERS (BOTTOM)



Source: de Sherbinin et al., 2014

Spatial layers representing cropping systems, land cover types (e.g., forests, biomes), water resources, fisheries, or other exposed elements tend to vary in spatial resolution depending on the data collection mechanism. Global land cover maps vary in resolution from 300m to 1km, based on the resolution of the satellite sensors utilized.[5] Cropping system maps tend to be coarser in resolution, at closer to 5 arc-minutes (20km) (e.g., Ramankutty et al., 2010). Livelihood systems can be even coarser, encompassing broad areas with common livelihood strategies.

Regarding the "recency" of data, up-to-date data can be difficult to obtain in many regions, and it is not uncommon to find vulnerability maps with input layers that are more than 10 years old. If the situation on the ground has changed dramatically owing to an ensuing event (e.g., conflict, economic downturn, or a major disaster), then the indicators may no longer be valid. There may be little that can be done regarding the recency of data other than to document clearly the reference date of all the data layers in the metadata, and to highlight major uncertainties owing to out-of-date data in the document that accompanies the maps.

The last two evaluation criteria are reliability and validity. From a statistical standpoint, reliability is the degree to which an instrument or assessment tool produces stable and consistent results. Validity refers to how well an instrument measures what it is purported to measure. Thus, a survey of poverty may be said to be reliable to the degree that it captures certain metrics consistently over time and space, and it is valid insofar as it accurately captures parameters relevant to poverty (e.g., it captures income to within a few cents per day or malnutrition with a modest standard error). For productive systems, some land cover types are easier to map than others, and most global land cover maps are derived from semi-automated techniques (i.e., decision-tree algorithms) that require relatively little visual interpretation, meaning that the approach is likely to be more accurate to some regions than others.[6] While land cover may be measured with fairly high degrees of confidence (and quantifiable uncertainty), other parameters may require accurate *in situ* data from agricultural censuses or river gauges that may be difficult to obtain or contain important gaps. These data collection systems are notoriously sparse in the most climate-sensitive regions such as Africa.

Typically it is very difficult to obtain information on the reliability and validity of many data layers; even when this information is available, time constraints and the multi-disciplinary nature of spatial VAs may make it difficult in practice to document and assess uncertainties in the underlying data fully. This is certainly best practice and should be encouraged; indeed, all composite vulnerability maps should ideally include an accompanying uncertainty map. Process-based impact model outputs typically either provide multiple scenarios or an accompanying uncertainty map. Even where information on the standard errors for data layers are absent, judgment calls need to be made concerning data sources. Developers of spatial VAs would do well to read through data documentation and to assess the data visually (in map form) and statistically to understand better spatial patterns and basic descriptive statistics such as mean, median, standard deviations, skewness, and outliers. For example, if administrative units with extremely high values are surrounded by units with very low values for the same parameter, this may point to data quality issues unless there is an explanation for the anomaly. Running spatial statistical tests in Geoda or other spatial statistics packages (Moran's I or mapping of residuals for ordinary least squares [OLS] regressions) can help to identify patterns in the data that may be difficult to pick up visually.

Whereas many spatial VAs do include future climate scenarios, they generally do not include projected changes in the spatial distribution of populations or other exposed elements (Preston 2012), which themselves have considerable uncertainties, nor do they generally factor in likely adaptation responses,

---

5 New Landsat resolution (30m) land cover products will soon be available as well.

6 For example, global land and forest cover maps have difficulty accurately capturing woody vegetation cover in the Sahel, which is sparsely vegetated. Much has been made of the regreening in this region, yet owing to the coarseness of their resolution and the algorithms used, greenness maps based on the normalized difference vegetation index (NDVI) are almost entirely reflecting the presence of herbaceous vegetation (Tappan, *personal communication*).

which may be hard to predict. Work by Giannini et al. (2011) and Preston (2013) represent exceptions to this general rule, in that they do include population and economic projections. Efforts are now underway to develop spatially explicit population scenarios for the shared socioeconomic pathways (SSPs) (Jones, 2013), but the task of anticipating likely future population distributions can be rendered difficult by unanticipated economic or conflict events that can alter migration patterns. Because of the difficulty of projecting the exposed elements, most spatial VAs extrapolate from *current* vulnerability to climate variability and extremes to identify how climate change *may* alter the climate component, leaving aside changes in the populations or sectors/systems that will be impacted. Yet, Preston (2013) notes that natural disaster losses have increased significantly in the United States owing more to growth in socioeconomic exposure than to changes in the frequency or intensity of extreme events, so ignoring future changes in the spatial distribution and "density" of exposed systems is likely to yield suboptimal results in a risk assessment framework.

3.3 MEASURING THE CLIMATE STRESSORS

Turning to climate data, or the "exposure" aspect of vulnerability assessments, it should be stated up front that all vulnerability assessments — spatial or not — encounter issues with the use of climate data. The intent here is not to develop a comprehensive list of issues, which can be found elsewhere (e.g., PROVIA, 2013b), but rather to focus on the issues most commonly encountered in spatial VAs.

Given difficulties in using climate scenario data from general circulation models (GCMs), many spatial VAs use past climate variability or recent histories of extreme events (e.g., flood or drought occurrence or economic losses associated with them) as proxies for future changes. The underlying assumption is that those regions that are most exposed today will likely have similar or greater levels of exposure in the future. Frequently used data collections that assess the frequency of extremes include the World Bank Hazard Hotspots collection (Dilley et al., 2005; Center for Hazards and Risks Research (CHRR) et al., 2005) and the United Nations Environment Programme (UNEP) Global Assessment Reports (United Nations Internationals Strategy for Disaster Risk Reduction [UNISDR], 2009). Both efforts faced significant methodological challenges to map the frequency of extremes, since flooding is generally a local phenomenon that is difficult to characterize globally (the UNEP report was more sound in this regard), and drought metrics are heavily dependent on regional definitions of rainy seasons and long-term historical averages of rainfall that are difficult to capture in global maps (Lyon, *personal communication*). Furthermore, data sparseness and gaps can plague efforts to map historical climate extremes. Local-level fine scale analyses,[7] particularly in developing countries, may run into problems with obtaining adequate meteorological station data to adequately represent local climatology.

Broad-scale efforts, from regional to global, generally have to rely on long-term historical climate data sets, all of which rely to some extent on meteorological station data networks and satellite data. This may be less problematic for temperature data, for which interpolation techniques are reasonably robust; for precipitation, these data sets may run into issues with the spatial coverage of the underlying gauge-based data. This affects drought mapping and a range of other applications. In an eight-country study of climate variability, livelihoods, and migration (Warner et al., 2012a), assessment of climate reanalysis data for given localities compared to local rain gauge data often produced different conclusions with regard to variability, drought, or even trends over recent decades. Common historical data sets range in

[7] Note: Cartographers and geographers use the term "small-scale" to refer to maps that cover large areas (regional to global) and "large-scale" for maps that cover small areas (provinces/states down to localities). These scales refer to the number of map units to real world units, so a small scale map with a scale of 1:1,000,000 is a map in which 1cm on the map represents 10km on the Earth's surface. However, this often creates confusion on the part of non-specialists. To avoid confusion we use the terms "broad-scale" for maps that cover large areas and "fine-scale" for maps that cover small areas.

scale from 0.5 degrees to 2.5 degrees, or grid cells of 55km to 275km on a side at the equator (e.g., Climate Prediction Center Merged Analysis of Precipitation, National Centers for Environmental Prediction [NCEP]/National Center for Atmospheric Research [NCAR] Reanalysis, and European Centre for Medium-Range Weather Forecasts [ECMWF] Reanalysis). In data-poor developing regions, characterizing past climate accurately can be difficult owing to gaps in monitoring networks, temporal gaps in measurement at given stations, and discrepancies between satellite measurement and gauges (Dinku et al., 2011).

Those that do use climate model outputs run into a number of issues that are common to any assessment that seeks to incorporate information about likely future climate. A fundamental challenge for vulnerability mapping that relies on accurate prediction of extremes, such as that for disaster response or humanitarian needs, is the limited ability of GCMs to capture historical variance or future extremes (IPCC, 2012; Brown and Wilby, 2012). For example, in a comparison of observed and GCM-based downscaled annual streamflow estimates for the northeastern United States, Brown and Wilby found that "downscaled GCMs underestimate both the standard deviation and [temporal] autocorrelation when compared with observations" (2012: 401). The use of multi-model ensembles only tends to reduce variance further, since they average multiple model runs together, resulting in a dampening of the extremes.

Coarseness of the model outputs, ranging in resolution from 1 to 2 degree grid cells (110–220km on a side at the equator), is also a concern. Because of their inability to accurately represent some local-scale climate phenomena (e.g., orographic precipitation), downscaled climate information is increasingly being used for climate vulnerability assessments. For those studies that do use regional models, a significant issue is variability across model runs. For example, in a study of regional models as inputs to crop modeling in Africa, Oettli et al. (2011: 1) find that "the performances of regional models in reproducing the most crucial variables for crop production are extremely variable." The result is that there is a large dispersion in crop yield prediction due to the different physics in each regional model and also the choice of parameterizations. Oettli et al. note that two configurations of the same regional model are sometimes more distinct than those of different regional models.

While climate model downscaling may be an option for well-resourced spatial VAs, most do not have the resources to do so. Only a handful of the studies reviewed here used downscaled climate models. Fortunately, a new generation of higher resolution GCMs with outputs in the range of 20km^2 is being produced for the IPCC Fifth Assessment report (e.g., Kitoh, 2012). An issue with these models, however, is the sheer volume of data that is generated, considering that GCM time steps are generally every 30 minutes. Given the volumes of data, users will need to rely on pre-calculated parameters of variability, since desktop computers are unlikely to be able to handle the processing. The complexity of formats and outputs can also overwhelm the non-climate scientists who often conduct spatial VAs. Another common issue is that the broad changes in temperature and precipitation are used as proxies for climate variables that are most relevant for the system under consideration. For agricultural systems, water management, or natural hazard prediction, the most important variables would be anticipated change in rainy season onset, gaps in rainfall during growing seasons, changes in drought periodicity, or changes in rainfall duration and intensity. Many of these changes are already occurring (IPCC, 2012; Warner et al., 2012a; Warner et al., 2012b). Yet these parameters require significant additional processing to extract from either historical climate data or climate model outputs. Finally, most climate models do not take into account the possibility for abrupt change or tipping points in the climate system (e.g., Duarte et al., 2012). The primary way to address this in spatial VA is to develop scenarios of future extreme events, or a "stress test" approach (Storch et al., 2011; Brown and Wilby, 2012).

It is worth noting that even something as "simple" as mapping vulnerability to sea level rise (SLR) can hold uncertainties. SLR impacts in theory are easy to model, since the impacts are constrained to low elevation coastal zones and can be approximated with a digital elevation model (DEM), and exposure is simple to assess: you are either in or outside the area at risk. Several reports and articles have assessed global SLR impacts on coastal populations and assets (e.g., de Sherbinin et al., 2012; McGranahan et al., 2007; Dasgupta et al., 2007; Nicholls et al., 1999), and Klein (2012) found 13 articles covering the Nile Delta alone. Yet, here again, there are significant uncertainties. Most mapping efforts rely on maps of current mean sea level and elevation as defined by the Shuttle Radar Topography Mission (SRTM), one of two high-resolution globally available DEMs, which has a vertical accuracy in low slope areas of only +/- 4–5m (Gorokhovich and Voustianiouk, 2006). This means that areas that are mapped at 0 m, or current sea level, could in fact be -5 m (submerged) or +5 m (well out of harm's way for years to come). Furthermore, the time by which a given sea level will be attained is not known with great certainty (Rahmstorf, 2012; Pfeffer et al., 2008), SLR will vary regionally, and SLR will be complicated by tides and storm surge in certain locations (Strauss et al., 2012; Tebaldi et al., 2012). The best approach for local assessment is to rely on lidar, Geographic Positioning System (GPS), or high-resolution stereoscopic imagery for elevation data, and to develop local models for storm surge.

Taken together, the data challenges translate into higher levels of uncertainty. While the list of data problems may seem like an insurmountable challenge to spatial VAs, it should be underscored that any effort to characterize an uncertain future will face challenges; yet for decision making related to climate adaptation, there are few alternatives to making do with the best available data. A key issue is uncertainty and risk communication, which is addressed further in Section 5.3. Here it is worth noting that the power of maps to summarize information is partially offset by their ability to hide uncertainties, and that developers of climate vulnerability or hotspot maps need to think about how to communicate those uncertainties and increase the level of transparency regarding likely sources of error both in the reports that accompany the maps and (to the extent possible) in the maps themselves.

4.0 METHODOLOGIES FOR SPATIAL VULNERABILITY ASSESSMENTS

This section reviews four broad types of spatial vulnerability mapping by providing examples and assessing the appropriateness of each type to different kinds of applications. The first is the production of spatial vulnerability indices, where components of vulnerability are normalized as indicators and aggregated to create a spatial index. The architecture often is guided by a vulnerability framework such as the IPCC's exposure, sensitivity, and adaptive capacity, with indicators that are more or less closely related to these three components. The second approach is community-based and stakeholder-driven vulnerability mapping, which typically takes place in local jurisdictions over fairly small areas. Community-based mapping is in the tradition of participatory rural appraisal (PRA) and its variants, while the stakeholder-driven VA generally engages local authorities though it may include community members. The third approach, impact mapping, while technically not part of the "VA family," is commonly used for climate risk assessment; because it is part of the broader toolkit for assessing climate impacts spatially, we include it for completeness. The approach involves either the direct use of climate data or the integration of climate scenario data into process-based crop or hydrological models to generate maps of likely areas of high climate impacts.

None of the methods are necessarily superior to the others, nor are they mutually exclusive (e.g., one could have a participatory VA involving vulnerability indices), but the choice of method will depend on objectives, data availability, funding, and the time frame for the assessment. Spatial vulnerability indices are the most widely used, so we begin with these and give them slightly more treatment than the other methods. Examples in this section are meant to be illustrative rather than comprehensive; the literature in this area is large and growing rapidly, so it is difficult to be exhaustive.

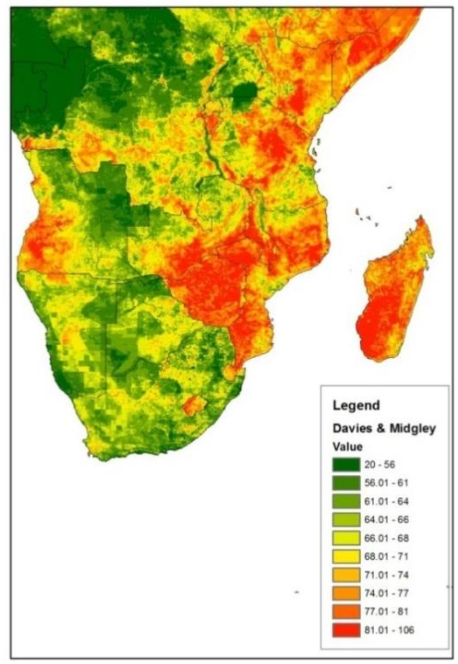
4.1 SPATIAL VULNERABILITY INDICES

Spatial vulnerability indices combine multiple data layers (or indicators) representing different aspects of vulnerability in such a way that vulnerability "hotspots" as well as areas of relatively lower vulnerability emerge from the integration of the layers. Here we review four approaches to aggregating or summarizing the information contained in the indicators in an overall index (the averaging/additive approach, principal components analysis, cluster analysis, and "geons") providing examples of mapping efforts that have used each method. We address in Section 5.1 some issues related to the bounding box, scale, resolution, and units of analysis that need to be addressed in any of these four approaches. A broader literature addresses some of the methods and pros and cons of aggregate indicators (e.g., Organization for Economic Cooperation and Development [OECD], 2006; Barnett et al., 2008; Klein, 2009; Hinkel, 2011; Baptista, 2013), which owing to space constraints we cannot address here.

4.1.1 Averaging and Additive Approaches

In the averaging or additive approach, a first step is normalization of the indicators. Owing to problems of incommensurability in measurement units of the raw data, the values for each layer need to be normalized (or transformed) to a consistent ordinal or unit-less scale (e.g., drought frequency or poverty levels on a scale from 0–10, from lowest to highest). As discussed in Section 2.0, the rescaled indicator layers are then averaged or added together to come up with a vulnerability score. The IPCC definition of vulnerability is the most frequently used framework, and one advantage of this approach is that separate maps for each vulnerability component (e.g., into exposure, sensitivity and adaptive capacity) can help decision-makers to analyze adaptation options.

FIGURE 7. VULNERABILITY MAP FOR SOUTHERN AFRICA



Sources: Davies and Midgley, 2010; Midgley et al., 2011

While the additive/averaging approach has a number of advantages, including a relatively high degree of transparency in its methods, there are a few challenges that need to be addressed. One challenge concerns how to weight the indicators, since the weighting will ultimately affect the visualization and interpretation of results. Most often, one finds that authors either weight factors equally or justify weights based on a number of criteria such as those discussed at the beginning of Section 3.2. Sensitivity analysis can assess the degree to which results are sensitive to the weightings applied. Other issues include issues of trade-offs and the functional form of the relationship among indicators. The issue of trade-offs addresses the underlying assumption that a strong score on one indicator can be seen to compensate for a low score on another, suggesting that they are perfect substitutes (Hinkel, 2011). For example, the same grid cell or census unit may have high average income and a high proportion of the population over the age 65. The former would theoretically be associated with low vulnerability and the latter with higher vulnerability. By averaging them together, one loses information that may be of value for adaptation planning (Fekete, 2012). The issue of functional form is related, and reflects the fact that most often in additive/averaging approaches, the indicators are added in a way that assumes a linear relationship among indicators, whereas the relationship could be log linear, curvilinear, parabolic, or exhibit strong thresholds. These issues are dealt with in more detail in Section 5.2.

A good example of this approach is the one developed for Southern Africa by Midgley et al. (2011) and Davies and Midgley (2010). They combine 16 exposure indicators (eight representing historical climate exposure and eight representing future exposure), 23 sensitivity indicators, and 12 adaptive capacity indicators into an overall vulnerability map (Figure 7). They apply differential weights (multipliers) ranging from 1 to 3 based on the degree to which the variable was felt to approximate the relevant IPCC term of interest and data quality considerations (Annex 1). They add all the indicators together (multiplying some of the indicators by a value of 1–3 depending on weight), and then rescale the final aggregation to produce the final map.

4.1.2 Principal Components Analysis

The second common approach is principal components analysis (PCA) and the allied method, factor analysis.[8] In this approach, the indicators are not grouped *a priori* into components of vulnerability, but rather the statistical relationships among the indicators are used to group them according to similarity in their spatial distributions. The idea is to break the n-dimensional (where n = the number of indicators) cloud of relationships among the indicators into a smaller set of uncorrelated principal components (PCs) that are linear combinations of the input variables. Because the PCs are uncorrelated, the scores associated with each PC encapsulate a unique aspect of the overall socio-ecological vulnerability represented by the original set of vulnerability indicators (Abson et al., 2012).

The number of PCs is equal to the number of variables, but each successive PC explains less of the overall total variation, thus the main information can usually be meaningfully captured by a few leading PCs. The developer needs to decide how many PCs to retain; a common method of component selection, the Keiser criterion, suggests keeping all components with an eigenvalue (which is output with other PCA statistics in common statistical packages) higher than 1. Each PC is interpreted as a z-score, though the directionality (whether positive z-scores represent high or low vulnerability) needs to be tested against the underlying data.

One advantage of the PCA is that it can help to illuminate the statistical relationships among the indicators used for a spatial VA. Each PC captures spatial covariance or correlation among the indicators and different PCs reflect uncorrelated patterns. The indicators with the highest loadings for a given PC can be functionally grouped to describe that component. This allows the developer to identify where different aspects of vulnerability are most intensely present. While the IPCC approach does allow development of component sub-indices, it does it on the basis of the theoretical rather than on statistical relationships among the indicators. Thus, a PCA approach can be complementary to the additive/averaging approach, providing additional information to policy makers. That said, there can be challenges in explaining the concept of principal components to stakeholders without much background in statistics.

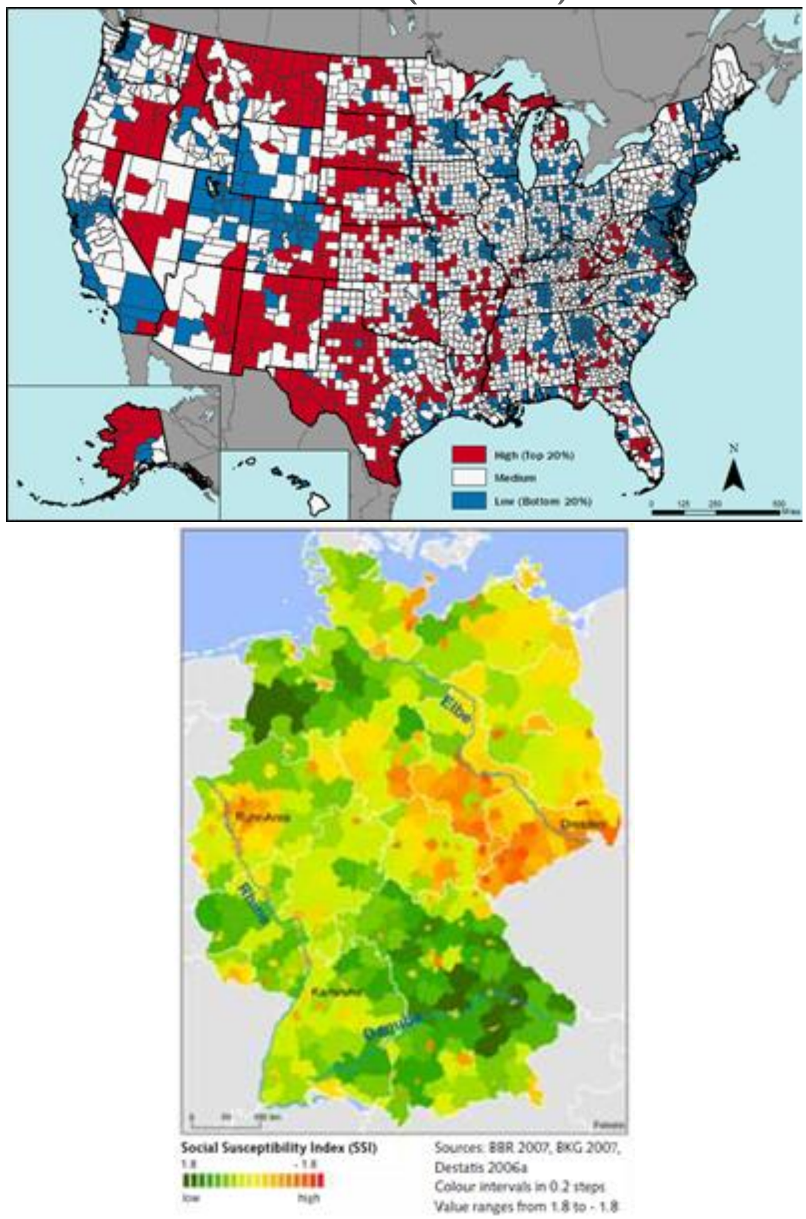
One of the first vulnerability indices to use this family of methods was the Social Vulnerability Index (SoVI) developed by Cutter et al. (2003) to measure the social component of vulnerability in the absence of climate and other biophysical hazards. They selected a subset of 42 variables among those collected by the U.S. Census Bureau and other government agencies that have been found to be highly predictive of vulnerability, and used those in a factor analysis to reduce the dimensions of vulnerability to 11 factors which are then averaged to produce an overall SoVI (Figure 8, top). Social and socio-economic vulnerability indices identified through PCA have been used in a number of contexts around the world. Examples include the social susceptibility index (SSI) for German counties (Fekete, 2010) (Figure 8, bottom), an elderly social vulnerability index for Jamaica (Crooks, 2009), and a socio-economic vulnerability index for a climate change and health assessment of Brazilian states (Confalonieri et al., 2009).

---

8 PCA is used to find optimal ways of combining variables into a small number of subsets, while factor analysis may be used to identify the structure underlying such variables and to estimate scores to measure latent factors. These approaches are particularly useful in situations where the dimensionality of data and its structural composition are not well known (University of Wisconsin, *undated*).

Abson et al. (2012) argue that the standard practice of averaging or summing indicator scores hides important information regarding the relations between the original variables. They created vulnerability maps for southern Africa based on PCA and compared them to the ones generated using the averaging approach. Although the patterns are broadly similar, they find that the averaging approach reflected patterns found in the individual PCs, but the "trade-offs" between different components of vulnerability reduced the extremes. While PCA has many strengths, since the components are statistically derived rather than being based on theoretical considerations, this study reveals that it may be challenging to attribute an intuitive meaning to a specific PC (see also Fekete, 2012 for a discussion of this point). For example, their first PC, which they term "poverty and health vulnerability," is dominated by infant mortality, poverty, agricultural constraints, and malnutrition. Their third PC, termed "infrastructure poverty and population pressure vulnerability," combines the following indicators with high loadings: population per net primary productivity, infrastructure poverty (a measure of population divided by night time lights), and travel time to major cities. It is hard to make sense of this except perhaps as a proxy for spatial isolation and population density.

FIGURE 8. SOVI PER COUNTY, USA (TOP), AND SOCIAL SUSCEPTIBILITY INDEX PER COUNTY, GERMANY (BOTTOM)



Sources: Hazards and Vulnerability Institute, 2013 (top); Fekete, 2010: 61 (bottom)

de Sherbinin et al. (2014) developed vulnerability maps for Mali using a number of data layers (Table 1), and aggregated them using both an averaging approach and PCA. For the averaging approach, each indicator was normalized to a 0–100 score, and these were averaged first into components (we doubled the weights for four sensitivity indicators: child stunting, household wealth, infant mortality rate, and poverty index by commune), and then the components were averaged to produce an overall vulnerability index. The overall vulnerability maps are quite similar (Figure 9), but the individual IPCC component and PC maps reveal different patterns (Figure 10). On the top row of Figure 10, for exposure (left) the south to north gradient of temperature and precipitation (total and interannual variation) is clearly evident. Sensitivity is more varied, showing pockets of high sensitivity in the northern and northwestern areas of the country and in southeastern Mali (owing in part to high infant mortality rates) and less sensitivity around Bamako (the capital) and in the west and the east. Adaptive capacity declines with distance from Bamako and other urban centers, as well as from the Niger River. For the PCs (bottom row), PC1 largely comprises climate indicators and those that are strongly influenced by climate, such as malaria and soil organic carbon, so it looks quite similar to the exposure component on the row above. PC2 combines (in the order of their loadings) maternal education, household wealth, health infrastructure, and the poverty index; hence it can be straightforwardly interpreted as a measure of household social vulnerability. PC3 includes two indicators with positive loadings, child stunting and household wealth; and two with negative loadings, the decadal component of precipitation and malaria stability. This component overwhelmingly is driven by child stunting and hence could be seen as a stand-in for child wellbeing and malnutrition. Overall, the two approaches bring out different information that is complementary and may help to understand spatial patterns of vulnerability that can be useful for targeting interventions.

TABLE 1. INDICATORS UTILIZED BY COMPONENT OF VULNERABILITY

Component	Indicator Code	Data Layer
Exposure	PRCP	Average annual precipitation
	IACV	Inter-annual coefficient of variation in precipitation
	DCVAR	Percentage of precipitation variance explained by decadal component
	NDVICV	Coefficient of variation of normalized difference vegetation index (NDVI) (1981–2006)
	TTREND	Long-term trend in temperature in Jul.-Aug.-Sept. (1950–2009)
	FLOOD	Flood frequency
Sensitivity	HHWL	Household wealth
	STNT	Child stunting
	IMR	Infant mortality rate
	POVI	Poverty index by commune
	CONF	Conflict data for political violence
	CARB	Soil organic carbon or soil quality
	MALA	Malaria stability index
Adaptive Capacity	EDMO	Education level of mother
	MARK	Market accessibility (travel time to major cities)
	HEALTH	Access to community health centers
	ANTH	Anthropogenic biomes
	IRRI	Irrigated areas (area equipped for irrigation)

In summary, comparing spatial index approaches to PCA, the PCA appears to be a useful exploratory tool as it permits the developer to uncover spatial relationships between different components of vulnerability and to avoid biasing the results of a purely additive approach by the use of too many components that share the same spatial patterns. It can also provide additional insight into the vulnerability patterns and components. However, individual PCs, especially of higher order, are often not easy to interpret. Moreover, Midgley (*personal communication*) argues in favor of the additive approach on a conceptual basis, in the sense that each indicator may contribute separately to overall vulnerability. For example, while child malnutrition and poverty levels may co-vary across space, and hence be collapsed into one PC, that does not mean that they don't contribute separately to the ability of people to cope with stressors.

FIGURE 9. MALI VULNERABILITY MAPS: AVERAGE OF IPCC COMPONENTS (LEFT) AND OF FIRST FOUR PCS (RIGHT)

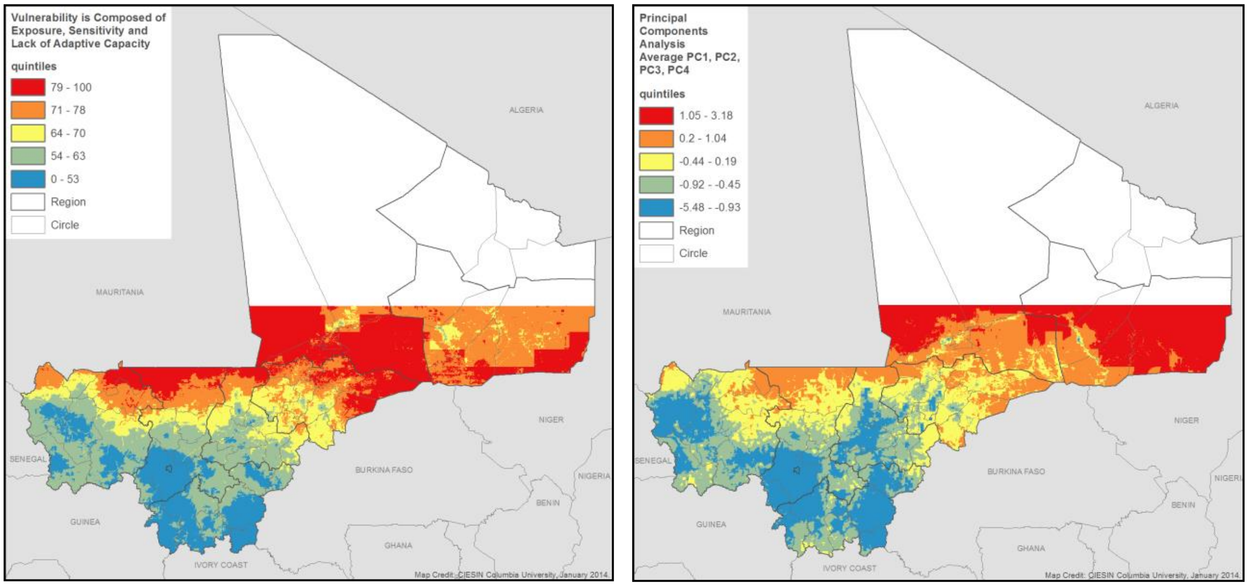
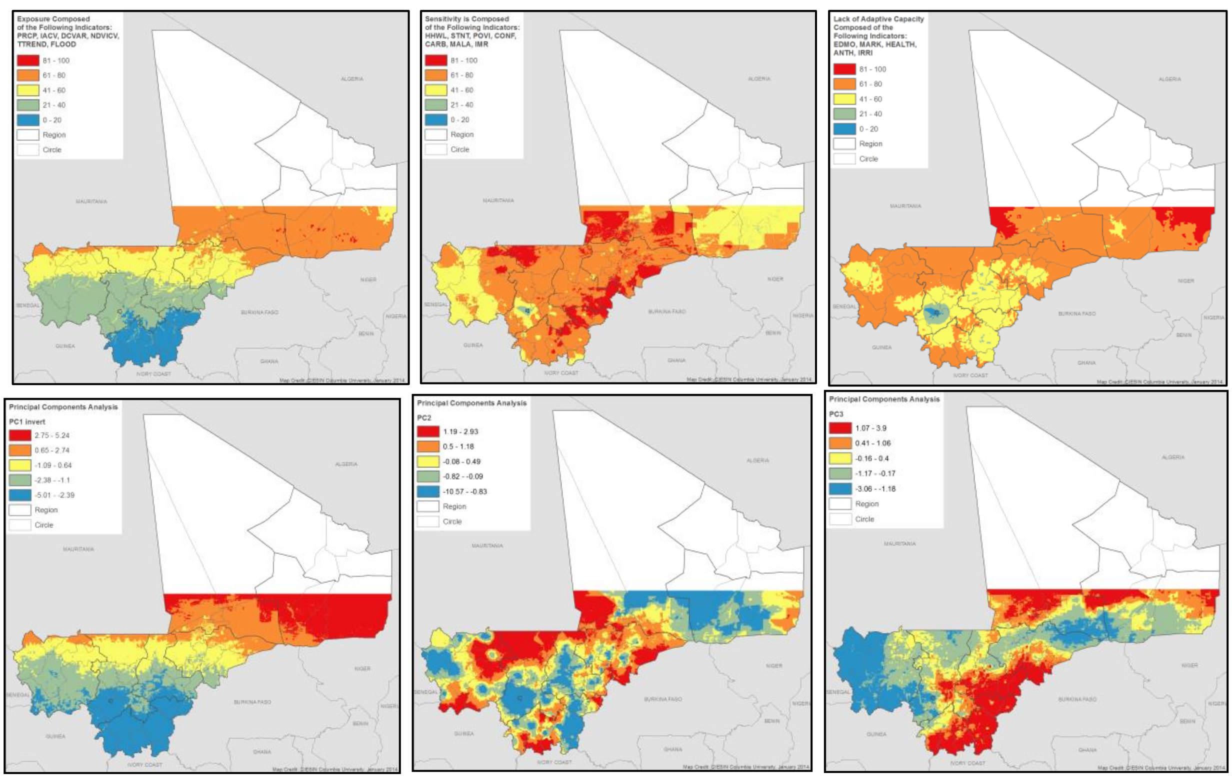


FIGURE 10. COMPONENTS OF VULNERABILITY: EXPOSURE, SENSITIVITY, ADAPTIVE CAPACITY (TOP ROW) AND PC1, PC2, AND PC3 (BOTTOM ROW)



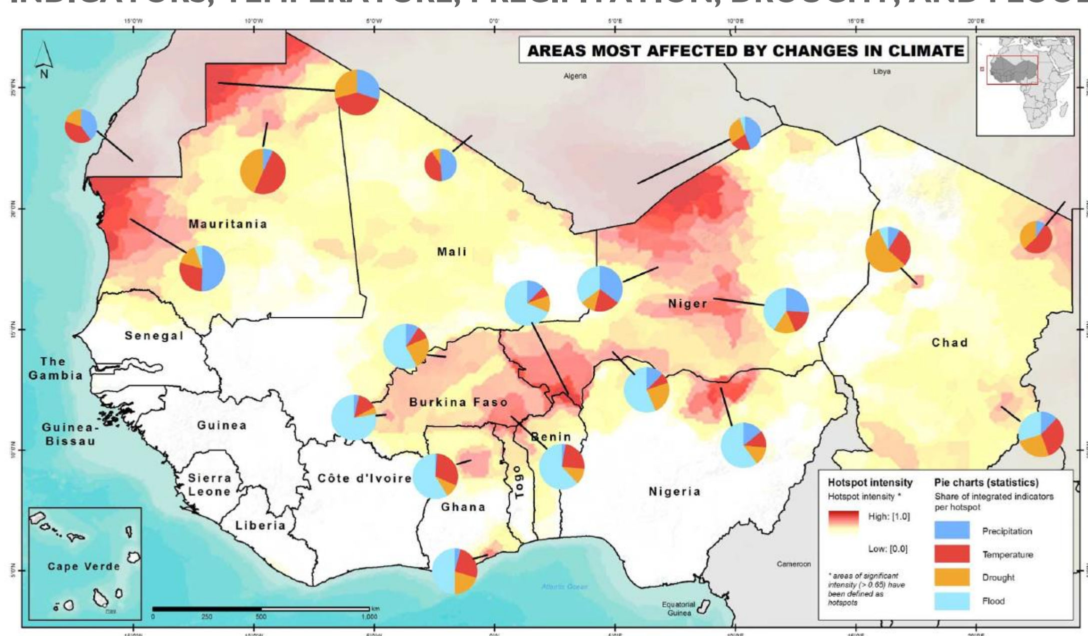
4.1.3 Cluster Analysis

The third approach to aggregation is cluster analysis. In cluster analysis, the number of desired clusters is identified *a priori* and units are assigned to clusters on the basis of their profiles across all indicators. Thus, one cluster of units might have high poverty, low access to markets and health infrastructure, and high vulnerability to droughts, whereas another cluster might show the inverse. The resulting map will show patches of pixels with similar statistical profiles across the entire suite of indicators. As with PCA, some degree of interpretation is required to label the clusters (e.g., Kok et al., 2010).

4.1.4 Geons

A new approach to aggregation and regionalization is based on what are called "geons" (Lang et al. 2008). Kienberger et al. (2009) and subsequently Kienberger (2012), Hagenlocher et al. (2013), and Kienberger et al. (2013a) have applied the concept of geons, which is an aggregation method for modeling spatial units where similar (homogeneous) conditions apply with respect to a set of previously defined sub-indicators as well as spatial heterogeneity. Using object-based image analysis processing software and approaches (Blaschke, 2010), the geon approach takes information on the statistical properties but also the location of units/cells in constructing geons (or objects). Thus, building out from a core grouping, the object-based approach will preferentially assign neighboring cells to that geon if their statistical and spatial properties are broadly similar, thus avoiding the "speckling" effect common in many cell-based image processing and statistical approaches. Geons are also independent of any given set of defined boundaries, as for example administrative boundaries, which are commonly used as reference units in the construction of composite indicators. In hotspots mapping, data can also be provided on the proportional contribution of different components or indicators to the hotspots identified (e.g., see example for a cumulative climate change index in Figure 11). While this approach has many strengths, it has yet to be widely adopted, perhaps because of the requirements for special software (e.g., eCognition) and data processing and analysis skills.

FIGURE 11. CUMULATIVE CLIMATE CHANGE INDEX IN WEST AFRICA (BASED ON THE AGGREGATION OF A SET OF FOUR CLIMATE-/HAZARD-RELATED SUB-INDICATORS, TEMPERATURE, PRECIPITATION, DROUGHT, AND FLOODING)



Source: Hagenlocher et al. 2012, reprinted with permission

4.1.5 General Considerations

Beyond aggregation methods, some of the innovation in spatial index approaches derives from metrics that are developed to measure the different components of vulnerability. Antwi-Agyei et al. (2012) developed a vulnerability index using the IPCC formulation to identify and map relative vulnerabilities of regions in Ghana, finding that the northernmost regions have the greatest sensitivity to drought and social vulnerability. The innovation was in the development of a crop yield sensitivity index, which measures harvest losses owing to drought. Many of the more innovative metrics are developed for specific countries or local areas, since globally comparable data may not be available. Examples include use of census-based variables in the US (Cutter et al, 2003; Rygel et al, 2006) and Germany (Fekete, 2010), and multiple specialized climate model outputs, environmental variables, and socioeconomic data for a European vulnerability mapping (ESPON Climate, 2011).

Preliminary evidence suggests that spatial index approaches are useful to policy audiences (Midgley, *personal communication*; Preston, 2009; de Sherbinin et al., 2014), but as mentioned previously, special care needs to be given to the communication of uncertainties to end users. A combination of approaches may help to highlight ways in which results differ depending on assumptions concerning the underlying relationships among variables or the causal mechanisms of vulnerability. This needs to be counterbalanced by recognition that some policy audiences may prefer one set of maps offering "conclusive evidence" rather than being left the task of drawing their own conclusions from a range of maps.

4.2 COMMUNITY-BASED AND STAKEHOLDER-DRIVEN VULNERABILITY MAPPING

Community-based vulnerability mapping is part of a long tradition of participatory rural appraisal, which often used mapping to identify the location of villages, fields, forests, water sources, and other resources, and as an aid to local planning (Barton et al., 1997; Chambers, 1994). There are relatively few examples of community-based vulnerability mapping published in the peer-reviewed literature, perhaps because the results are intended largely for the benefit of the communities themselves rather than academic audiences. Stakeholder-driven vulnerability mapping engages those with a "stake" in outcomes — e.g., decision makers, agency staff, business leaders, or community members — in a co-production of knowledge that will lead to research that directly supports decision making. Beyond ownership of results, community-based vulnerability mapping is suitable in local contexts where there is a clearly defined resource or issue of interest that is likely to be impacted by climate change. It should be stated up front that participatory mapping approaches need to be embedded within specific planning/decision-making processes. Without an understanding of the planning and implementation processes, stakeholder engagement will not necessarily result in specific changes on the ground, and in fact may only serve to increase stakeholder frustration and disempowerment if results are not linked to action.

Kienberger (2012) embeds participatory mapping in the context of DRR, with multiple goals of assisting in the development of DRR measures; identifying community needs; and defining, analyzing, and prioritizing the driving forces of vulnerability. Beyond generic methods such as identifying a facilitator and introducing the project to community leaders, specific methods include compilation of existing geospatial data, analysis of aerial or satellite imagery and identification of community features (e.g., boundaries, high-risk zones, agricultural zones, settlement areas, and special infrastructure such as wells, schools and markets) (Image 1), integration of the community data into a GIS environment, spatial analysis (e.g., using buffers, distance functions, and kernel density functions), and the use of the data for community-based DRR planning. He also derived indicators from community exercises (brainstorming, weighting) which are then used to create a spatial vulnerability index at the district level.

IMAGE 1. COMMUNITY MEMBERS IN MOZAMBIQUE USE SATELLITE IMAGERY TO IDENTIFY FLOOD AND DROUGHT-PRONE AREAS

Source: Photos courtesy Stefan Kienberger, Department of Geoinformatics, University of Salzburg, Austria

Preston et al. (2009) worked with the Sydney Coastal Councils Group, a group of local government stakeholders, to assess the drivers of vulnerability to bush fires. They conclude that "When presented in a workshop setting, vulnerability maps were successful in capturing the attention of stakeholders while simultaneously conveying information regarding the diversity of drivers that can contribute to current and future vulnerability" (Preston et al., 2009: 251). The engagement of stakeholders up-front ensures greater uptake by policymakers, and may also help to uncover socio-political barriers to decision making and policy action (Preston et al., 2011).

Moser and Ekstrom (2011) draw attention to emerging participatory climate change adaptation planning processes at the local level in the United States. They describe and critically evaluate a pilot project tested in two California local communities (San Luis Obispo and Fresno Counties) to illustrate how active engagement of local government and other stakeholders with experts can advance climate change adaptation planning. The results of this pilot project indicate that this approach served as an effective conversation opener, created a sense of expectation and accountability among local leaders and stakeholders, and "succeeded in developing an initial set of adaptation strategies for key climate-sensitive sectors out of the dialogue between local and external experts and a broad range of stakeholders" (Moser and Ekstrom, 2011: 72). These authors stress that a stakeholder engagement process alone is not enough and that adequate funding is necessary to maintain interest, advance the policy agenda, and implement adaptation strategies.

Community-based and stakeholder-driven vulnerability assessments may be the most effective form of spatial VA, insofar as decision makers with local knowledge are directly engaged at all stages, can interpret the results, and may plan responses according to the new information. Data layers that are not typically available for coarser-scale national or regional assessments are generally available and at high resolution (assuming government agencies or industry groups are willing to share their data), or can be developed at relatively lower costs based on high-resolution remote sensing imagery (e.g., Kienberger, 2012).[9] These approaches are also typically more time consuming then expert-generated approaches, and researchers need to be transparent about methods and guide community members/stakeholders through the results rather than simply deliver a report.[10] This can lead to the building of shared understanding of the drivers of vulnerability (Preston et al., 2007), which can be an important component of consensus building to drive action.

4.3 CLIMATE IMPACT MAPPING AND MODELING

In climate impact assessment and mapping, rather than examining the interactions among climate, social, and economic drivers that influence risk, the assessment primarily focuses on the biophysical implications of climate change for infrastructure or other valued assets, and economic loss estimates are derived for events of particular magnitudes (Preston et al., 2007). There are also efforts to model climate impacts on cropping or hydrological systems that result in estimated impacts on crop yields or water availability rather than economic loss estimates. In both cases the "human" component of the system is limited to specific sectors, such as infrastructure, agriculture, and water supply, and the assessments do not address broader issues of societal vulnerability. Although not technically in the category of spatial *vulnerability* assessment, we include these approaches because they have strong spatial components and the results (e.g., model outputs) could potentially be used in broader spatial VAs.

In a multi-level stakeholder approach to impact assessment (illustrating a cross over between stakeholder/community approaches and impact assessment), a team led by University of Twente carried out mapping of areas at risk of flooding in Kampala, Uganda, using land cover data and an integrated runoff-flood model called the LImburg Soil Erosion Model (LISEM) (UN-HABITAT, 2013). The project mapped areas currently at risk based on land cover change models and scenarios of future extreme events, they were able to identify areas at future risk. Beyond working with the Kampala Capital City Authority, regular contact with local nongovernmental organizations (NGOs) and community groups were established from the outset. They found that the governance component is essential for success, since stakeholders are not only affected by floods, but their actions also contribute to their own risks as well as those of others through land conversion and garbage disposal that blocks drainage networks. Ultimately, the flood mapping and modeling of future population growth scenarios (Figure 12) are directed at identifying and gaining stakeholder commitment to adopt and implement a range of possible integrated flood risk management strategies such as improved solid waste management, regular drain cleaning, and better growth management policies. Preston et al. (2007) underwent a similar process of flood risk modeling with local councils around Western Port, Australia, generating estimates of area, infrastructure, roads, and other assets at risk of sea level rise and storm surge at different future time periods.

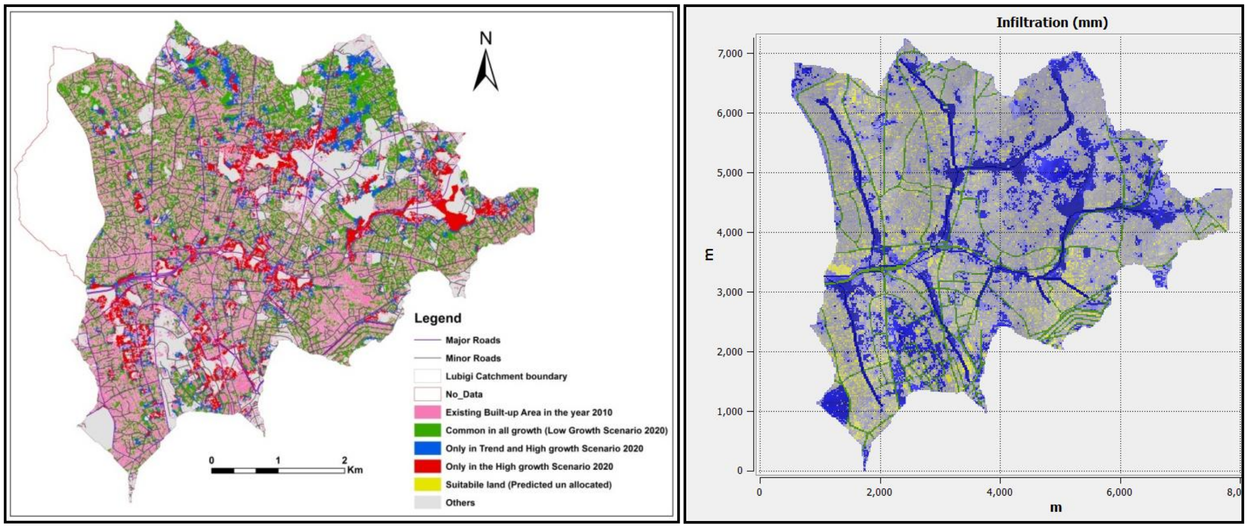
---

9 Kienberger also has produced a manual for community vulnerability mapping available in English, French, and Portuguese, Retrieved from http://projects.stefankienberger.at/vulmoz/?page_id=54.

10 Restitution of data to community/stakeholders should also be part of the plan.

A common approach in the physical sciences is to integrate climate data into process-based crop or hydrological models to generate maps of likely hotspots of climate impacts. Examples include global crop modeling (Fraser et al., 2013; Erickson et al., 2011) and global groundwater resources (Döll, 2009). Typically the models produce multiple outputs (or scenarios) based on climate model outputs using different emissions scenarios from the IPCC Special Report on Emissions Scenarios (SRES); in some cases, they include scenarios for other variables such as population distribution or gross domestic product (GDP). Here we focus on a two crop modeling tools and associated results.

FIGURE 12. LIKELIHOOD OF FUTURE CONSTRUCTION (LEFT) AND EXPECTED INFILTRATION RATE (RIGHT) FOR UPPER LUBIGI CATCHMENT, KAMPALA, UGANDA



Source: Maps courtesy of Richard Sliuzas, Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, The Netherlands.

Regional and country assessments of future crop suitability have been conducted using the EcoCrop tool in conjunction with DivaGIS (Hijmans, 2005). EcoCrop uses minimum, maximum, and mean monthly temperatures; total monthly rainfall; and length of growth period to predict areas suitable for cultivation of a certain crop under future climatologies. EcoCrop does not assess likely changes in yields.[11] For example, Eitzinger et al. (2012) use EcoCrop to model future areas suitable for bean cultivation in Central America, and find that bean yields will decrease along the dry corridor in Central America (Figure 13, top). The team also used Decision Support for Agro-technology Transfer (DSSAT) and find hotspots of yield reduction with more than 50 percent declines in some areas. Similarly, Nyabako and Manzungu (2012) use EcoCrop in Zimbabwe to predict that areas suitable for the highest yielding late maturing maize varieties will shrink to only 2 percent of the country's land area. Jarvis et al. (2012) assess impacts of climate change on cassava production in Africa based on projections to 2030, finding that cassava is positively impacted in many areas of Africa, with –3.7 percent to +17.5percent changes in climate suitability across the continent. However, they also use an ecological niche model for key pests affecting cassava to understand how the distribution of those pests may change. Jarvis et al. (2012: 6) also summarize the caveats in using EcoCrop, including "the inability of the model to capture the effect of short-duration stress periods, the lack of a clear relationship between the suitability index and crop

11 Note that it does not take into account soil type, soil organic matter, changes in fertilizer management, and other production practices that may affect crop distribution.

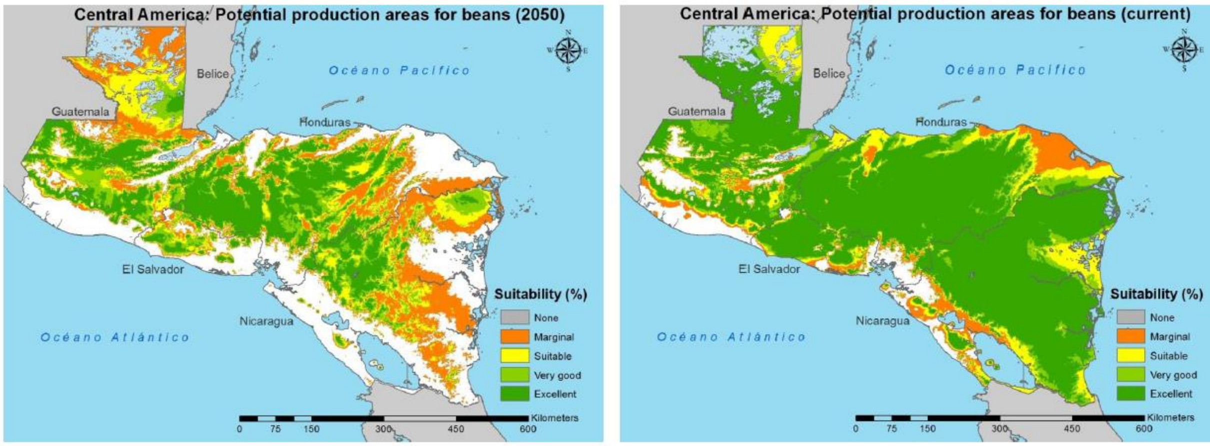
yields, the scale at which the model can suitably be applied, the lack of representation of soil-related processes and constraints, among others."[12]

By contrast, the Maximum Entropy (MAXENT) model begins with the observed distribution of a crop, and then applies climate parameters for different climate change scenarios to determine how that distribution may change in the future. It has been applied to cacao production in Ghana and Côte d'Ivoire with good results (Läderach, 2011) (Figure 13, bottom). Areas of predicted future suitability that are urban and water bodies as well as forested and protected areas were masked out as not available for cocoa production. The maps depict severe reductions of areas suitable for cacao within a relatively short time horizon of 20 years. Läderach et al. (2011) assess the strengths and weaknesses of these models and three others (DOMAIN, Bioclim, and Crop Niche Selection for Tropical Agriculture [CaNaSTA]) for an assessment of climate impacts on coffee supply chains, and find that EcoCrop is useful in situations where there is no data on current crop ranges and one is forced to use environmental variables to predict ranges, whereas MAXENT is a general purpose model for making predictions from incomplete information based on probability distributions. They found that MAXENT is generally considered the most accurate model.

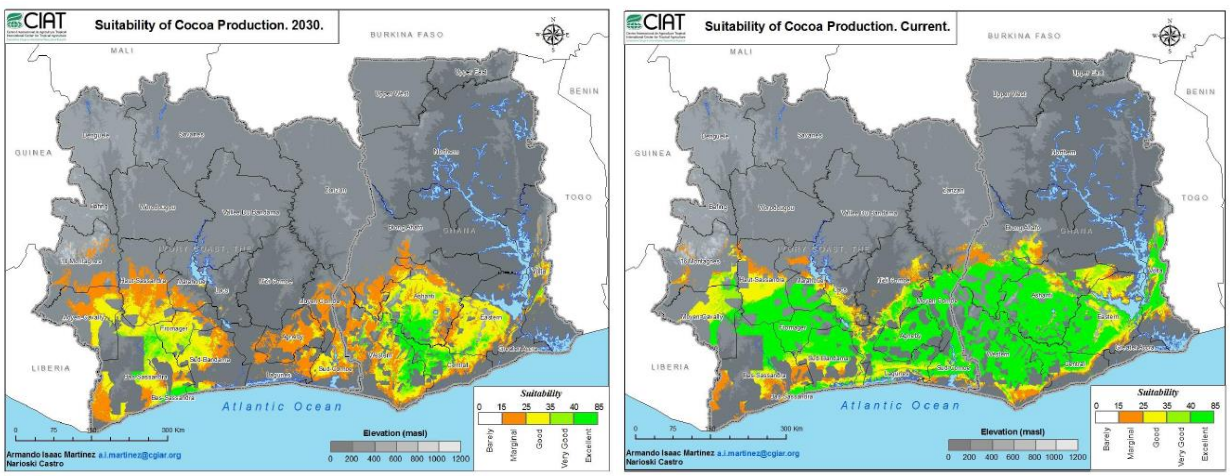
The Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) is intended to provide a framework to collate a consistent set of climate impact data across sectors and scales. This will serve as a basis for model evaluation and improvement, allowing for improved estimates of the biophysical and socio-economic impacts of climate change at different levels of warming. As part of ISI-MIP, Piontek et al. (2013) undertook a global impact assessment to look at regions in which climate change might cause thresholds to be crossed in four important sectors: water, agriculture, ecosystems, and health. The authors use the outputs of three GCMs simulating the highest representative concentration pathway (RCP8.5) to feed multiple Global Impact Models (GIMs), and then identify temperature thresholds in each sector where impacts could be considered to be severe. For example, the thresholds for the water and agriculture sectors are defined as the 10th percentile of the reference period distribution (1980–2010) of river discharge and crop yields, respectively. For each GIM-GCM combination and at each grid cell, they define a "crossing temperature" that is the global mean temperature change at which the sectoral metric crosses the respective impact threshold. A similar approach could be taken for national or regional assessments, though the data and modeling requirements are significant.

[12] A VA in Uganda conducted by the ARCC project included crop modeling using EcoCrop (USAID, 2013). It was found that suitability was predicted to be high for certain crops under current conditions even in areas where the crop is not currently grown, and predicted to be marginal to non-existent for some other crops in areas where they are staple crops. These differences may be partly explained by differences in soil quality, cultivars, and cultural preferences (Trzaska, *personal communication*).

FIGURE 13. SUITABLE AREAS FOR BEAN PRODUCTION IN CENTRAL AMERICA (CURRENT AND 2050) USING ECOCROP (TOP) AND CACAO IN GHANA AND CÔTE D'IVOIRE (CURRENT AND 2030) USING MAXENT (BOTTOM)



Source: Eitzinger et al., 2012: 28-29



Source: Läderach/CIAT, 2011: 12-13

Preston et al. (2007 and 2009) address a number of the pros and cons of spatial VA versus impact assessment. The vulnerability approach is "conducive to diagnosing the various factors and interactions that contribute to vulnerability and climate risk as a means of generating thought regarding processes that affect risk and its management within local government" (2007: 262). This can spur a "complex systems" approach to understanding the system. On the other hand, VAs can often raise more questions than they answer, since as one of the challenges is to identify the precise contributions of the different indicators that account for the spatial patterns on the maps. Furthermore, in stakeholder meetings, Preston et al. (2009) found that while efforts were made to clearly communicate the contributions of the individual components of vulnerability, local stakeholders had difficulty interpreting vulnerability as anything other than "hazard."

Impact assessment, on the other hand, is often scenario-based (e.g., projected changes in temperature or rainfall, or scenarios of extreme rainfall or storm surge events), and may focus on the return periods of extreme events or on changes in crop suitability, as seen in the examples above. Because they are more narrowly focused and can provide estimates of the costs of impacts and potential adaptation options, they are attractive in decision-making contexts. Modeling also tends to lend itself more readily to uncertainty assessment than VA approaches because multiple scenarios based on different assumptions or underlying data inputs can be compared side-by-side. (We return to the issue of uncertainty assessment in Section 5.3.) However, the requirements for data and technical capacity are generally much higher for impact assessment than for VA. Furthermore, while stakeholders may be predisposed to prefer quantitative assessments, it is difficult to account for endogenous social and environmental change (e.g., population growth or development) within impact assessment models. Summarizing, Preston et al. (2007) note that VA is better for assessing how complex systems *behave* when confronted with climate variability and change, while impact assessment is better for understanding how systems *respond*.

5.0 COMMON ISSUES WITH SPATIAL ASSESSMENTS

A number of issues commonly arise in spatial vulnerability assessments, yet developers often fail to address them or even to acknowledge the potential problems, and users may not be aware of the degree to which they affect results. This section addresses issues related to spatial and temporal scale, the functional form among indicators and components, uncertainty and decision making, and cartographic representation.

5.1 SPATIAL RESOLUTION AND SPATIAL AND TEMPORAL SCALE ISSUES

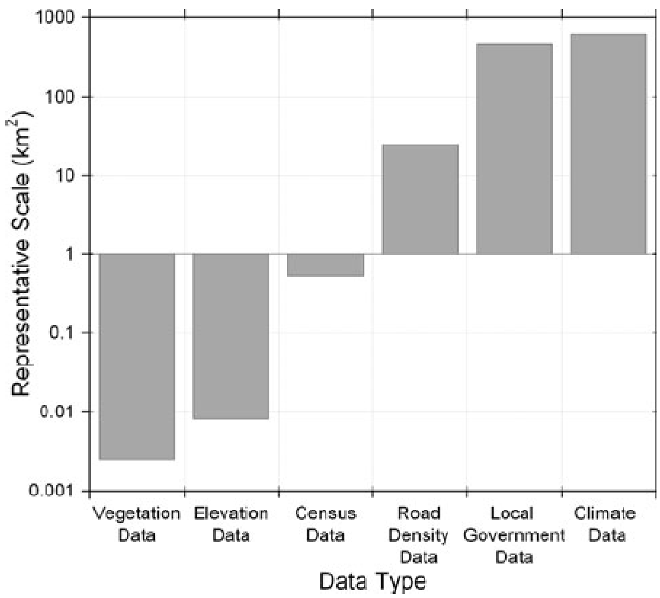
Several choices in any vulnerability assessment relate to spatial scale. One is the choice of spatial units of analysis and another is the geographic extent (bounding box) of the system under consideration. Both are affected by the resolution of the available data. A good overview on scale issues in global change research can be found in Gibson et al. (1998), and a more specific discussion of issues of spatial and temporal resolution in vulnerability assessments is found in Kienberger et al. (2013b).

5.1.1 Spatial Resolution and Temporal Scale

Preston et al. (2011) describe the common resolutions of data sets used in vulnerability mapping (Figure 14). On the one end are biophysical data, often derived from remote sensing, that are at high spatial resolutions. On the other end are climate data, which are generally coarse. Sandwiched between are the socio-economic data from censuses and surveys. This is a generalized view, as there are obvious exceptions, such as remote sensing-derived vegetation data that are only available at 1km pixel sizes, or climate data from individual meteorological stations that represent highly localized areas. Yet it is a useful representation since it highlights the fact that spatial VAs need to draw on data at different spatial scales, and hence the choice of output resolution in spatial VA needs to be considered carefully. Often this is determined by the highest resolution data sets available (e.g., for the Mali VA described above flood risk was mapped at 1km resolution and hence grid cells of one kilometer resolution were chosen as the mapping unit), but it is important to remember that even if coarser data are resampled at a high resolution, their nominal resolution is much lower. For local VAs, a resolution of 1 kilometer is probably too coarse for available data, nor would it adequately resolve local features, so a higher resolution of 30–250 meters may be desirable. Developers of spatial VAs should seek to map at a resolution appropriate for the end users (decision makers), and should avoid using coarse-resolution data when higher-resolution alternatives are available.

Integrating data at different spatial scales can result in artifacts in the maps that unintentionally draw attention to differences between areas that are not necessarily present on the ground. For example, abrupt discontinuities across borders may be an artifact of using national level adaptive capacity indicators (see Figure 14), or it may reflect actual changes owing to different governance regimes. Apart from rigorous ground-level data collection, it would be difficult to determine if these discontinuities actually reflect "real" changes in on-the-ground vulnerability. Maps that include continuous variables derived, for example, from remote sensing data (e.g., forest or crop land cover) may result in maps with pixelated results that may appear noisy; in these cases, the use of a low-pass filter may help to reduce the noise and increase the communication value.

FIGURE 14. SPATIAL SCALE DIFFERENCES AMONG DIFFERENT DATA SOURCES



Source: Preston et al., 2011: 189

Temporal scale relates to the time frame of the assessment (the "when?" identified by Füssel [2007]) as well as the temporal frequency of the phenomena of interest, which is the generally the climate stressor to which the system is exposed (Kienberger et al., 2013b). It can also refer to the frequency of measurement, e.g., from hourly (for climate data) to weekly (for higher-resolution remote sensing data) to decadal (for census data). Generally speaking, spatial VAs integrate data representing multiple time periods. Climate analyses may require historical data for 50–100 year periods in order to adequately capture trends or the frequency of extreme events. Socioeconomic data may be limited to the dates of the most recent census or survey, and land cover data may be available for several points in time. For local assessments, quite recent data may be collected by community members themselves (UN-HABITAT, 2013; Kienberger, 2012) or provided by local agencies (Preston et al., 2007). Developers should communicate clearly the approximate time frame that the assessment represents, and incorporation of older data owing to data limitations should be clearly documented.

5.1.2 Scale and Spatial Level

The spatial level of analysis relates to the bounding box of the spatial VA. Measures of relative vulnerability will necessarily depend on the bounding box one uses to delimit one's study. For example, in an assessment of vulnerability in southern Africa, Abson et al. (2012) created vulnerability indices for all countries in the Southern African Development Cooperation (SADC) zone and the same set of indices for one ecosystem, drylands, within the SADC. They found that "the spatial extent over which the analysis is undertaken is likely to have a considerable influence on the resulting indices" (Abson et al., 2012: 20), such that for the larger region, vulnerability differences between ecoregions were found to be high. Within ecoregions, vulnerability differences were generally lower. For the Mali VA mapping described above, all data layers were obtained for the whole country. However, in the normalization process, we excluded from consideration all areas north of 17.2°N latitude, a region that is very sparsely populated. We did this on two grounds. Firstly, because vulnerability results are less meaningful for a region that is so thinly populated and where climate variability and change may have less of an impact owing to already harsh conditions; secondly, for methodological reasons, because inclusion of indicator data values for this region might skew results for the remainder of Mali (owing to extreme values for many indicators in this region), which is the primary region of interest.

Choice of bounding box can be straightforward, for example, for country-based assessments where the unit of analysis is everything within the country's borders. Yet, as Preston et al. (2011) suggest, choice of geographic bounds are often determined by the availability of relevant data or stakeholder needs, rather than by the dynamics of the system under investigation. It is important to have a clear rationale for choosing the extent of the study area (e.g., a watershed or an administrative area); and if the study is longitudinal, to be sure to retain the same extent over time (de Sherbinin et al., 2002).

Interactions across scales, teleconnections (e.g., trade networks) and non-climatic shocks are often overlooked in spatial VAs. For example, demand for a cash crop such as coffee could be affected by economic downturn in Europe or North America or competition from growers in other countries; this could be a greater determinant of local vulnerability than short-term climate fluctuations (Eakin et al., 2006). Some have suggested a "hot systems" approach as an alternative to hotspots mapping, which would consider perturbations to socio-economic and ecological systems in disparate geographic locations (Shen et al., 2010). An example of an approach that looks at teleconnections and systems is the syndromes approach developed by researchers at the Potsdam Institute for Climate Impact Research (Lüdeke et al., 2004).

Fekete et al. (2010) recognize that each scale of analysis has benefits and drawbacks and that these should be examined and documented within each study. They argue "that a more transparent and thorough understanding of which vulnerability phenomena can be detected at which spatial level and scale might help enormously in the aggregation and combination of single aspects" (Fekete et al., 2010: 744). By developing sound theoretical frameworks and achieving better understandings of *scale implications*, investigators are better able to determine how studies focused on single levels can benefit from each other and how best to approach multi-scale or cross-scale vulnerability assessments.

5.1.3 Units of Analysis

A choice needs to be made regarding the units of analysis. For example, Abson et al. (2012) and de Sherbinin et al. (2014) used grid cells as the units of analysis, gridding all socio-economic variables and re-sampling grids at various spatial resolutions to common 10 arc-minute and 30 arc-second grids, respectively. The grid cells then became the units of analysis. Alternatively, Antwi-Agyei et al. (2012) aggregated all data to sub-regional units within Ghana, and de Sherbinin (2011) analyzed the correlates of malnutrition in Africa using 364 subnational units. This implies some sort of spatial averaging (zonal statistics) of the biophysical data so that they conform to administrative units. The geon approach, described above, permits developers to create units independent of administrative boundaries based on underlying similarities in their vulnerability profiles and spatial contiguity.

There is no one "right" answer for the choice of units, and often these are driven by the needs of stakeholders or the goals of the assessment. It is important to recognize that the choice of units will affect results owing to the modifiable area unit problem (MAUP) (Openshaw, 1983). MAUP refers to the fact that the results of a statistical analysis can be substantially altered by the choice of areal units that are chosen as the unit of analysis (e.g., enumeration areas or post codes or higher levels of aggregation such as counties). Values for almost all parameters (e.g., population count, density, or characteristics) will depend in part on the choice of unit, with larger units tending to average out extremes in the data. Interpolation of data, area averaging, and aggregation can all introduce errors and spatial biases in statistical relations owing to the MAUP.

Decisions on appropriate units of analysis and how to aggregate are generally driven by theory and data availability. Some choose census units since those are the native units of the social vulnerability factors. In some cases, administrative units may vary greatly in spatial extent; for example, units in sparsely populated areas tend to be much larger than those in urban areas. Hence, averages of biophysical features in rural areas (e.g., rainfall levels or soil quality) are likely to have much wider variance than those in urban areas. Furthermore, if the purpose of assessment is to understand how a biophysical factor such as rainfall amount or variability affects the population within a large unit, it is best to mask out portions of the unit that are not densely populated (de Sherbinin, 2011).

This ties in with risk communication as well, as described below. For example, a district level map of vulnerability simply will not permit an identification of risks associated with particular households or allow decision makers to target resources with adequate precision (Fekete, 2012).

5.1.4 Ecological Fallacy

If one is not careful in one's understanding of scalar dynamics, it is possible to commit what is termed an "ecological fallacy." A textbook definition of ecological fallacy is "the danger of making an analysis at one level apply at other levels, for example, of inferring individual characteristics from group characteristics" (Mayhew, 1997). Wood and Skole (1998: 87) extend this definition to the spatial realm, writing that "the ecological fallacy can be thought of as a special case of spuriousness in which the relationships found in… regression analyses are due to a shared spatial location, rather than a causal connection." Clearly one cannot not infer that a given household is vulnerable based on spatial location alone, even if it is located in a highly vulnerable grid cell or unit and has characteristics associated with high exposure and sensitivity. Much comes down to local context. For example, elderly residents living alone will be differently vulnerable to floods or heat waves than elderly residents living in assisted living facilities. Thus, care must be taken not to infer a high level of vulnerability to climate stressors based solely on a vulnerability metric on the proportion of elderly in a geographic area.

5.2 RELATIONSHIPS AMONG THE INDICATORS AND COMPONENTS

Spatial indexing approaches are hampered by an inadequate understanding of the best approach to transforming data from the raw scale to the indicator scale as well as the functional form of the relationship among indicators and components. These are taken up in turn.

A number of issues with data transformation were addressed in Section 4.1. A complete discussion of transformation approaches is beyond the scope of this report (readers may refer to OECD, 2006), but here we highlight a few issues. Ideally, one would be able to identify precise transition points for a given indicator from low to medium to high vulnerability on the normalized 0–100 scale, and to apply these thresholds across all indicators. The reality is that the precise levels at which given indicators transition is largely unknown. That said, it is worth developing histograms of the data distribution for each indicator; where outliers force the bulk of the distribution towards one end of the normalized scale, developers may wish to consider winsorization ("trimming the tails") or conversion to a logarithmic scale before normalization.

Once indicators are transformed, in the averaging approach they are averaged together. Yet we do not fully understand the functional form of the relationship between indicators and components and between components and vulnerability (Hinkel, 2011). A common practice is to assume that the observed minimum and maximum values have the same meaning across input layers. For example, the method implies that a travel time of 48 hours to the nearest population center has the same impact on adaptive capacity as having an IMR of 135 deaths per 1,000 live births, since they both may have a score of 90 on the transformed scale. Yet it may be that an area with an IMR of 135 is significantly more vulnerable. One simple factor that makes the extremes not comparable relates to the MAUP; for some indicators the extremes are calculated with fairly high spatial precision, which makes the tails go out far, whereas others are averaged within spatial units, and this removes the effects of the extreme values.

Another assumption that is often made is to assume a linear relationship between the input layers and the conceptual category being measured. Yet the relationship might be very different. It might be a step function, or sigmoid, or asymptotic if there are critical thresholds involved, or it might be exponential if high values trigger cascading problems that don't show up at lower levels. The interaction among the components is a further issue. The averaging/additive approach combines the components, but the interaction might be multiplicative. For example, if capacity is high enough it may not matter much if sensitivity or exposure are very high. Another way to put this is that the assumption that the three components are fungible — that good levels in one component compensate for bad levels in another, across the whole range of values — might not be true. For example, it could be that moving from 60th to 80th percentile in the exposure indicator has such dramatic impacts on overall vulnerability that it wouldn't really make a difference if the same area moved from 30th to 10th percentile on the capacity indicator. Even if the core relationship is additive, the assumption of equal weights across components may be incorrect. For example, it could be that one unit of exposure has the same effect on vulnerability as ten units in sensitivity. Hinkel (2011: 201) points out that PCA does not avoid this problem, since it does not "reveal anything about the influence of the indicating variables on the theoretical variable (vulnerability)."

All of these issues underline the importance of moving from a heuristic approach, based on theory, to a calibrated or inductive approach, and that requires independent measures of outcomes or observed harm (Hinkel, 2011). One possible approach is to take an outcome measure such as child malnutrition, which may reflect climate shocks (de Sherbinin, 2011), and determine what combination of indicators and components best predicts the outcome we observe. These approaches will generally have data requirements that exceed those of traditional methods.

5.3 UNCERTAINTIES, VALIDATION, AND DECISION SUPPORT

A number of issues related to uncertainty in data commonly used in spatial VAs were brought out in Section 3.0. As Fekete (2012: 1175) points out, "uncertainties in primary data are inherited by secondary data sets," and these uncertainties may be made obvious when units have missing values, made opaque when averages are used, or hidden altogether when numbers are based on assumptions, miscalculations or errors. According to Preston et al. (2011: 191), the failure on the part of spatial VAs to address uncertainty "often results in questions regarding the validity, accuracy and precision of vulnerability maps, or, in other words, whether maps themselves represent sufficiently robust visions of vulnerability to guide stakeholders regarding the potential for harm."

Researchers coming from the climate and integrated assessment communities tend to produce map arrays depicting multiple scenarios. One strength of process-based modeling is the ability to run multiple scenarios reflecting uncertainties in likely futures, which gives decision makers a better sense of the spread in relative risk. However, this often reduces legibility (since map arrays often present many maps of the same area at very low resolution) and can lead to confusion in the reader's mind since there is seldom any guidance on how to interpret the range of scenarios, or whether under certain assumptions one outcome is more likely than another. This can result in information overload. As Patt and Dessai (2005: 427) point out, users have varying abilities to understand probabilistic information, and "people will either choose to ignore information that is too complicated for them, or will respond in ways that disproportionately makes use of some types of information over others." One approach commonly employed by the climate research community is to provide crosshatching of various densities on maps representing climate ensemble outputs, which indicates the percentage of scenarios that agree on the direction of change. Additional methods are described in Section 5.4.

Partly to compensate, spatial VA results are often couched in highly tentative terms. Representative quotes from recent global scale reports (Box 5.1) illustrate how results are often presented as preliminary, suggesting that the authors recognize that the results cannot be viewed as definitive but rather as part of an ongoing process of knowledge generation. The primary means of moving beyond highly tentative conclusions would be through rigorous validation. Preston et al. (2009: 270) caution that because "vulnerability assessments specifically attempt to build understanding about future states where uncertainty regarding drivers and outcomes is high (or simply unknown)… validation of vulnerability assessments is inherently challenging," but they argue that it is clearly preferable to at least partially validate a VA against an independent set of metrics or criteria. Although validation is still relatively rare in spatial VA (though more widely employed in impact assessment), Preston et al. (2009) and Fekete (2009) are examples where validation was employed using an independent set of metrics.

BOX 5.1 REPRESENTATIVE QUOTES HIGHLIGHTING THE CONTINGENT NATURE OF SPATIAL VULNERABILITY ASSESSMENT

"Given the extreme complexity of climate change and human vulnerability, this study should be considered as indicative only. We have taken a pragmatic approach in order to produce useful results and analysis within the scope and resources of this project." (Thow and de Blois, 2008: 6)

"Local vulnerability analyses are often case studies that address the usually complex context-specific situations that shape specific vulnerabilities. Out of necessity, global vulnerability assessments are based on aggregated data and rather crude assumptions about the underlying mechanisms being assessed. The gap between both is a major challenge for integrated assessments of vulnerability." (Kok et al., 2010: 13)

Finally, there are broader questions regarding the use of information in policy contexts that are not unique to spatial VA, but which may be particularly germane in these contexts (Hinkel, 2011; de Sherbinin et al., 2013). A fundamental question is whether the maps are fulfilling their purported intent, which is to guide decisions. Preston et al. (2011) describe vulnerability mapping projects in two Australian contexts in which the direct link between the map and decision making was difficult to trace. Recognizing the fact that policy makers may act (or fail to act) regardless of available information, they suggest that such maps probably best serve as boundary objects, linking "communities together as they allow different groups to collaborate on a common task" (Wenger, 1998). This suggests that maps can facilitate debate and deliberation, but are at best one input into broader decision-making processes that are inherently political (de Sherbinin et al., 2013).

5.4 CARTOGRAPHY, MAP ILLUSTRATIONS, AND RISK COMMUNICATION

Much of the focus in spatial VA (and of this report) has typically been on methods and data. However, as Kaye et al. (2012) point out, since "the quality of graphic design can directly impact decision-making by revealing or obscuring information, it is vital that suitable consideration is given to map design." Yet it must be acknowledged that many vulnerability mapping studies fall short of their potential because of a failure to consider how best to present the results. This crucial last step of map layout and presentation needs to be taken seriously. To be effective, maps need to be visually appealing, easily understood, and legible. While a full primer in cartography is beyond the scope of this report, there are some basic conventions that should be remembered to enhance the comprehension of map content. This section first covers the cartographic conventions, then addresses map design and illustrations before turning to risk communication.

Appropriate use of color in maps is central to good communication. Monochromatic color scales with increasing saturation or decreasing brightness to represent higher map values are probably the easiest to understand and the least subject to misinterpretation, but they may also be considered bland or boring. Where multi-hued color scales are deemed preferable (or more eye catching), map producers should avoid green-to-red scales, since red-green color blindness is the most common form of color blindness, affecting roughly 4 percent of the male population in the United States. Blue-to-red color scales may be preferable, with red signifying "hotspots" in need of greater policy attention. Map producers should consider how the overlay of multiple data layers, each with its own hues and saturation levels, may cover up information or lead to confusion among map users. Combinations of data layers in multiple colors with transparencies can result in color combinations that do not appear in the legend (e.g., red and blue will make purple). If overlays are needed, it is generally preferable to represent only one layer in color with increasing saturation, while using gray scale or cross-hatching to represent the other layer. Alternatively, maps representing different data layers may be positioned next to each other, allowing the user to scan back and forth to identify patterns in a given location (e.g., Figure 15).

Map producers need to evaluate alternative approaches to the application of breakpoints used to categorize results in the map and map legend. The default setting for Esri GIS products is Jenk's natural breaks. This is probably the least defensible categorization method, since it relies on an algorithm that finds gaps in the data distribution that may have little meaning substantively. Quantiles are better for representing the distribution of raw or transformed data values, and equal intervals can be useful for spatial indices that have meaning. In the Mali vulnerability mapping study (de Sherbinin et al. 2014), equal intervals were used: 0-20 represented low vulnerability, 21-40 represented medium-low vulnerability, etc., with 81-100 representing high vulnerability. Owing to the underlying data distribution, the result was that for some maps only very small geographic areas fell in the highest and lowest categories. Continuous scales (gradations in color or saturation) may be appropriate in some cases, but because these scales most often only record the high and low values it is generally not possible to read a value on the map. They may also be affected by extreme values, such that only a few places on the map show up as having very high values.

Legibility is critical, and many reports suffer from having maps so small that legends, map source, and other supporting information cannot be read without the aid of a magnifying glass. This is often because maps are resized to fit the available space in the report, such as when landscape dimension maps intended for an entire letter or A4-sized page are reproduced on pages in portrait mode, with text above or below. Knowing in advance the dimensions of the maps that will be presented in published reports can help cartographers to produce maps in which all map elements are legible. Additional recommendations for map production are found in Box 5.2.

BOX 5.2 RECOMMENDATIONS FOR MAP PRODUCTION

1. Insert a title and a description text into your map. This way, you can avoid misinterpretations when your map is examined independently from your report.
2. Provide a scale, a north arrow and labels for key elements in your map to foster the regional understanding and highlight the relationship between two map elements. If your map represents a region of country, then provide a map inset of the country with a bounding box showing the region being represented.
3. Name the source and the year of your data.
4. Specify what you have mapped (e.g. land use classes) in a legend to avoid misunderstandings.
5. Explain the map (as all other graphs, diagrams etc.) in the text body of your report with a reference to the respective figure.

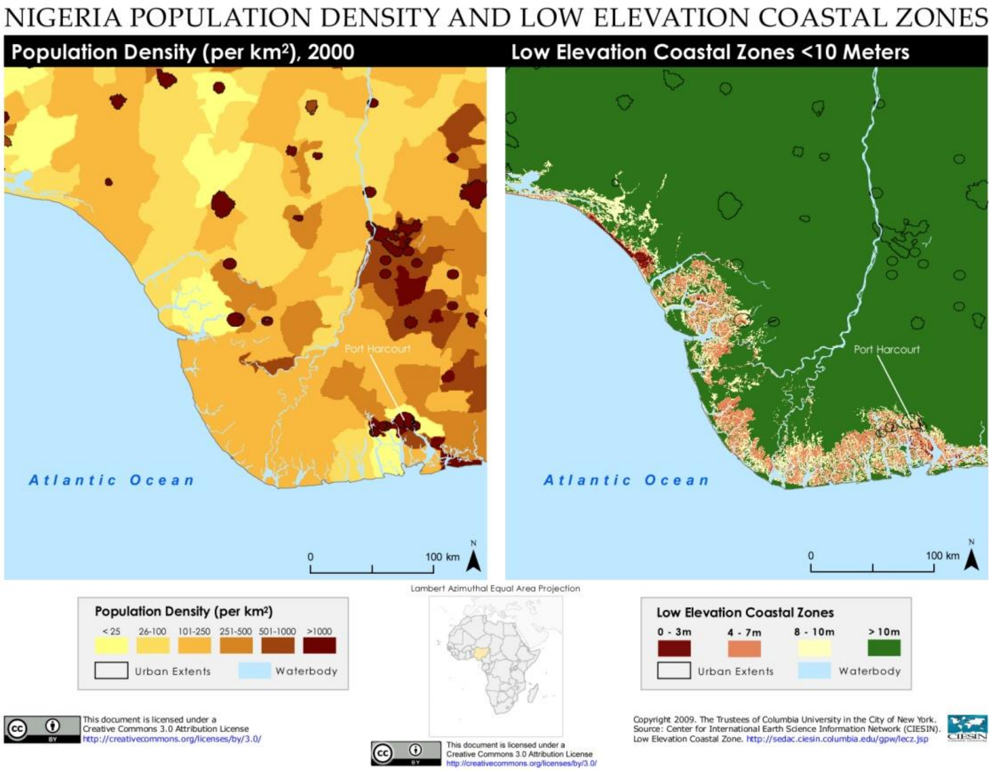
Additional guidelines on map design can be found at http://www.gsd.harvard.edu/gis/manual/style/.

Adapted from: BMZ, 2014.

Uncertainty communication is also important in map design, and there are a number of common methods for cartographic communication of uncertainty. One is to cross hatch areas or increase the color saturation in areas where results are more certain, such as where multiple climate model scenarios agree (Kaye et al. 2012). Another is to create fuzzy boundaries (Kienberger 2012) or to run a low-pass filter (spatial averaging) over results. Additional methods for communicating uncertainty include providing inset maps that characterize the measurement error in key underlying data sets. The final Mali vulnerability map in de Sherbinin et al. (2014) provides insets describing standard errors in the climate data and in the DHS data that provided the basis for seven out of 18 indicators. Although uncertainty levels could not be assessed for all data sets, this approach helped to show that some regions had higher levels of uncertainty owing to the spatial gaps in measurements for both data types.

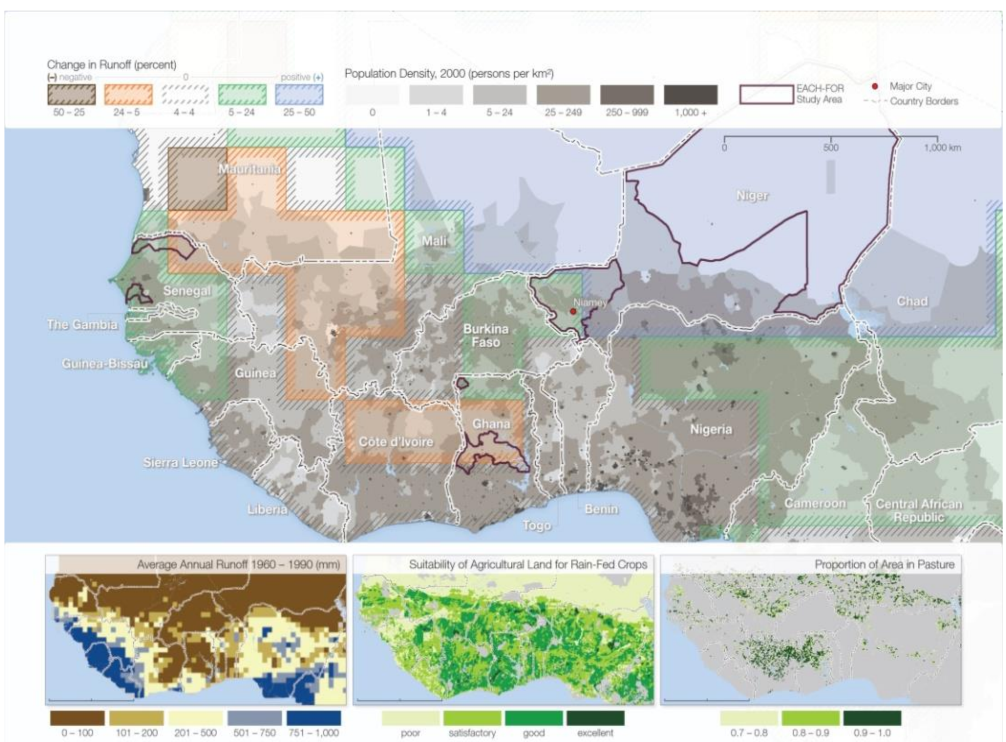
Although little research has been conducted as to the ways in which such maps may influence policy, it is widely recognized that map illustrations represent an important tool for conveying information in an easily digestible form for policy makers (Preston et al. 2011). Professionally designed map illustrations can provide important contextual information for the interpretation of the results of field or model based studies. The spatial data layers are used to visualize the spatial extent of various stressors and target systems, sectors or groups. Examples include: SLR impacts on coastal population (McGranahan et al., 2007) (Figure 15) and wetlands (de Sherbinin et al., 2012); projected changes in precipitation on pasture lands and rain-fed agriculture (Warner et al., 2009) (Figure 16); rainfall variability and migration (Warner et al., 2012a); climate parameters and loss and damage (Warner et al., 2012b); and temperature change on migration and conflict (UNEP, 2011). This method is particularly effective for policy communication through the isolation of the primary drivers of climate impacts and vulnerability. Typically these approaches are used in professionally produced publications for policy audiences. The visualization serves to illustrate and encapsulate the issues (to “tell a story”) without necessarily quantifying the vulnerability.

FIGURE 15. MAP ILLUSTRATING PROJECTED CHANGES IN SEA LEVEL IN NIGERIA'S COASTAL ZONE



Source: McGranahan et al., 2007

FIGURE 16. MAP ILLUSTRATING PROJECTED CHANGES IN RAINFALL RUNOFF IN WEST AFRICA



Source: Warner et al., 2009: 8

Turning briefly to risk communication, Dransch et al. (2010) discuss the usefulness of maps for improving risk perception by improving awareness and understanding of risk among key target groups and the public. They develop a frame to guide map-based risk communication efforts. This frame helps the designer to systematically formulate the risk communication objectives, tasks, and suitable visualization methods and assists the designer in identifying important challenges and constraints. They point out that map designs should aim to meet the needs of differentiated target groups, i.e., primary audiences, which may be those most affected by a hazard, those least informed about a hazard and its consequences, and those most involved in the risk management decision-making process. In some cases, the target audience may be the general public. Key considerations in map design include how to increase attractiveness and how to reduce the complexity of the information presented.

6.0 RECOMMENDATIONS

The field of spatial VA and impact assessment is expanding rapidly. There are evolving standards for conducting spatial VAs, though the field is still characterized by experimentation. A number of these practices have been described in this review (along with critiques), and recommendations have been included throughout the text. These final recommendations to USAID and its development partners are borne out of several years of experience in the development of vulnerability maps for different clients and purposes, multiple capacity building workshops in spatial assessment methods, and interactions with end users. They also build on recommendations developed by Preston et al. (2011: 179).

1. **State the goals and objectives of a spatial VA or impact assessment up front.** For participatory mapping exercises, conduct a stakeholder consultation to ensure agreement. Clarity about the audience and potential uses (and misuses) of the vulnerability maps is important at this stage.
2. **Identify the system of analysis, the valued attributes of concern, the external hazard, and a temporal reference**. While these may seem obvious, it is not uncommon for one or more of these to be missing, or for the "valued attributes" to be so ill-defined as to make any results meaningless. Identify the specific sectors, systems, or groups being assessed, and why they are of concern.
3. **Adhere to general and sectoral vulnerability assessment guidelines.** There are emerging guidelines for the conduct of VAs, such as the PROVIA *Guidance on Assessing Vulnerability, Impacts and Adaptation* (PROVIA, 2013b) and BMZ's *The Vulnerability Sourcebook* (BMZ, 2014). These documents provide sound guidance on broad approaches and issues for any VA. Where appropriate, spatial VAs should also take into account sectoral vulnerability assessment guidelines, such as those that have been developed for the health sector (e.g., Health Canada, 2011; Ebi and Burton, 2008) or coastal VAs (e.g., Klein et al., 1999).
4. **Choose a conceptual framework and specify it in any reports.** Alternative framings of vulnerability were addressed in Section 2.0. O'Brien et al. (2004) argue that before developing adaptation plans, it is necessary to first build an understanding of the biophysical and socio-economic drivers that contribute to the vulnerability of the populations or systems under study. The conceptual framework should make this understanding explicit and guide the mapping methods.
5. **Choose a method appropriate to the goals and target sector/system/group of concern.** This report describes a number of different methods and details which ones may be most appropriate in different contexts. Methods and approaches will continue to evolve in this area and practitioners would do well to consult the literature and review the results of other spatial VAs before settling on a given method.
6. **Carefully evaluate data layers**. Data layers that are used in vulnerability mapping are often produced for entirely different purposes, and hence their fitness for use (in terms of scale, resolution, and proximity to a given vulnerability component) needs to be evaluated. As discussed in Section 3.2 and 3.3, common issues with data used in vulnerability mapping include;
   a. Out-dated data.
   b. Low spatial resolution data.

c. Data that contain unacceptable amounts of measurement error.

d. Spatial mismatches that results in artefacts when combining data layers.

e. Global or regional data sets that contain unacceptable levels of accuracy for smaller countries and regions.

7. **Where spatial indices are created, test the results using different aggregation methods.** It is helpful to test results of both the additive and PCA approaches to see how results differ. PCA can also contribute additional understanding about relationships among the indicators that can assist with the interpretation of results. Sensitivity analysis can assist in understanding the impact of individual indicators and alternative weighting schemes, which in turn reflect assumptions regarding the construction of vulnerability.

8. **Document all data, methods, and assumptions.** The main report should provide a summary of data and a description of the methods. A data documentation annex (map metadata) is vital. It should provide source information for each data layer, data processing steps, maps of raw and transformed versions of the data layers, histograms representing statistical transformations, and information on data limitations.

9. **Map uncertainty levels wherever possible.** While it may not be possible to provide maps quantifying the uncertainty in overall vulnerability levels, maps quantifying spatial errors in key data layers (e.g., climatic data or poverty maps) can help the user to assess the robustness of findings for different geographic regions.

10. **Invest in map design and communications.** As mentioned in Section 5.4, too often investments in spatial VA are squandered because of a lack of attention to map design and the clear communication of results. Repackaging maps in summary reports and posters along with the development of internet-map services can represent value added that will reap substantial dividends at a small marginal cost.

11. **Work directly with end users to improve understanding of the results.** It is often assumed that once the report or map is produced, the scientist's job is done. However, it is enriching for both the stakeholders (policy makers, managers, technicians, or communities) and the scientists for the science to be a two-way dialog (see Section 4.3). As with other indicator approaches, stakeholder engagement in an iterative process of evidence generation, evaluation, and decision-making can only enrich this process and make the results more valuable.

This review has sought to describe some of the uncertainties inherent in spatial VA that result from weaknesses in the underlying data and methodologies. This does not mean that the entire enterprise is pointless, but it does mean that a critical assessment of the utility of maps and the alternatives to producing maps is warranted. Spatial VA shares the shortcomings inherent in any effort to model a complex world. So long as sufficient documentation is provided, the methods are transparent, and the uncertainties are assessed to the best of ones abilities, the results can be quite helpful in decision-making contexts.

7.0 SOURCES

Abson, D.J., Dougill, A.J., and Stringer, L.C. (2012). Using Principal Component Analysis for information-rich socio-ecological vulnerability mapping in Southern Africa. *Applied Geography, 35*(1–2), 515-524. Retrieved from http://dx.doi.org/10.1016/j.apgeog.2012.08.004

Adamo, S.B., Razafindrazay, L., and de Sherbinin, A. (2012). Áreas de alta vulnerabilidad ambiental en América Latina y el Caribe: una perspectiva regional a escala subnacional (Areas of high environmental vulnerability in Latin America and the Caribbean: a regional perspective at the subnational level). *Notas de Población, 94*, 177-209.

Adger, W.N. (2006). Vulnerability. *Global Environmental Change, 16*(3), 268-281. Retrieved from http://dx.doi.org/10.1016/j.gloenvcha.2006.02.006

Andrienko, G., Andrienko, N., Jankowski, P., Keim, D., Kraak, M. J, MacEachren, A., and Wrobel, S. (2007). Geovisual analytics for spatial decision support: Setting the research agenda. *International Journal of Geographical Information Science, 21*(8), 839-857. Retrieved from http://dx.doi.org/10.1080/13658810701349011

Antwi-Agyei, P., Fraser, E.D.G., Dougill, A.J., Stringer, L.C., and Simelton, E. (2012). Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socioeconomic data. *Applied Geography, 32*(2), 324-334. Retrieved from http://dx.doi.org/10.1016/j.apgeog.2011.06.010

Baptista, S. (2014). Design and Use of Composite Indices in Assessments of Climate Change Vulnerability and Resilience. *ARCC Project Working Paper*.

Barnett, J., Lambert, S., and Fry, I. (2008). The Hazards of Indicators: Insights from the Environmental Vulnerability Index. *Annals of the Association of American Geographers, 98*(1), 102-119. Retrieved from 10.1080/00045600701734315

Barton, T., Borrini-Feyerabend, G., de Sherbinin, A., and Warren, P. (1997). Our people, our resources. Gland, Switzerland and Cambridge, UK: IUCN.

Birkmann, J. (2006). Measuring vulnerability to promote disaster-resilient societies: conceptual frameworks and definitions. In J. Birkmann (Ed.), *Measuring vulnerability to natural hazards: towards disaster resilient societies*. Tokyo: United Nations University.

Birkmann, J., Cardona, O. D., Carreño, M. L., Barbat, A. H., Pelling, M., Schneiderbauer, S., . . . Welle, T. (2013). Framing vulnerability, risk and societal responses: the MOVE framework. *Natural Hazards, 67*(2), 193-211. Retrieved from http://dx.doi.org/10.1007/s11069-013-0558-5

Birkmann, J., and Wisner, B. (2006). Measuring the unmeasurable: the challenge of vulnerability: UNU Institute for Environment and Human Security (UNU-EHS).

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing, 65*(1), 2-16. Retrieved from http://dx.doi.org/10.1016/j.isprsjprs.2009.06.004

BMZ (German Federal Ministry for Economic Cooperation and Development). (2014). The Vulnerability Sourcebook: Concept and guidelines for standardised vulnerability assessments. Berlin, Germany: GIZ (Deutsche Gesellschaft fur Internationale Zusammenarbeit).

Brown, C., & Wilby, R. L. (2012). An alternate approach to assessing climate risks. *Eos, Transactions American Geophysical Union, 92*(41), 401-412.

Canada, H. (2011). Adapting to extreme heat events: guidelines for assessing health vulnerability: Water, Air and Climate Change Bureau Healthy Environments and Consumer Safety Branch.

Carney, D. (1998a). Sustainable rural livelihoods: What contribution can we make? . In D. Carney (Ed.), *Department for International Development's Natural Resources Advisers' Conference*. London: DFID.

Carney, D. (1998b). Implementing the Sustainable Rural Livelihoods Approach. London, UK: Overseas Development Institute.

Chambers, R. (1994). Participatory Rural Appraisal (PRA): analysis of experience. *World Development, 22*(9), 1253-1268.

Chen, R.C., de Sherbinin, A., Miner, T.W., & Levy, M.A. (2011). *Conceptual Framework for a Global Resilience Index*. White paper prepared by CIESIN, Columbia University, for the Global Fund for Disaster Risk Reduction (GFDRR) of the World Bank.

CHRR, CIESIN, and World Bank. (2005). Natural Disaster Hotspots Data Collection. Palisades, NY: Center for Hazards and Risk Research (CHRR), Columbia University, Center for International Earth Science Information Network (CIESIN), Columbia University, and World Bank.

Confalonieri, U. E. C., Marinho, D. P., and Rodriguez, R. E. (2009). Public health vulnerability to climate change in Brazil. *Climate Research, 40*, 175-186. Retrieved from http://dx.doi.org/10.3354/cr00808

Crooks, D. (2009). *Development and testing of the Elderly Social Vulnerability Index (ESVI): a composite indicator to measure social vulnerability in the Jamaican elderly population. Ph.D. Dissertation, Comparative Sociology.* Florida International University. Retrieved from http://digitalcommons.fiu.edu/etd/186

Cullis, J., and O'Regan, D. (2004). Targeting the water-poor through water poverty mapping. *Water Policy, 6*, 397-411.

Cutter, S.L., Boruff, B.J., and Shirley, W.L. (2003). Social Vulnerability to Environmental Hazards*. *Social Science Quarterly, 84*(2), 242-261. Retrieved from 10.1111/1540-6237.8402002

Dasgupta, Susmita, Laplante, Benoit, Meisner, Craig M., Wheeler, David, & Jainping Yan, David. (2007). The impact of sea level rise on developing countries: a comparative analysis. *World Bank Policy Research Working Paper No. 4136*.

Davies, R.A.G., & Midgley, S.J.E. (2010). Risk and vulnerability mapping in Southern Africa: a hotspot analysis *Adaptation Series*. Cape Town, South Africa: OneWorld Sustainable Investments (Pty) Ltd.

de Sherbinin, A. (2011). The biophysical and geographical correlates of child malnutrition in Africa. *Population, Space and Place, 17*(1), 27-46. doi: 10.1002/psp.599

de Sherbinin, A. (2013). Climate change hotspots mapping: what have we learned? *Climatic Change*, 1-15. Retrieved from http://dx.doi.org/10.1007/s10584-013-0900-7

de Sherbinin, A., Chai-Onn, T., Giannini, A., Jaiteh, M., Levy, M., Mara, V., and Pistolesi, L. (2014). *Mali Climate Vulnerability Mapping*. Technical Report for the USAID African and Latin American Resilience to Climate Change (ARCC) project. Washington, DC: USAID. Retrieved from http://community.eldis.org/.5bf8c6aa de Sherbinin, A , Lacko, A, and Jaiteh, M. (2012). Evaluating the risk to Ramsar Sites from climate change induced sea level rise. *Ramsar Convention on Wetlands of international Importance Scientific and Technical Review Panel (STRP) Briefing Note*. Gland, Switzerland: Ramsar Secretariat.

de Sherbinin, A., Reuben, A., Levy, M., and Johnson, L. (2013). Indicators in Practice: How Environmental Indicators are Being Used in Policy and Management Contexts. New Haven and New York: Yale and Columbia Universities.

de Sherbinin, A., VanWey, L., McSweeney, K., Aggarwal, R., Barbieri, A., Henry, S., . . . Walker, R. (2008). Household Demographics, Livelihoods and the Environment. *Global Environmental Change, 18*(1), 38-53.

de Sherbinin, A., Schiller, A., and Pulsipher, A. (2007). The vulnerability of global cities to climate hazards. *Environment and Urbanization, 19*(1), 39-64. Retrieved from http://dx.doi.org/10.1177/0956247807076725

de Sherbinin, A., Balk, D., Yaeger, K., Jaiteh, M., Pozzi, F., and Giri, C. (2002). Social science applications of remote sensing *A CIESIN Thematic Guide*. Palisades, NY: Center for International Earth Science Information Network of Columbia University.

De Stefano, L., Duncan, J., Dinar, S., Stahl, K., Strzepek, K., and Wolf, A.T. (2010). Mapping the resilience of international river basins to future climate change-induced water variability. Water Sector Board Discussion Paper Series, Paper No. 15. Washington DC: The World Bank.

DiGregorio, M., and Van, H. C. (2012). Living with floods: a grassroots analysis of the causes and impacts of typhoon Mirinae. Hanoi, Vietnam: ISET-Vietnam.

Dilley, M., Chen, R., Deichmann, U., Lerner-Lam, A., and Arnold, M. (2005). Natural Disaster Hotspots. Washington, DC: World Bank.

Dinku, T., Connor, S., and Ceccato, P. (2011). Evaluation of Satellite Rainfall Estimates and Gridded Gauge Products over the Upper Blue Nile Region. In A. Melesse (Ed.), *Nile River Basin* (pp. 109-127): Springer Netherlands.

Döll, P. (2009). Vulnerability to the impact of climate change on renewable groundwater resources: a global-scale assessment. *Environmental Research Letters, 4*(3), 035006. Retrieved from http://dx.doi.org/10.1088/1748-9326/4/3/035006

Dransch, D., Rotzoll, H., and Poser, K. (2010). The contribution of maps to the challenges of risk communication to the public. *International Journal of Digital Earth, 3*(3), 292-311. Retrieved from 10.1080/17538941003774668

Duarte, C.M., Lenton, T.M., Wadhams, P., and Wassmann, P. (2012). Abrupt climate change in the Arctic. *Nature Climate Change, 2*(2), 60-62.

Eakin, H., Tucker, C., and Castellanos, E. (2006). Responding to the coffee crisis: a pilot study of farmers' adaptations in Mexico, Guatemala and Honduras *The Geographical Journal, 172*(2), 156–171.

Ebi, K.L., and Burton, I. (2008). Identifying practical adaptation options: an approach to address climate change-related health risks. *Environmental Science & Policy, 11*(4), 359-369. Retrieved from http://dx.doi.org/10.1016/j.envsci.2008.02.001

Eitzinger, A., Läderach, P., Rodriguez, B., Fisher, M., Rizo, L., and Ocon, S. (2012). TOR - Tortillas on the roaster: Central American maize-bean systems and the changing climate *CIAT final technical report*. Cali, Colombia: International Center for Tropical Agriculture (CIAT).

ESPON Climate. (2011). Climate Change and Territorial Effects on Regions and Local Economies. Applied Research 2013/1/4. Final Report, Version 31/5/2011.

Ericksen, P., Thornton, P., Notenbaert, A., Cramer, L., Jones, P., and Herrero, M. (2011). Mapping hotspots of climate change and food insecurity in the global tropics *CCAFS Report no. 5*. Copenhagen, Denmark: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Faramarzi, M., Abbaspour, K.C., Vaghefi, S.A., Farzaneh, M.R., Zehnder, A.J.B., Srinivasan, R., and Yang, H. (2013). Modeling impacts of climate change on freshwater availability in Africa. *Journal of Hydrology*. Retrieved from http://dx.doi.org/10.1016/j.jhydrol.2012.12.016

Fekete, A. (2009). Validation of a social vulnerability index in context to river-floods in Germany. *Natural Hazards Earth System Science, 9*(393–403).

Fekete, A. (2010). *Social vulnerability to river floods in Germany.* UNU-EHS Graduate Research Series, PhD Dissertation. (Vol. 4)

Fekete, A. (2012). Spatial disaster vulnerability and risk assessments: challenges in their quality and acceptance. *Natural Hazards, 61*(3), 1161-1178. Retrieved from 10.1007/s11069-011-9973-7

Fekete, Alexander, Damm, Marion, & Birkmann, Jörn. (2010). Scales as a challenge for vulnerability assessment. *Natural Hazards, 55*(3), 729-747. Retrieved from 10.1007/s11069-009-9445-5

Fraser, E.D.G., Simelton, E., Termansen, M., Gosling, S.N., and South, A. (2013). "Vulnerability hotspots": Integrating socio-economic and hydrological models to identify where cereal production may decline in the future due to climate change induced drought. *Agricultural and Forest Meteorology, 170*(0), 195-205. Retrieved from http://dx.doi.org/10.1016/j.agrformet.2012.04.008

Füssel, H.M. (2007). Vulnerability: a generally applicable conceptual framework for climate change research. *Global Environmental Change, 17*(2), 155-167. Retrieved from http://dx.doi.org/10.1016/j.gloenvcha.2006.05.002

Füssel, H.M. (2009). Review and quantitative analysis of indices of climate change exposure, adaptive capacity, sensitivity, and impacts. Background note to the World Development Report 2010. Washington, D.C.: World Bank.

Gbetibouo, G.A., Hassan, R.M., and Ringler, C. (2010). Modelling farmers' adaptation strategies for climate change and variability: the case of the Limpopo Basin, South Africa. *Agrekon, 49*(2), 217-234. Retrieved from http://dx.doi.org/10.1080/03031853.2010.491294

Gbetibouo, G.A. and Ringler, C. (2009). *Mapping South African farming sector vulnerability to climate change and variability: a subnational assessment. IFPRI Discussion Paper 885*. International Food Policy Research Institute (IFPRI). Retrieved from http://www.ifpri.org/publication/mapping-south-african-farming-sector-vulnerability-climate-change-and-variability

Giannini, V., Ceccato, L., Hutton, C., Allan, A. A., Kienberger, S., Flügel, W. A., and Giupponi, C. (2011). Development of responses based on IPCC and "what-if?" IWRM scenarios. *Advances in Science and Research, 7*, 71-81. Retrieved from http://dx.doi.org/10.5194/asr-7-71-2011

Gorokhovich, Y., and Voustianiouk, A. (2006). Accuracy assessment of the processed SRTM-based elevation data by CGIAR using field data from USA and Thailand and its relation to the terrain characteristics. *Remote Sensing of Environment, 104*(4), 409-415. Retrieved from http://dx.doi.org/10.1016/j.rse.2006.05.012

Hagenlocher, M., Lang, S., Holbling, D., Tiede, D., and Kienberger, S. (2013). Modeling Hotspots of Climate Change in the Sahel Using Object-Based Regionalization of Multidimensional Gridded Datasets. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*.

Hazards & Vulnerability Research Institute. (2013). Social Vulnerability Index for the United States - 2006-10. Retrieved from http://webra.cas.sc.edu/hvri/products/sovi.aspx

Hijmans, R.J., Guarino, L., Jarvis, A., O'Brien, R., Mathur, P., Bussink, C., . . . Rojas, E. (2005). DIVA-GIS: Version 5.2 Manual: DIVA-GIS.

Hinkel, J. (2011). "Indicators of vulnerability and adaptive capacity": Towards a clarification of the science–policy interface. *Global Environmental Change, 21*(1), 198-208. Retrieved from http://dx.doi.org/10.1016/j.gloenvcha.2010.08.002

Holling, C.S. (2001). Understanding the Complexity of Economic, Ecological, and Social Systems. *Ecosystems, 4*, 390-405.

IPCC. (2012). Managing the risks of extreme events and disasters to advance climate change adaptation. In C. B. e. a. Field (Ed.), *A Special Report of Working Groups I and II* Cambridge: Intergovernmental Panel on Climate Change.

Janssen, M.A., and Ostrom, E. (2006). Resilience, vulnerability, and adaptation: A cross-cutting theme of the International Human Dimensions Programme on Global Environmental Change. *Global Environmental Change, 16*, 237-239.

Jarvis, A., Ramirez-Villegas, J., Herrera Campo, B.V., and Navarro-Racines, C. (2012). Is Cassava the Answer to African Climate Change Adaptation? *Tropical Plant Biology, 5*(1), 9-29. Retrieved from http://dx.doi.org/10.1007/s12042-012-9096-7

Jones, B. (2013). *Improving research across scales: the shared socio-economic pathways* Panel contribution to the Population-Environment Research Network Cyberseminar, "IPCC's New Scenario Process: Shared Socioeconomic Pathways."

Kasperson, R.E., Dow, K., Archer, E.R.M., Cáceres, D., Downing, T.E., Elmqvist, T., . . . Ziervogel, G. (2005). Chapter 6: Vulnerable people and places. In R. Norgaard & D. Rapport (Eds.), *Millennium Ecosystem Assessment* (pp. 143-164). Washington, D.C.: Island Press.

Kaye, N.R., Hartley, A., and Hemming, D. (2012). Mapping the climate: guidance on appropriate techniques to map climate variables and their uncertainty. *Geoscience Model Development*, 5:245-256. Available at http://www.geosci-model-dev.net/5/245/2012/.

Kienberger, Stefan. (2012). Spatial modelling of social and economic vulnerability to floods at the district level in Búzi, Mozambique. *Natural Hazards, 64*, 2001-2019. Retrieved from http://dx.doi.org/10.1007/s11069-012-0174-9

Kienberger, S, Blaschke, T., and Zaidi, R.Z. (2013b). A framework for spatio-temporal scales and concepts from different disciplines: the 'vulnerability cube'. *Natural Hazards, 68*(3), 1343-1369. Retrieved from http://dx.doi.org/10.1007/s11069-012-0513-x

Kienberger, S., Hagenlocher, M., and Zeil, P. (2013a). *Mapping hotspots of vulnerability to vector-borne diseases in East Africa*. Paper presented at the Presentation at the Global Geospatial Conference, Addis Ababa, Ethiopia.

Kienberger, S., Lang, S., & Zeil, P. (2009). Spatial vulnerability units – expert-based spatial modelling of socio-economic vulnerability in the Salzach catchment, Austria. *Natural Hazards Earth System Science, 9*, 767–778.

Kitoh, A. (2012). High-resolution climate modeling for projecting hydro-meteorological extremes in the future. Maui: Meteorological Research Institute, Japan Meteorological Agency.

Klein, Richard J.T. (2009). Identifying Countries that are Particularly Vulnerable to the Adverse Effects of Climate Change: An Academic or a Political Challenge? *Carbon & Climate Law Review, 3*(3), 284-291.

Klein, Richard J. T. (2012). *Enhancing the rigour of climate change vulnerability, impact and adaptation research* Paper presented at the Climate Adaptation Futures: Second International Climate Change Adaptation Conference, Tuscon, Arizona.

Klein, Richard J.T., Nicholls, R.J., and Mimura, N. (1999). Coastal adaptation to climate change: can the IPCC technical guidelines be applied? *Mitigation and Adaptation Strategies for Global Change, 4*(3-4), 239-252. Retrieved from http://dx.doi.org/10.1023/a:1009681207419

Kok, M.T.J., Lüdeke, M.K.B., Sterzel, T., Lucas, P.L., Walter, C., Janssen, P., and de Soysa, I. (2010). Quantitative analysis of patterns of vulnerability to global environmental change: Netherlands Environmental Assessment Agency (PBL).

Kurczy, S., Montgomery, L., and Ryan, E. (2010). Chile earthquake facts: Chile vs. Haiti, in numbers *The Christian Science Monitor.*

Läderach, P. (2011). Predicting the impact of climate change on the cocoa-growing regions in Ghana and Cote d'Ivoire *Final Report*: International Center for Tropical Agriculture (CIAT).

Laderach, P., Lundy, M., Jarvis, A., Ramirez, J., Portilla, E.P., Schepp, K., and Eitzinger, A. (2011). Predicted Impact of Climate Change on Coffee Supply Chains. 703-723. Retrieved from http://dx.doi.org/10.1007/978-3-642-14776-0_42

Lang, S., Zeil, P., Kienberger, S., and Tiede, D. (2008). *Geons – policy-relevant geo-objects for monitoring high-level indicators*. Paper presented at the Geospatial Crossroads @ GI_Forum. Proceedings of the Second Geoinformatics Forum, Salzburg, Germany.

le Blanc, D., and Perez, R. (2008). The relationship between rainfall and human density and its implications for future water stress in Sub-Saharan Africa. *Ecological Economics, 66*(2–3), 319-336. Retrieved from http://dx.doi.org/10.1016/j.ecolecon.2007.09.009

Levy, M. (2012). *Data Implications of Priority Research Needs*. Paper presented at the UNEP PRO-VIA panel of the Adaptation Futures Conference, Tucson, Arizona.

Lucas, P.L., & Hilderink, H.B.M. (2004). Vulnerability Concept and its Application to Food Security: RIVM report 550015004.

Lüdeke, M.K.B., Petschel-Held, G., and Schellnhuber, H.J. (2004). Syndromes of Global Change. *GAIA - Ecological Perspectives for Science and Society, 13*(1), 42-49.

Lyon, B. (2012). Personal Communication.

Mayhew, S. (1997). A Dictionary of Geography. New York: Oxford University Press.

McGranahan, G., Balk, D., and Anderson, B. (2007a). The rising tide: assessing the risks of climate change and human settlements in low elevation coastal zones. *Environment and Urbanization, 19*(1), 17-37. Retrieved from http://dx.doi.org/10.1177/0956247807076960

McGranahan, G., Balk, D., and Anderson, B. (2007b). Low Elevation Coastal Zone (LECZ) urban-rural population estimates, Global Rural-Urban Mapping Project (GRUMP), alpha version. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC).

Midgley, S.J.E., Davies, R.A.G., and Chesterman, S. (2011). Climate risk and vulnerability mapping in southern Africa: status quo (2008) and future (2050). Report produced for the Regional Climate Change Programme for Southern Africa (RCCP), UK Department for International Development (DFID). Cape Town, South Africa: OneWorld Sustainable Investments.

Moser, S.C., and Ekstrom, J.A. (2011). Taking ownership of climate change: participatory adaptation planning in two local case studies from California. *Journal of Environmental Studies and Sciences, 1*(1), 63-74. Retrieved from http://dx.doi.org/10.1007/s13412-011-0012-5

Moser, S.C., and Boycoff, M.T. (2013). *Succesful Adaptation to Climate Change: Linking Science and Policy in a Rapidly Changing World*. New York, NY: Routledge.

Nicholls, R.J., Hoozemans, F.M. J., and Marchand, M. (1999). Increasing flood risk and wetland losses due to global sea-level rise: regional and global analyses. *Global Environmental Change, 9, Supplement 1*(0), S69-S87. Retrieved from http://dx.doi.org/10.1016/S0959-3780(99)00019-9

Notenbaert, A., Massawe, S., and Herrero, M. (2010). *Mapping risk and vulnerability hotspots in the COMESA region: technical report*. Regional Strategic Analysis and Knowledge Support System (RESAKSS) Working Paper 32. IFPRI. Washington, D.C. Retrieved from http://hdl.handle.net/10568/2430

Nyabako, T., and Manzungu, E. (2012). An assessment of the adaptability to climate change of commercially available maize varieties in Zimbabwe. *Environment and Natural Resources Research, 2*(1), 32-46. Retrieved from http://dx.doi.org/10.5539/enrr.v2n1p32

O'Brien, K., Leichenko, R., Kelkar, U., Venema, H., Aandahl, G., Tompkins, H., . . . West, J. (2004). Mapping vulnerability to multiple stressors: climate change and globalization in India. *Global Environmental Change, 14*(4), 303-313. Retrieved from http://dx.doi.org/10.1016/j.gloenvcha.2004.01.001

O'Brien, K., Eriksen, S., Nygaard, L.P., and Schjolden, A.N.E. (2007). Why different interpretations of vulnerability matter in climate change discourses. *Climate Policy, 7*(1), 73-88. Retrieved from http://dx.doi.org/10.1080/14693062.2007.9685639

OECD. (2006). Handbook on Constructing Composite Indicators: Methodology and User Guide. Paris: Organization for Economic Cooperation and Development.

Oettli, P., Sultan, B., Baron, C., and Vrac, M. (2011). Are regional climate models relevant for crop yield prediction in West Africa? *Environmental Research Letters, 6*(1), 014008.

Openshaw, S. (1983). *The Modifiable Areal Unit Problem*: Geo.

Pahl-Wostl, C., Giupponi, C., Richards, K., Binder, C., de Sherbinin, A., Sprinz, D., . . . van Bers, C. (2013). Transition towards a new global change science: Requirements for methodologies, methods, data and knowledge. *Environmental Science & Policy, 28*(0), 36-47. Retrieved from http://dx.doi.org/10.1016/j.envsci.2012.11.009

Parish, E.S., Kodra, E., Steinhaeuser, K., and Ganguly, A.R. (2012). Estimating future global per capita water availability based on changes in climate and population. *Computers & Geosciences, 42*(0), 79-86. Retrieved from http://dx.doi.org/10.1016/j.cageo.2012.01.019

Parry, M.L., Canziani, O.F., Palutikof, J.P., van der Linden, P.J., and Hanson, C.E. (2007). Climate Change 2007: Impacts, Adaptation and Vulnerability. In M. L. Parry, O. F. Canziani, J. P. Palutikof, P. J. v. d. Linden & C. E. Hanson (Eds.), *Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 23-78). Cambridge, UK: IPCC.

Patt, A., and Dessai, S. (2005). Communicating uncertainty: lessons learned and suggestions for climate change assessment. *Comptes Rendus Geoscience, 337*(4), 425-441. Retrieved from http://dx.doi.org/10.1016/j.crte.2004.10.004

Pérez-Foguet, A., and Giné Garriga, Ricard. (2011). Analyzing water poverty in basins. *Water Resources Management, 25*(14), 3595-3612. Retrieved from http://dx.doi.org/10.1007/s11269-011-9872-4

Pfeffer, W. T., Harper, J. T., and O'Neel, S. (2008). Kinematic constraints on glacier contributions to 21st-century sea-level rise. *Science, 321*(5894), 1340-1343. Retrieved from 10.1126/science.1159099

Piontek, F., Müller, C., and Pugh, T.A.M. (2013). Multisectoral climate impacts in a warming world. *Proceedings of the National Academy of Sciences,* Retrieved from 10.1073/pnas.1222471110

Polsky, C. (2013, January 17, 2013). [Personal communication].

Preston, B. (2012). Vulnerability mapping for climate change: a critical look at a common practice. Tucson, AZ: Climate Adaptation Futures.

Preston, B.L, Yuen, E.J., and Westaway, R.M. (2011). Putting vulnerability to climate change on the map: a review of approaches, benefits, and risks. *Sustainability Science, 6*(2), 177-202. Retrieved from http://dx.doi.org/10.1007/s11625-011-0129-1

Preston, B.L. (2013). Local path dependence of U.S. socioeconomic exposure to climate extremes and the vulnerability commitment. *Global Environmental Change, 23*(4), 719-732. Retrieved from 10.1016/j.gloenvcha.2013.02.009

Preston, B.L. (2013). Personal communication.

Preston, B.L., Abbs, D., Beveridge, B., Brooke, C., Goddard, R., Hunt, G., . . . Withycombe, G. (2007). *Spatial Approaches for Assessing Vulnerability and Consequences in Climate Change Assessments* Paper presented at the Proceedings of MODSIM 2007: International Congress on Modelling and Simulation, Christchurch, NZ. .

Preston, B. L., Brooke, C., Measham, T. G., Smith, T. F., and Gorddard, R. (2009). Igniting change in local government: lessons learned from a bushfire vulnerability assessment. *Mitigation and Adaptation Strategies for Global Change, 14*(3), 251-283. Retrieved from http://dx.doi.org/10.1007/s11027-008-9163-4

PROVIA. (2013a). Research Priorities on Vulnerability, Impacts and Adaptation: Responding to the Climate Change Challenge. Nairobi, Kenya: United Nations Environment Programme.

PROVIA. (2013b). PROVIA Guidance on Assessing Vulnerability, Impacts and Adaptation to Climate Change *Consultation document*. Nairobi, Kenya: United Nations Environment Programme.

Rahmstorf, S. (2012). Modeling sea level rise. *Nature Education Knowledge, 3*(10), 4.

Ramankutty, N., Evan, A.T., Monfreda, C., and Foley, J.A. (2010). Global Agricultural Lands: Croplands, 2000. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC).

Reid, W.V., Mooney, H.A., Cropper, A., Capistrano, D., Carpenter, S.R., Chopra, K., . . . Zurek, M.B. (2005). Ecosystems and Human Well-being: Synthesis (pp. 155). Washington, D.C.: Island Press.

Rygel, L., O'Sullivan, D., and Yarnal, B. (2006). A method for constructing a social vulnerability index: an application to hurricane storm surges in a developed country. *Mitigation and Adaptation Strategies for Global Change, 11*(3), 741-764. Retrieved from 10.1007/s11027-006-0265-6.

Schiller, Andrew, de Sherbinin, Alex, Hsieh, W., & Pulsipher, Alex. (2001). The vulnerability of global cities to climate hazards *2001 Open Meeting of the Human Dimensions of Global Environmental Change Research Community*. Rio de Janeiro, Brazil.

Shen, X., Downing, T. E., & Hamza, M. (2010). Tipping Points in Humanitarian Crisis: From Hot Spots to Hot Systems: Studies of the University: Research, Counsel, Education (SOURCE) Publication Series of UNU-EHS.

Slocum, T.A , McMaster, R.B., Kessler, F.C, and Howard, H.H. (2009). *Thematic Cartography and Geovisualization (3rd Edition)* Pearson Prentice Hall.

Storch, H., Downes, N., and Rujner, H. (2011). A scenario-based approach to assessing the exposure and flood risk of Ho Chi Minh City's urban development strategy in times of climate change. In W. Pillmann, S. Schade & P. Smits (Eds.), *EnviroInfo 2011: Innovations in Sharing - Environmental Observations and Information*. Shaker Verlag, Ispra.

Strauss, B.H., Ziemlinski, R., Weiss, J.L., and Overpeck, J.T. (2012). Tidally adjusted estimates of topographic vulnerability to sea level rise and flooding for the contiguous United States. *Environmental Research Letters,* 7(1), 014033.

Szlafsztein, C., and Sterr, H. (2007). A GIS-based vulnerability assessment of coastal natural hazards, state of Pará, Brazil. *Journal of Coastal Conservation, 11*(1), 53-66. Retrieved from http://dx.doi.org/10.1007/s11852-007-0003-6

Tappan, G. (2013, 6/21/13). [Personal communication].

Tebaldi, C., Strauss, B.H., and Zervas, C.E. (2012). Modelling sea level rise impacts on storm surges along US coasts. *Environmental Research Letters,* 7(1), 014032.

Thow, A., and de Blois, M. (2008). Climate change and human vulnerability: mapping emerging trends and risk hotspots for humanitarian actors *Discussion Paper*. Bath, UK: Maplecroft.

Torres, Roger A., Lapola, David M., Marengo, Jose A., & Lombardo, Magda A. (2012). Socio-climatic hotspots in Brazil. *Climatic Change, 115*, 597-609. Retrieved from http://dx.doi.org/10.1007/s10584-012-0461-1

Trzaska, S. (2013). Personal Communication.

Turner, B. L., Kasperson, R.E., Matson, P.A., McCarthy, J.J., Corell, R.W., Christensen, L., . . . Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences, 100*(14), 8074-8079. Retrieved from http://dx.doi.org/10.1073/pnas.1231335100

UNDP. (2010). Mapping climate change vulnerability and impact scenarios: A guidebook for sub-national planners. New York: UNDP. Retrieved from http://europeandcis.undp.org/uploads/public1/files/Mapping%20CC%20Vulnerability%20publication%20-%20November%202010.pdf

UNEP. (2011). Livelihood security: climate change, migration and conflict in the Sahel: United Nations Environment Programme (UNEP), the International Organization for Migration (IOM), the Office for the Coordination of Humanitarian Affairs (OCHA) and the UN University, and the Permanent Interstate Committee for Drought Control in the Sahel (CILSS).

UN-HABITAT. (2013). Flood Risk Assessment, Strategies and Actions for IMproving Flood Risk Management in Kampala. Nairobi, Kenya: UN-HABITAT.

UNISDR. (2009). Global Assessment Report on Disaster Risk Reduction. Geneva: United Nations.

University of Wisconsin. (n.d.). Factor analysis versus PCA. Retrieved 22 November 2013, from http://psych.wisc.edu/henriques/pca.html

USAID. (2013). Uganda Climate Change Vulnerability Assessment Report *African and Latin American Resilience to Climate Change (ARCC) report*. Washington, D.C.: Tetra Tech/ARD.

Vörösmarty, C.J., Douglas, E M., Green, A., and Revenga, C. (2005). Geospatial indicators of emerging water stress: an application to Africa. *AMBIO: A Journal of the Human Environment, 34*(3), 230-236. Retrieved from http://dx.doi.org/10.1579/0044-7447-34.3.230

Warner, K., Afifi, T., Henry, K., Rawe, T., Smith, C., and de Sherbinin, A. (2012a). Where the rain falls: climate change, food and livelihood security, and migration. Bonn, Germany: United Nations University and CARE.

Warner, K., Erhart, C., de Sherbinin, Alex, Adamo, Susana B., and Chai-Onn, T. (2009). In search of shelter: mapping the effects of climate change on human migration and displacement. Bonn, Germany: United Nations University, CARE, and CIESIN-Columbia University.

Warner, K., van der Geest, K., Kreft, S., Huq, S., Harmeling, S., Kusters, K., and de Sherbinin, A. (2012b). Evidence from the frontlines of climate change: loss and damage to communities despite coping and adaptation *Loss and Damage in Vulnerable Countries Initiative. Policy Report.* Bonn: United Nations University Institute for Environment and Human Security (UNU-EHS).

Wenger, E. (1998). *Communities of Practice: Learning, Meaning, and Identity*. Cambridge, UK: Cambridge University Press.

Wilhelmi, O.V., and Hayden, M.H. (2010). Connecting people and place: a new framework for reducing urban vulnerability to extreme heat. *Environmental Research Letters, 5*(1), 014021.

Wood, C., & Skole, D. (1998). Linking satellite, census, and survey data to study deforestation in the Brazilian Amazon. In D. Liverman, E. Moran, R. Rindfuss & P. Stern (Eds.), *People and Pixels: Linking Remote Sensing and Social Science*. Washington, D.C.: National Academy Press.

YCELP, CIESIN, WEF, and JRC. (2005). Environmental Sustainability Index. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC).

ANNEX 1. LIST OF INDICATORS USED IN A VULNERABILITY ASSESSMENT FOR SOUTHERN AFRICA

The following tables include the indicators used in a spatial VA conducted in southern Africa by Midgley et al. (2011). This is a representative effort that followed the IPCC framework of Exposure, Sensitivity, and Adaptive Capacity, but with current and future exposure using climate scenario data broken out separately.

TABLE A1.1 INDICATORS USED IN A VULNERABILITY ASSESSMENT FOR SOUTHERN AFRICA

Component of vulnerability (category)	Indicator	Abbreviation	Assumed relationship between indicator and category	Relative weighting within category	Web links, sources, credits, references
Exposure (present)	Coefficient of variation for inter-annual rainfall	max2methsraincv	Positive	2	International Water Management Institute (IWMI), using the 100 year gridded precipitation dataset (CRU TS 2.0) developed by the University of East Anglia. Eriyagama *et al.* 2009. Global Risk Data Platform (PreventionWeb), World Bank, UNEP, UNDP, UN/ISDR. Credit: IRI and CIESIN (Columbia University). McKee *et al.*, 1993.
	Coefficient of variation for monthly rainfall	E_mcv_monthly	Positive	2	Worldclim (Hijmans *et al.*, 2005) Bioclimatic variable 'Bio15'
	Risk of cyclones	E_cyclones	Positive	2	Center for Hazards and Risk Research (CHRR), Dilley *et al.*, 2005; Center for International Earth Science Information Network (CIESIN), Columbia University; International Bank for Reconstruction and Development/The World Bank; United Nations Environment Programme Global Resource Information Database Geneva (UNEP/GRID-Geneva).
	Risk of floods	floodfreq	Positive	2	Global Risk Data Platform (PreventionWeb), World Bank, UNEP, UNDP, UN/ISDR. Credit: GIS processing UNEP/GRID-Europe, with key support from USGS EROS Data Center, Dartmouth Flood Observatory 2008.
	Standardised precipitation index	SPI	Positive	2	Global Risk Data Platform (PreventionWeb), World Bank, UNEP, UNDP, UN/ISDR. Credit: IRI and CIESIN (Columbia University). McKee *et al.*, 1993.

Component of vulnerability (category)	Indicator	Abbreviation	Assumed relationship between indicator and category	Relative weighting within category	Web links, sources, credits, references
	Fire frequency	firefreq	Positive	1	Global Risk Data Platform (PreventionWeb), World Bank, UNEP, UNDP, UN/ISDR. Credit: GIS processing World Fire atlas (ESA-ESRIN).
	Disaster events: Number of events by area	E_dis_event	Positive	1	WHO Collaborating Centre for Research on the Epidemiology of Disasters (CRED): Emergency Events Database EM-DAT
	Disaster events: Numbers affected per population	E_dis_affect	Positive	1	WHO Collaborating Centre for Research on the Epidemiology of Disasters (CRED): Emergency Events Database EM-DAT
Exposure (future – 2050)	Additional population density	E2_add_dens	Positive	3	United Nations Department of Economic and Social Affairs/Population Division 9 World Population to 2300
	1 in 10 year drought	E2_GCM1in10drought	Positive	1	Climate Explorer (climexp). Shongwe *et al.*, 2009.
	GCM ensemble precipitation change	E2_GCM_precipchange	Positive or negative	3	Climate Explorer (climexp). The following GCMs were used: HADCM3, CSIRO, ECHAM5, CCCMA and MIROC (high resolution); and the SRES A1b futures scenario.
	GCM ensemble temperature change	E2_GCM_tempchange	Positive	3	Climate Explorer (climexp). An ensemble of five models was used (HADCM3, CSIRO, ECHAM5, CCCMA and MIROC (high resolution) and the SRES A1b scenario.
	Worldclim ensemble precipitation change	E2_WCprecipchange	Positive or negative	1	Worldclim
	Worldclim HADCM3 maximum temperature change	E2_WCmaxtempchange	Positive	1	Worldclim
	Loss of suitability for cropland	E2_cropchange	Positive	2	FGGD / IIASA (FAO 2007). Holdridge Life Zones. Pilot Analysis of Global Ecosystems (PAGE): Agroecosystems Dataset. ILRI, 2006; FAO, 2007; Jones and Thornton, 2009. IFPRI.
	Sea level rise	E2_searisk	Positive	2	Shuttle Radar Topography Mission. U.S. Geological Survey Center for Earth Resource Observation and Science (EROS), National Aeronautics and Space Administration (NASA), National Geospatial-Intelligence Agency (NGA), ESRI

Component of vulnerability (category)	Indicator	Abbreviation	Assumed relationship between indicator and category	Relative weighting within category	Web links, sources, credits, references
Sensitivity	Percent land under irrigation	S_irrigated	Negative	3	The data are an IIASA modification of FAO and University of Kassel (2002), Digital Global Map of Irrigated Areas v. 2.1.
	Human appropriation of net primary productivity	S_app_NPP	Positive	2	Columbia University Center for International Earth Science Information Network (CIESIN). Imhoff *et al.*, 2004.
	Volume of rainfall per person on agricultural land	S_rain_pp_crop	Negative	3	UNEP population database. FAO/IIASA GAEZ. Worldclim. Hijmans *et al.*, 2005.
	Crowding on agricultural land	S_popd_agric	Positive	2	UNEP population database. FAO/IIASA GAEZ.
	Length of growing period	S_lgp	Negative	2	The FGGD Digital Atlas: This dataset is contained in Module 4 "Environmental conditions" of Food Insecurity, Poverty and Environment Global GIS Database (FGGD) (FAO and IIASA, 2007). ILRI, 2006.
	Easily available soil moisture	S_avail_soilM	Negative	3	FAO; derived from Digital Soil Map of the World
	Soil degradation	S_soil_deg	Positive	2	Global Assessment of Human Induced Soil Degradation (GLASOD). Credit: International Soil Reference and Information Centre (ISRIC) at Wageningen, The Netherlands, and United Nations Environment Programme (UNEP). Oldeman *et al.*, 1990.
	Slope	S_slope	Positive	2	Shuttle Radar Topography Mission. U.S. Geological Survey Center for Earth Resource Observation and Science (EROS), National Aeronautics and Space Administration (NASA), National Geospatial-Intelligence Agency (NGA), ESRI
	Net primary productivity	S_npp	Negative	2	Global Climatological Net Primary Production of Biomass dataset from CLIMPAG, FAO. Lieth, 1972.
	Major agricultural systems	S_agric_syst	Table linking system to vuln. (RCCP)	1	World Bank, FAO
	Own food production	S_food_prod	Negative	1	FAO. De Wit, 2009.
	Protein consumption	S_prot_cons	Negative	1	FAO. De Wit, 2009.
	Dietary diversity	S_diet_div	Negative	1	FAO
	Water withdrawals	S_waterwithd	Positive	2	FAO: AQUASTAT
	People living in water stress	S_water_str	Positive	2	WWDRII. African Water Stress Study. Vörösmarty *et al.*, 2005.
	Forest loss	S_forestloss	Positive	2	Global Gross Forest Loss; WCMC Global Forests Dataset: disturbed forests and historic extent of forests; current extent of forest cover MODIS Vegetation Continuous Fields. Hansen *et al.*, 2010.

Component of vulnerability (category)	Indicator	Abbreviation	Assumed relationship between indicator and category	Relative weighting within category	Web links, sources, credits, references
	Contribution of agriculture to Gross Domestic Product	A_agric_GDP	Negative	2	http://web.worldbank.org/WBSITE/EXTERNAL/DATASTATISTICS/0,,contentMDK:21298138□pagePK:64133150□piPK:64133175□theSitePK:239419,00.html World Bank (2007). World Development Indicators 2007. World Bank, Washington. 432pp.
	Water discharge	A_water_dis	Positive	1	http://wwdrii.sr.unh.edu/download.html Vörösmarty *et al.*, 2005.
	Irrigation potential	A_irrigpot	Positive	2	http://www.ifpri.org/publication/what-irrigation-potential-africa
	Conflicts	A_conflicts	Negative	1	http://www.prio.no/CSCW/Datasets/Armed-Conflict/Armed-Conflict-Location-and-Event-Data/; http://www.ucdp.uu.se/gpdatabase/search.php . Raleigh *et al.*, 2005.
	Governance	A_governance	Negative	2	http://www.moibrahimfoundation.org/en/section/the-ibrahim-index
	Forest resources	A_forestres	Positive	1	http://glcf.umiacs.umd.edu/data/vcf/
	Biodiversity	A_biodiv	Positive	2	http://www.zmuc.dk/CommonWeb/research/biodata.htm
Adaptive capacity	Infrastructure poverty	A_pov_infra	Negative	2	NOAA: NOAA websites are provided as a public service by the U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Environmental Satellite, Data and Information Service. Information presented on these web pages is considered public information and may be distributed or copied.. Doll *et al.*, 2000; Sutton *et al.*, 2007; Elvidge *et al.*, 2009; World Bank, 2006.
	Economic wealth	A_GDP_pc	Positive	3	United Nations Development Programme (2007)
	Malnourishment in children under 5 years old	A_abovewt	Negative	3	Center for International Earth Science Information Network (CIESIN, 2005), Columbia University.
	Education index	A_educ_ind	Positive	2	United Nations Development Programme (2007)
	Health expenditure	A_health_exp	Positive	2	United Nations Development Programme (2007)
	Malaria incidence	A_malaria	Negative	1	Malaria Atlas Project (MAP); Hay *et al.*, 2010
	Tsetse fly habitat suitability	A_tsetse	Negative	1	FAO and DFID. Credit: Environmental Research Group Oxford (ERGO Ltd) in collaboration with the Trypanosomosis and Land Use in Africa (TALA) research group at the Department of Zoology, University of Oxford
	HIV prevalence	A_HIV_neg	Negative	2	United Nations Development Programme (2007)
	Access to improved water	A_imp_water	Positive	3	United Nations Development Programme (2007)
	Subscribers to a cellular network	A_cell_subs	Positive	1	United Nations Development Programme (2007)
	Travel time to nearest city	A_travelt	Negative	2	European Commission and World Bank. Nelson, 2008.
	Night lights	A_nightlights	Positive	3	http://www.ngdc.noaa.gov/dmsp/download.html Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by US Air Force Weather Agency. Doll *et al.*, 2000; Sutton *et al.*, 2007.

ANNEX 2. SAMPLE RESULTS: WATER VULNERABILITY ASSESSMENTS

This annex provides sample results for a number of spatial vulnerability assessments related to water resources, ranging from global to national scales. The purpose is to illustrate results that typical vulnerability assessments at different scales produce, including regions that are identified as vulnerable.

GLOBAL ASSESSMENTS

Global assessments have been conducted by Döll (2009) for climate change and population impacts on groundwater resources, focusing on ground water recharge rates; and by De Stefano et al. (2010) for hydrological exposure of international river basins to future climate change-induced water variability. Döll finds more consistent evidence across the global climate models utilized, with patterns of high vulnerability to decreases in groundwater resource availability in North Africa, Senegal and Mauritania, Namibia and western South Africa, and northeastern Brazil. De Stefano et al. (2010) find high projected water runoff variability by 2030 for the Colorado Basin in the U.S. Southwest, the Parana in South America, basins in West Africa and southern Africa, the Mekong, and southern China. Paradoxically, for reasons that apparently have to do with the climate projections but which are not fully discussed, the levels of variability across most basins decline by 2050.

Parish et al. (2012) integrate climate model and population data sources to develop first order water availability projections at the global scale. They sought to determine if there may be any new hotspots of water scarcity under a changing climate regime that would require planning and mitigation. In addition, they were interested in identifying the relative contributions of population and climate change as drivers of water availability. The study used climate projections and multiple SRES scenarios (A1B, B1, B2, and A1F1) as inputs to a hydrological model. To assess population growth, they apply SRES country-level population projections to the LandScan population grid, assuming a constant relative distribution of population within countries.

CONTINENTAL SCALE ANALYSES

Faramarzi et al. (2013) model the mid-term impact of climate change on freshwater availability in Africa at the sub-basin spatial scale and the monthly temporal scale to inform water management, planning of future developments, and climate adaptation strategies. This study aims to provide a systematic analysis of the likely impact of climate-induced scenarios on water resources availability on the continental scale by using the sub-basin as the basic hydrological unit to investigate the net effect of climate change on hydrological water balance and water resources components for the period 2020–2040. They highlight the need for information on seasonal and annual changes in water resources availability that explicitly quantifies "blue" and "green" water components in the context of global change, where blue water is defined as water yield plus deep aquifer recharge and green water is defined as soil moisture and evapotranspiration.

A hydrological simulation model, the Soil and Water Assessment Tool (SWAT), was used to integrate simulations of surface runoff, infiltration, evaporation, plant water uptake, lateral flow, and percolation to shallow and deep aquifers with climate projections derived from five global circulation models (GCMs) under four SRES scenarios (A1FI, A2, B1, and B2). The SWAT model was linked to ArcGIS which allows for analysis of large data sets at multiple spatial scales. Data sources included a digital elevation model (DEM), a land cover map, a soil map, daily weather input, and river discharge data. Watersheds were divided into 1,496 sub-basins based on topography, soil, and land use characteristics. For Africa overall, the results suggest an increase in the mean total quantity of water resources and an increase in the number and duration of drought events. Results for individual countries and sub-basins varied. Dry regions were found to have higher uncertainties in projected impacts on water resources than wet regions. The study projected that northern regions of the African continent will experience more severe droughts and that some eastern and southern regions will experience lesser rainfalls, decreased water availability, longer periods without a major rainfall event, and larger annual variations.

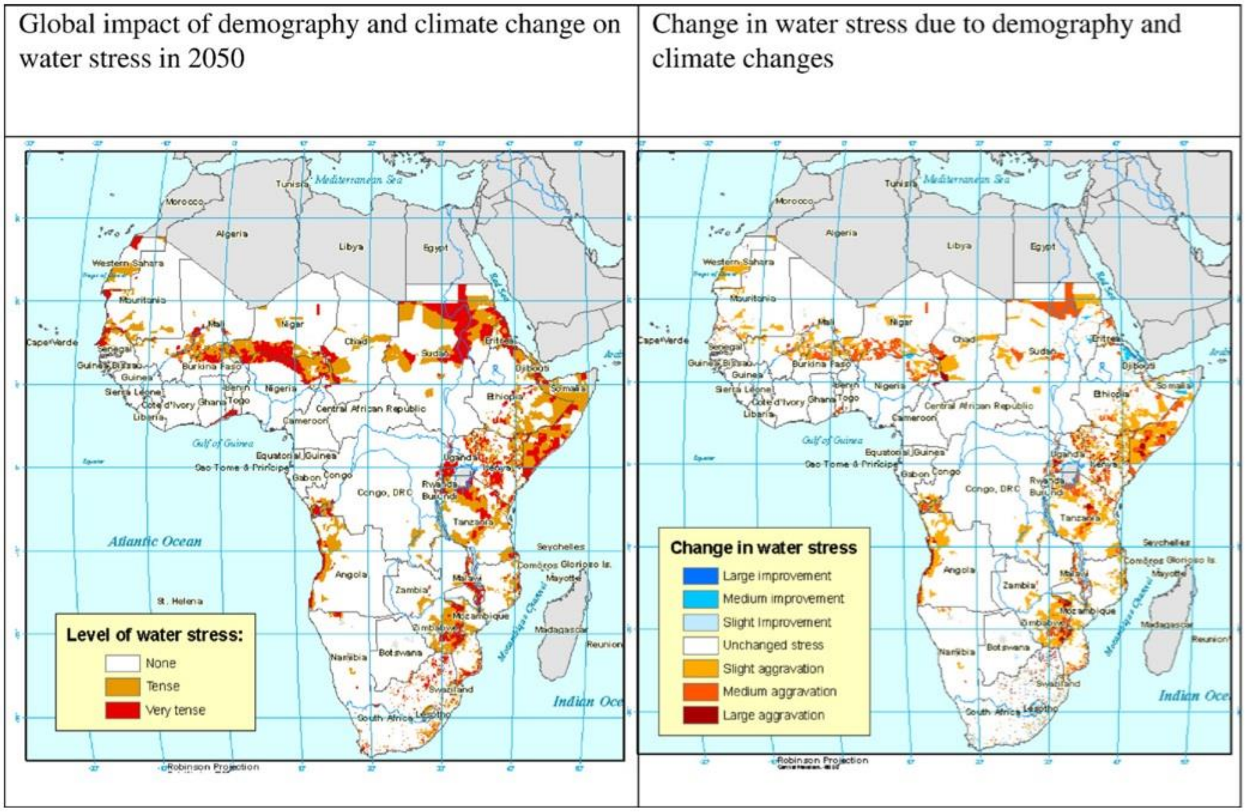
A previous continental-scale geospatial analysis conducted by Vörösmarty et al. (2005) investigated the condition of water resources and indicators of emerging water stress in Africa. This study aimed to demonstrate the use of widely available georeferenced, biogeophysical data sets — such as Earth systems science data from modeling experiments, weather prediction, remote sensing, and GIS — to study information-poor parts of the world at spatial scales that correspond to relevant policy and natural resource management needs. Their methodology estimated the scope of water scarcity over the African continent at 8km resolution, applying new capabilities to map subnational heterogeneities in climate moisture, river corridor discharge, population distribution, water supply, and water demands. Among their results, they find that "64% of Africans rely on water resources that are limited and highly variable," yet "water stress for the vast majority of Africans typically remains low, reflecting poor water infrastructure and service, and low levels of use" (Vörösmarty et al., 2005: 230). They conclude that well-engineered, modest increases in water use might mitigate water-related constraints on economic development, pollution, and human health challenges.

STUDIES IN SUB-SAHARAN AFRICA

To assess the likely consequences of climate and demographic changes for future water stress in Sub-Saharan Africa, le Blanc and Perez (2008) analyze the long-term relationship between average annual rainfall and human population density. The main objectives of this study are: (1) to identify zones in Sub-Saharan Africa under water tension based on the existing relationship between human population densities and average annual rainfalls, and (2) to estimate future evolution of the areas of stress, due to climate and demographic changes. They combine local GIS data on rainfall and population density with climate change scenarios to identify areas which will be subject to increased demographic pressures, given their precipitation levels. They first estimate the empirical relationship existing between average annual rainfall and population density across Sub-Saharan Africa. Zones falling on the right end of the distribution of densities conditional on rainfall are classified as tense (i.e., high stress). They then use localized population projections and changes in rainfall predicted by two climate change models to assess the respective impacts of those two factors on the changes in extent and distribution of tense zones over the continent. Out of five climate models downscaled by the Climate System Analysis Group (CSAG), le Blanc and Perez chose two data sets corresponding to the model of the Commonwealth Scientific and Industrial Research Organization (CSIRO) and the Hadley Center (HADAm) model.

They conclude that demographic growth will cause increased pressures on existing tense zones, in particular in the Sahel. Across Sub-Saharan Africa, demographic impacts will generally drive expansion of water-stressed zones. However, changes in rainfall will modulate the demographic impact with different implications in different subregions. They predict a somewhat favorable effect for Sahelian Africa and a negative impact on Eastern Africa. Even if the Sahel were to experience average rainfall increases, as predicted by most climate models, Le Blanc and Perez argue that these increases would perhaps ease, but not completely offset the pressure from demographic growth. In most of Eastern Africa, predicted decreases in average rainfall would work in the same direction as demographic changes to increase the pressure on much of the territory. For countries such as Burundi, Malawi, Mozambique, Tanzania, and Zimbabwe, the authors argue that changes in rainfall may be more important than population growth in contributing to increased water tension. In Southern Africa, demographic stagnation is likely to mitigate significantly the impact of climate change.

FIGURE A2.1. PROJECTED TENSE ZONES IN SUB-SAHARAN AFRICA IN 2050



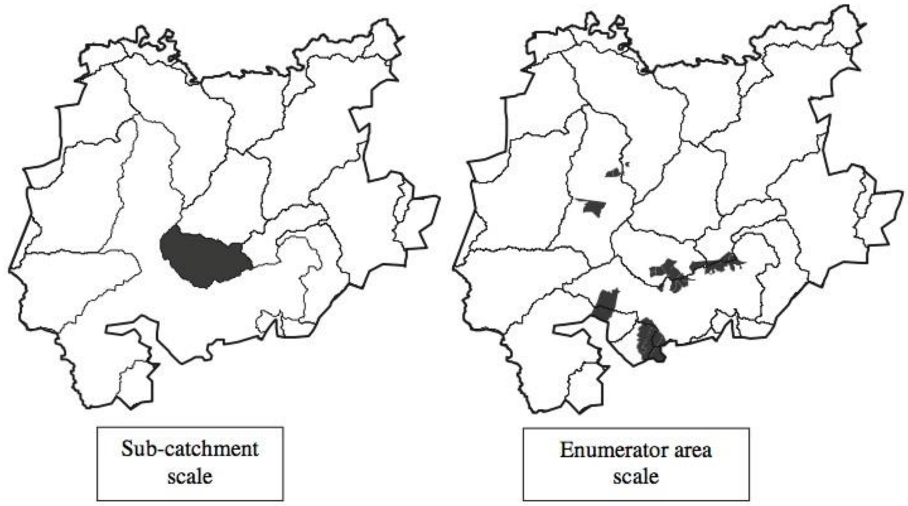
"Categories represented on the map have been defined in the following way. Large improvement: the area goes from very tense currently to no tension in the future. Medium improvement: the area goes down one category in the tension scale from very tense currently to tense in the future. Slight improvement: the area goes down one category in the tension scale from tense currently to no tension to in the future. The same concepts apply to the 'aggravation' categories."

Source: le Blanc and Perez, 2008: 332

LOCAL STUDIES

Cullis and O'Regan (2004) use census data and the Water Poverty Index (WPI), developed by Sullivan et al. (2003), to map water poverty for the Estcourt municipal district in South Africa. They created water poverty maps using available data sources at three different spatial scales: enumerator area, place names, and subcatchment. Their aim is to provide a practical way for water management authorities and decision makers to identify and target the most water poor households and to monitor the impacts and benefits of water supply development policies. The WPI is structured into five major components: Resources, Access, Capacity, Use, and Environment.

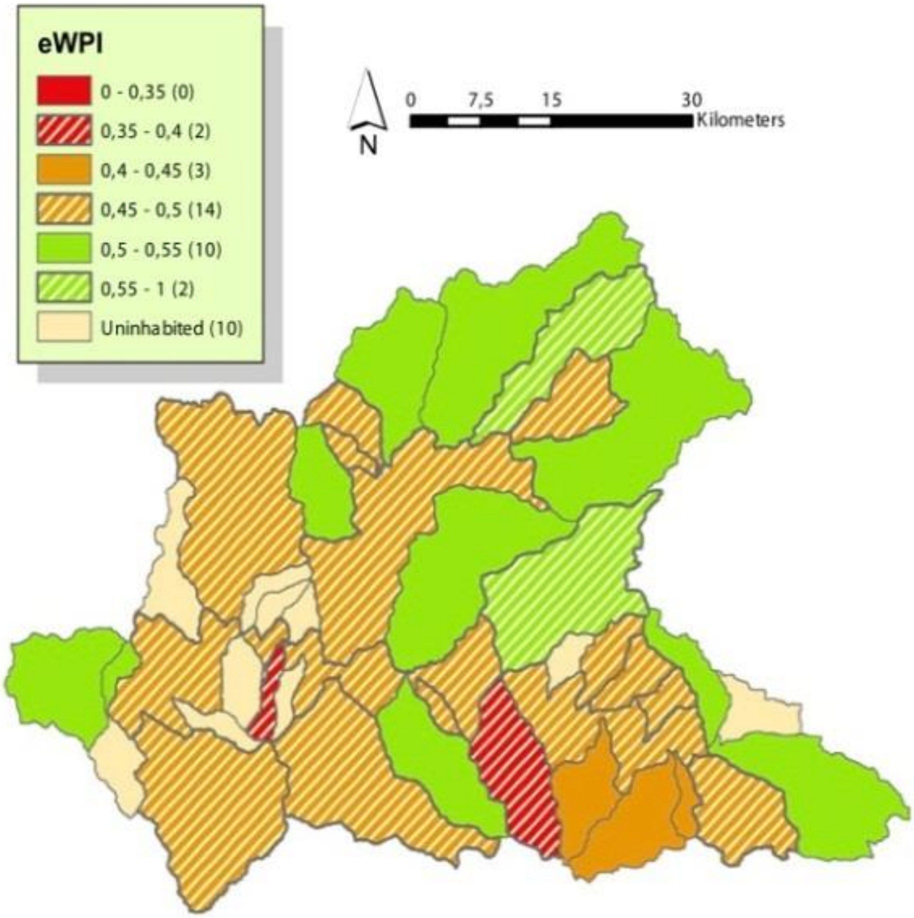
FIGURE A2.2. LOCATION OF THE 15 PERCENT MOST WATER-POOR HOUSEHOLDS, AS IDENTIFIED ON THE SUBCATCHMENT AND ENUMERATOR AREA SCALES



Source: Cullis and O'Regan, 2004: 406

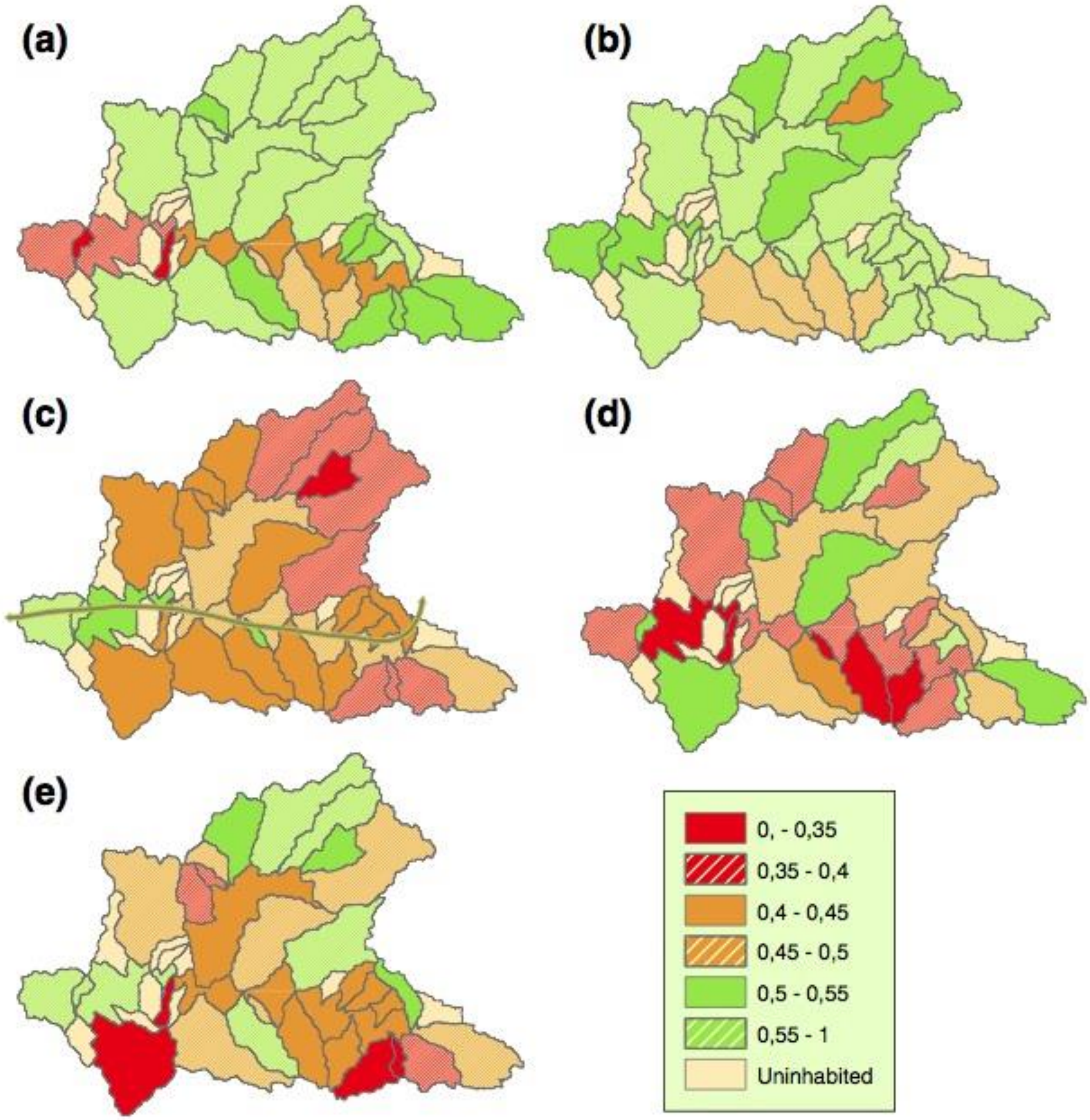
Pérez-Foguet and Giné Garriga (2011) develop an enhanced Water Poverty Index (eWPI) as an alternative to the WPI, with the objective of advancing a methodological framework for a multidimensional assessment of water poverty. The eWPI combines the WPI approach with the concept of causality captured by the Pressure-State-Response (PSR) model, which "accommodates the causal inter-relations between the components of the WPI, and integrates the policy cycle of problem perception, policy formulation, monitoring and policy evaluation" (Pérez-Foguet and Giné Garriga, 2011: 3598). They test the suitability and validity of the eWPI by implementing this tool in a pilot study focused on 31 inhabited sub-basins of the Jequetepeque Basin in northern Peru, a catchment area that drains into the Pacific Ocean. Relevant variables and indicators were selected and classified within the eWPI framework, which is structured into five components (Resources, Access, Capacity, Use, and Environment) and three states (Pressure, State, and Response).

FIGURE A2.3. THE EWPI VALUES AT SUBBASIN LEVEL. THE NUMBER OF SUBBASINS APPEARS IN BRACKETS.



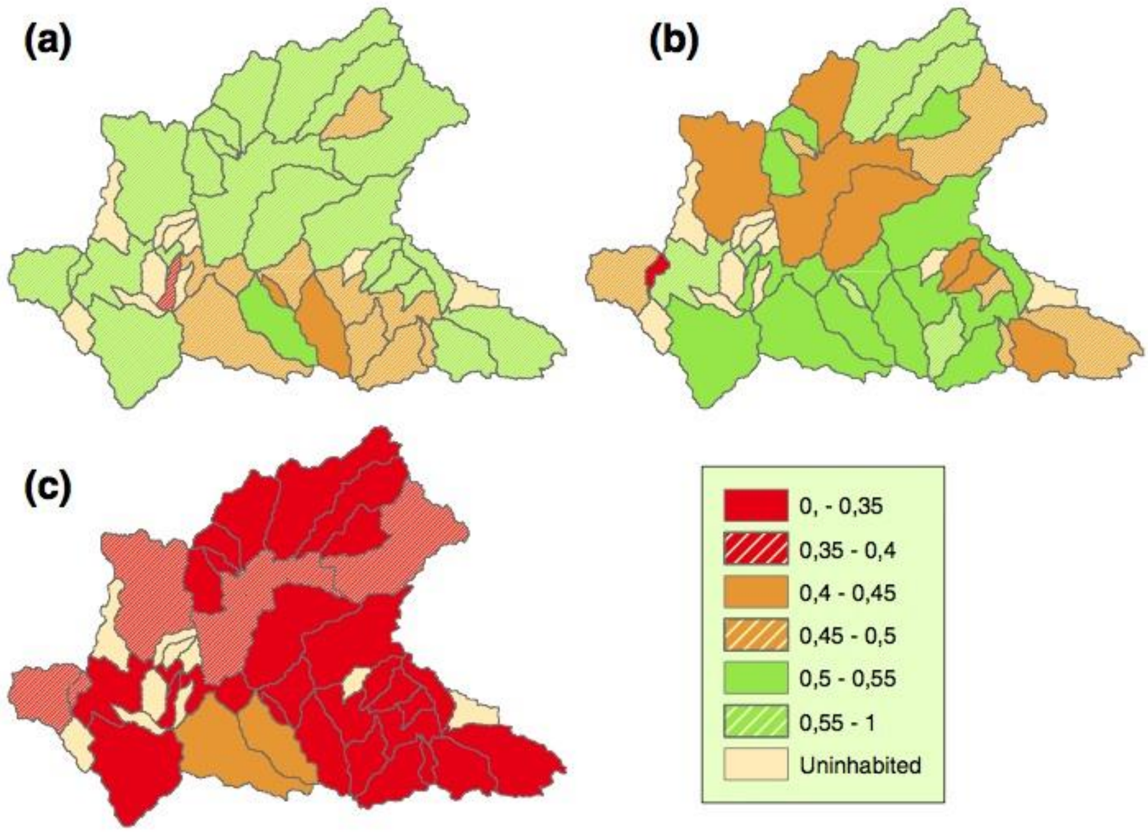
Source: Pérez-Foguet and Giné Garriga, 2011: 3607

FIGURE A2.4. THE EWPI COMPONENTS: (A) RESOURCES, (B) ACCESS, (C) CAPACITY, (D) USE, AND (E) ENVIRONMENT.



Source: Pérez-Foguet and Giné Garriga, 2011: 3608

FIGURE A2.5. THE EWPI STATES: (A) PRESSURE, (B) STATE, AND (C) RESPONSE.



Source: Pérez-Foguet and Giné Garriga, 2011

U.S. Agency for International Development
1300 Pennsylvania Avenue, NW
Washington, DC 20523
Tel: (202) 712-0000
Fax: (202) 216-3524
www.usaid.gov