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# METHODS FOR THE GEOGRAPHIC ALLOCATION OF CLIMATE CHANGE VULNERABILITY INDICATORS IN THE HEIHE BASIN

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**ABSTRACT:** Vulnerability to climate change is an increasingly relevant topic for "at risk" communities and ecosystems. An abundance of literature describes risk, impact, sensitivity and vulnerability with regard to climate change. These attributes of human and natural systems are difficult if not impossible to observe and measure, complicating their quantification. This paper presents an approach for quantitatively synthesizing these concepts. The use of indicators is a useful method of quantifying resource vulnerability. This paper presents a part of the research work of the AS25 project, a sub-project of the Assessments of Impacts of and Adaptation to Climate Change in Multiple Regions and Sectors (AIACC) focusing on an arid region of North West China. The paper reviews approaches for the formulation of indicators for agricultural, water resources and socioeconomic vulnerability to climate change in the Heihe River Basin. Quantitative issues involved with indicator formulation, computation and geographic allocation are discussed. Methods of fuzzy set construction are proposed for continuous, categorical, and qualitative indicators.

**KEYWORDS:** vulnerability, indicators, climate change, Heihe River, AS25 project

## 1. Introduction

The response of society and the environment to climate change is becoming a global concern (IPCC, 2001; Turner et al., 2003). In particular, the vulnerability of natural and human systems carries import for the future allocation of resources and planning of development (Kates et al., 2000). For this reason, the concept of vulnerability is related to concepts of sustainability, risk, social equity, and ecological stability (Vogel, 2001; Luers et al., 2003; Moss et al., 2001). Clearly, vulnerability, as an issue spanning such an array of resources and disciplines, requires an integration of information types for its assessment and evaluation. The "integrated assessment" approach has been suggested as an effective framework for analyzing this complex aspect of human-land systems (IPCC, 2001; Turner et al., 2003;

Polsky et al., 2003; Yin, 2001). Integrated assessment, as used here, implies a human dimension to environmental vulnerability.

Complicating the assessment is the fact that climate change vulnerability is generally not measurable or observable in the traditional sense. Additionally, the concept of vulnerability changes in context across spatial scales ranging from the individual human to country or global levels of aggregation (Polsky et al., 2003; Turner et al., 2003). It also changes in context geographically, as vulnerability in the middle of a city will likely be determined by a different set of criteria than vulnerability on a farm, or in a forest. However, climate change vulnerability can be conceptualized over multiple scales and arenas as a function of sensitivity (*s*), exposure (*e*), and adaptability (*a*) or lack thereof, as the case may be (Clark et al., 2000). From a probabilistic perspective, the likelihood (P) that a particular system of interest may be vulnerable is therefore expressed by the relationship:

$$\text{Vulnerability} = P(s)*P(e)*[1-P(a)]$$

With zero probability of any one of these factors (and 1-P(a) is considered as a factor), it can be argued that the system is not vulnerable. Unfortunately, as previously noted, these probabilities are very difficult to measure and must be estimated, determined by proxy, or otherwise qualitatively designated. In fact, the assumption that vulnerability can somehow be expressed in terms of various combinations of these three attributes is a necessary simplification for investigation of vulnerability in a variety of forms. Some researchers have suggested that a vulnerability including an adaptation term actually represents a “minimum potential vulnerability” and should be distinguished as such (Luers et al., 2003). This line of reasoning could be extended to the first terms of the equation as well, in that sensitivity is actually a form of endogenous vulnerability and the combination of sensitivity and exposure (to some form of climate change) indicates the degree of exogenous vulnerability (see Villa and McCleod, 2002; Vogel, 2001). The combination of adaptability with either endogenous or exogenous vulnerability would therefore indicate the respective minimum potential vulnerability. These terms will be used throughout this paper as descriptors of how indicators represent components of vulnerability. While Kaly and Pratt (2000) described a similar concept for the Environmental Vulnerability Index (EVI), it is not based on the probabilistic concept of vulnerability put forth above.

The use of indicators is valuable for the quantification and geographic allocation of vulnerability (United Nations, 2001; Moss et al., 2001). Since vulnerability is such a slippery subject to begin with, indicators may even be considered necessary for a description that is not completely qualitative and narrative. In order to assess vulnerability at a regional scale, a sufficient variety of indicators must be selected. This is necessary to insure that vulnerability at multiple spatial scales is represented, and that all components of the vulnerability equation are adequately represented. While it may not be possible to ensure equal representation, spatially or otherwise, the analysis should be transparent in terms of revealing these potential biases.

This paper presents methods for the geographic quantification and synthesis of vulnerability indicators. The objectives of the study were to devise a method to elucidate geographic patterns of vulnerability to climate change. In order to meet this objective, we conceptualize the elements of vulnerability and present indicators designed numerically represent these elements.

## 2. Study Site

The selection and spatial allocation of indicators is discussed in regard to the Heihe River basin, in North West China, illustrated in Figure 1. This area, located approximately between 37° and 43° North latitude and 97° and 103° East longitude, spans a wide variety of ecosystems and population densities. The basin encompasses approximately 128,000 square kilometers, with land cover ranging from irrigated agriculture to barren desert and including cities and other settlements of varying degrees of development. Elevation ranges between 688 and 5675 meters above sea level, with some of the highest areas experiencing extended periods of snow cover. Precipitation is generally between 100 and 250 millimeters per year, but can experience high variation geographically and temporally. Due to the wide variation in land cover, climate regime, and societal development, it is essential that vulnerability indicators are of sufficient number to capture the possible combinations of endogenous, exogenous and potential vulnerability at a variety of spatial scales.

## 3. Indicators

For practical reasons, the data sources and indicators considered here address spatial vulnerability at a limited number of spatial scales: square

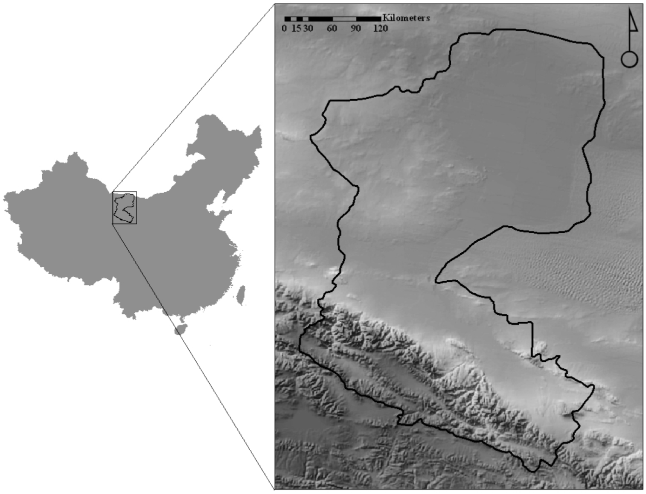


***FIGURE 1***

The Heihe River Basin.

kilometer, sub-watershed or water allocation district, and basin wide or regional scale. While some data are considered that represent vulnerability at the individual (health, per capita income) scale, these data are aggregated to the kilometer or county scale by necessity. Other data at intermediate scales are also presented, but will be either downscaled or aggregated to match the one-kilometer grid cells or county administrative units. Data sources are presented, where known, and indicated as to how they can be used in the calculation of the indicators.

The indicators derive from four fundamental categories: climatic, socioeconomic, hydrologic, and agro-ecosystematic. Clearly, these four categories are interrelated and it would be very difficult to create indices for any one category that are mutually exclusive of the others. Climatic indicators are the exception to this statement, though the other categories of indicators may incorporate climatic elements as exogenous vulnerability components. It is assumed that society and land cover at the Heihe basin level are of negligible influence on climatic indicators. The perceived representation in terms of the sector (socioeconomic, hydrologic, agricultural) and the vulnerability component in terms of exogenous or endogenous influences is described for each indicator and listed in Table 1.

**Table 1**

**Potential Vulnerability Metrics and Their Components**

| Indicator | Computation | Required Data | Sector | Vulnerability Type | Indicator Source |
|---|---|---|---|---|---|
| Dry periods | # of months over the last 5 years with rainfall >20% lower than 30 year average for that month | Monthly precipitation past 30 years and projected 5 years | Climate, hydrology | Exogenous | Kaly and Pratt, 2000 |
| Runoff yield change | (Projected yield)/(baseline yield) | Precipitation (baseline and projected), DEM, landcover, soil, other hydrologic model requirements | Climate, hydrology | Exogenous, endogenous | Kepner et al., 2004 |
| Runoff ratio | (Surface discharge)/(rainfall)/(unit area) | Precipitation (baseline and projected), DEM, landcover, soil, other hydrologic model requirements | Climate, hydrology | endogenous | Lane et al., 1999 |
| Irrigation ratio | ∅(water yield – irrigation)scenario/(water yield – irrigation)baseline | Water yields and irrigation requirements (baseline and projected) | Climate, hydrology, agriculture | Exogenous, endogenous | Izaurralde et al., 2003 |
| Irrigation deficit | Water yield – irrigation demand | Water yields and irrigation requirements (baseline and projected) | Climate, hydrology, agriculture | Exogenous, endogenous | Qi and Cheng, 1998 |
| Price | Intersection of supply and demand | Price of water | Hydrology, socio-economic | endogenous | Feitelson and Chenoweth, 2002 |
| Per Capita Water Resources | (annual surface water supply)/(population) | Water yields, population | Hydrology, socio-economic | endogenous | Multiple studies |
| Domestic deficit | Water yield – domestic demand | Water yields, domestic demand | Hydrology, socio-economic | Endogenous | Srdjevic et al., 2003 |
| Dependence ratio | (water transfer volume) / (domestic demand) | Water transfers, domestic demand | Hydrology, socio-economic | Endogenous | Lane et al, 1999 |
| Consumption ratio | (domestic demand)/(water) | Water yields, domestic demand | Hydrology, socio-economic | Endogenous | Moss et al., 2001 |
| Shortage | Average of (shortage)/(demand) over every occurrence of shortage | Water shortage, domestic demand | Hydrology, socio-economic | Endogenous | Srdjevic et al., 2003 |

**Table 1 Continued**

| Indicator | Computation | Required Data | Sector | Vulnerability Type | Indicator Source |
|---|---|---|---|---|---|
| Crop yield | Tons/hectare of crop | Crop yield | Agriculture | Endogenous, potential | Multiple studies |
| Yield index | (crop ET stressed)/(crop ET max) | Evapotranspiration, water availability, meteorological data | Agriculture, hydrology, climate | Endogenous | Thomas, 2000 |
| Yield reduction | (yield w/o irrigation)/(yield with irrigation) | Crop locations, water yields, meteorological data | Agriculture, hydrology, climate | Endogenous | This study |
| Irrigation ratio | (irrigated land area)/(cultivated land area) | Crop area, irrigation area | Agriculture, hydrology | Endogenous, potential | Lin and Shen, 1996 |
| Risk of hunger | (food energy required by population) – (food energy available from crops) | Crop productivity, energy conversion factors, population | Agriculture, socio-economic | Endogenous | Rosenzweig and Parry, 1994. |
| Crop land per capita | (cropland per unit area)/(population per unit area) | Crop area, population density | Agriculture, socio-economic | Endogenous | This study |
| Livestock per capita | (livestock by species per unit area)/(population per unit area) | Livestock, population | Agriculture, socio-economic | Endogenous, potential | Heilig, 1999 |
| Proximity to other land use | Distance to urban or desert pixels | Agriculture, urban, land cover data | Agriculture, socio-economic | Endogenous, exogenous | This study |
| Income per capita | Income/population | Income, population | socio-economic | Potential, endogenous | Multiple studies |
| Institutional wealth | GDP, institutional credit rating | GDP, institutional credit rating | socio-economic | Potential | Feitelson and Chenoworth, 2002 |
| Ginni index of income equity | Sum of differences between idealized income distribution and actual distribution | Income distribution by population | socio-economic | Potential, endogenous | United Nations, 2001 |
| Poverty index | Fraction of population represented by the lower quartile of income | Income distribution by population | socio-economic | Potential | This study |
| Employment diversity | Sum of [(employment fraction)*(natural log employment fraction)] | Employment by sector, industry | socio-economic | Potential, endogenous | This study |
| Health | Life expectancy, infant mortality, disease incidence | Life expectancy, infant mortality, disease incidence | socio-economic | Potential, | Moss et al., 2001 |

## 4. Mapping and Scaling

The reason for choosing quantifiable indicators for the estimation of vulnerability is in part to facilitate spatial allocation. As discussed, the indicators may represent phenomena at disparate spatial scales. The first question is, therefore, how to geographically distribute the indicators. For the purposes of this study, several spatial scales have been considered ranging between square kilometer and county administrative unit. These scales were chosen entirely on the basis of data availability and other logistical reasons. The important consideration in this case is the computation of indicators at the appropriate scale. For example, precipitation and crop yield are spatially variable and more accurately represented at a spatial scale less than the county unit (Figure 2). On the other hand, institutional frameworks that define social vulnerability may be administered on the county level and therefore would not be represented accurately by the square kilometer. Thus data that represents various components of the vulnerability equation may be mapped at different scales.

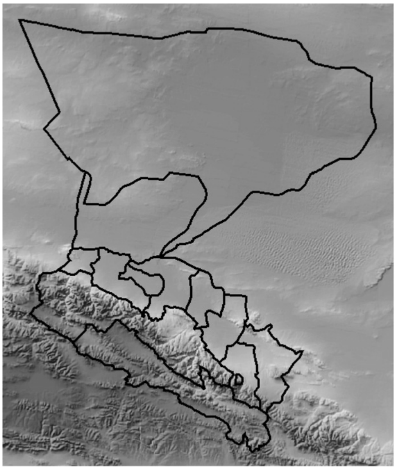

***FIGURE 2***

Counties of the Heihe Region.

The scaling issue is related to how the data should be conceptualized. Specifically, how observable phenomena, whatever forms the basis of the indicator, is actually related to vulnerability. Some information, such as available water for growing crops, may have a non-linear relationship with vulnerability - when the amount of water declines below a certain point, complete crop failure is expected. Consistent with the probabilistic definition of vulnerability, each indicator should be scaled to between 0 and 1, or a range between "not at all likely" and "100% likely." The question then becomes how to translate income, water shortage, yield reduction, or whatever is the indicator of interest to this scale.

Assimakopolous et al. (2003) present "Fuzzy Membership Functions" for converting continuous data to a membership grade between 0 and 1. The functions are defined as follows, where indicator value = x and c and d are parameters:

$$\text{Membership function} = f(x,c,d) = 1/(1+[(x\text{-}c)/d]^2)$$

In the case of a vulnerability ranking, the membership grade corresponds to probability of vulnerability. The membership function must be designed to reflect the relationship between the indicator value and the probability of vulnerability accurately as represented by the fuzzy membership value. Figure 3 shows how the membership function parameters presented by Assimakopolous et al. (2003) can be adjusted, based on expert judgment, to reflect vulnerability accurately. The parameter c is a threshold that defines the relative maximum location of the membership function (see Figure 3a) and d is a parameter that defines function width at 0.5 fuzzy membership (see Figure 3b).

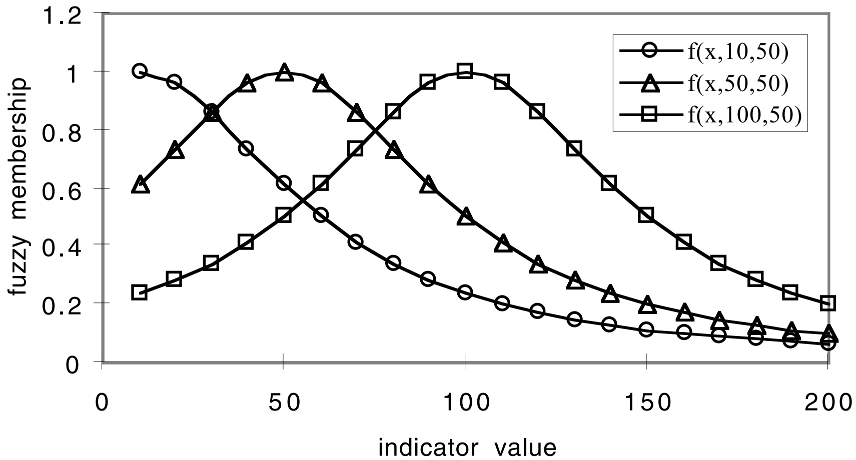


***FIGURE 3A***

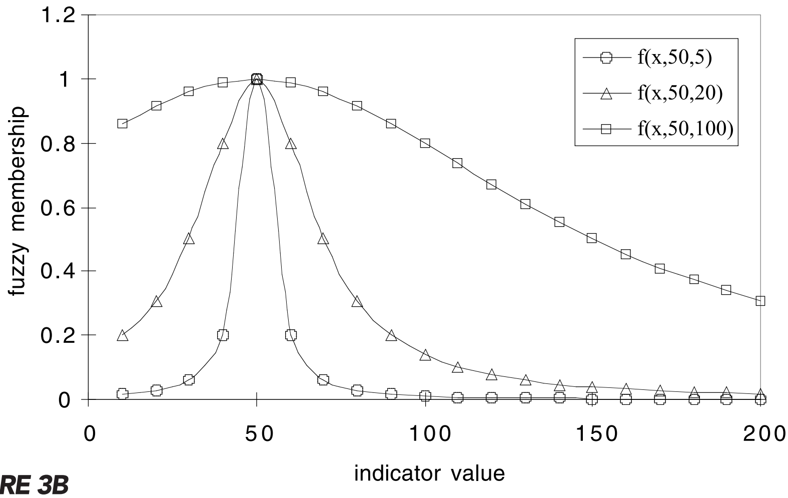


***FIGURE 3B***

***FIGURE 3***

Effect of c and d parameter variation in the fuzzy membership functions. 3a: the effect of varying c, the threshold value; 3b: the effect of varying d, the width of function parameter.

These functions should be defined according to the data. Linear or other relationships could also be defined as a way of transforming indicator values to vulnerability probability. Figure 4 shows the distribution of population density values in the Heihe basin according to two fuzzy membership functions. Scaled population data were allocated to fuzzy membership categories by dividing each population value by the maximum population density in the Heihe basin. A log transformation of the population results in a different distribution across the membership categories. As illustrated in Figure 4, log transformation of the population spreads low population densities over several fuzzy membership categories and compresses high population density into the upper fuzzy membership scale. The result is that vulnerability, as indicated by population density, is more evenly distributed over a scale of 0 to 1 according to the fuzzy membership function defined by:

$$\text{Membership function} = f(\text{population}) = \ln(\text{population})/[\ln(\text{maximum population})]$$

This function is useful from a cartographic perspective in terms of visualizing the spread of vulnerability according to population density. It is also valuable from an analytical perspective in that the geographic region is represented by a full range of vulnerability values after transformation by the membership function. The important consideration is whether the function logically describes the way an indicator actually "indicates" the likelihood of vulnerability. Assuming the relationship is accurate, it is then possible to convert spatially allocated indicator values to a map of vulnerability probability, with values between 0 and 1.

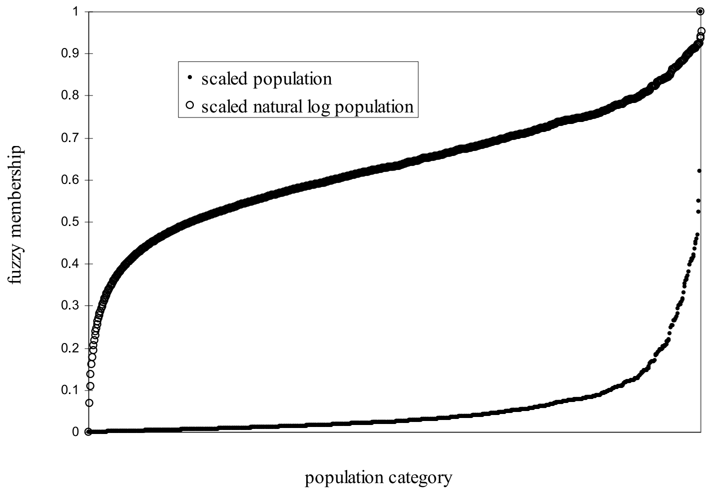


***FIGURE 4***

The use of a natural log transformation as a fuzzy membership function for population density in the Heihe Basin.

The previously discussed functions relate to the fuzziness of membership to only one category: vulnerable to climate change (or not). It may also be instructive to designate an arbitrary number of vulnerability classes, each corresponding to a particular level of probability. Let us assume there are 10 classes of vulnerability, ranging from 0-0.1 (low probability of vulnerability) to 0.9-1.0 (vulnerability extremely probable). Using the membership functions discussed above, it would be possible to allocate these values spatially, such that each pixel receives a probability corresponding to one of the classes of vulnerability. In general, the definition of a fuzzy partition of n observations (pixels) into c classes (vulnerability categories) is defined such that each pixel is represented by a vector with values Vi (Foody, 1994; McBratney and Moore, 1985):

$$\{V_1 \ldots V_c\};\ \ V_i \in [0,1];\ \ \Sigma\, V_i = 1,\ i=1\ldots c$$

In the context of vulnerability to climate change, this data organization becomes somewhat abstract. A fuzzy partition of the vulnerability probability classes would thus organize the information such that each vector entry describes the probability that the probability of vulnerability is in a particular class. While it may sound odd, this is actually just an awkward way of expressing the uncertainty of exactly how vulnerable a particular pixel may be. In this sense, a fuzzy partition formalizes the uncertainty with regard to vulnerability probability.

Using GIS and image processing approaches, a variety of methods have been proposed for how to accomplish this allocation (Foody, 1994; Maselli, 2001). However, these methods rely on a posteriori knowledge of the distribution of values within "training" areas. In the case of vulnerability to climate change, this is not the case (some of the empirical methods discussed above are an exception). For this reason, alternative methods are required.

Assuming that some number (*n*) of vulnerability indicators have been computed and geographically allocated, that would imply that in any one pixel, there are *n* different levels of vulnerability. A simple fuzzy partition could be constructed using the frequency distribution of pixel values over the vulnerability classes. For example, if an equal number of layers had probability of vulnerability in the highest and second to highest classes and no other classes were represented, the top two vulnerability classes would receive 0.5 values. It should be noted that there is potential for bias in this method (Srdjevic et al., 2003; Kaly and Pratt, 2000; Lane et al., 1999). The source of the bias derives from the original choice of indicators. Due to the equal weighting, if indicators representing one type of vulnerability or sector are over represented, then the fuzzy partition of vulnerability will be biased. Srdjevic et al. (2003) present an unbiased method of weighting based on information "entropy," but due to the regional extent of the analysis, this method is considered unfeasible. However, provided the choice of indicators is transparent, any potential biases in the ultimate classification can be taken into consideration.

## 5. Discussion

This paper presents a wide variety of indicators describing various sectors and various combinations of sensitivity, exposure and adaptability. It is often easy to exclude exogenous vulnerability from the indicators: either it includes climate data or it does not. If an indicator fails to account for a possible climate future or any climatic effects at all, it is fairly safe to say that it represents purely some combination of endogenous and minimum potential vulnerability. Amalgamation of indicators into an index is complicated and possibly biased because it is difficult to quantify the precise amounts of endogenous and minimum potential vulnerability. Even geographic overlay analysis runs the risk of over representation based on subjective rendering schemes and the information inherent to the indicators. It is recommended that any interpretation of a composite index be performed with prudent use of professional judgment.

This dilemma is exemplified by the problem of combination of data at different scales. If an indicator mapped at the county scale represents minimum potential vulnerability (for example, social adaptability to water shortage) and another indicator mapped by square kilometer represents exogenous vulnerability (for example, projected water shortage in terms of demand minus supply), is it appropriate to multiply the two to derive a composite vulnerability? This is the temptation since, according to the theoretical framework, probability of exposure, multiplied by the probability of sensitivity, multiplied by the probability of lack of adaptation would give the probability of vulnerability to climate change. In practice, however, it may be impossible to insure an equal weighting of exposure, sensitivity, and adaptation in the multiplication of probabilities. For this reason, concatenation of indicators into an index is problematic and should be performed with caution.

While it would be beneficial to control bias through the careful choice of indicators, this strategy is constrained by information availability and/or credibility. An integrated assessment of vulnerability on a geographic basis is thus limited to available data sources. Using what is available, an eclectic mixture of indicators may emerge and require synthesis into meaningful policy data. In order to facilitate this process, the organization of indicators into logical categories that represent specific sectors will help to clarify the information derived from the analysis.

The methodology proposed in this paper is untested. However, many of the indicators presented have been used successfully in other parts of the world. As such, this study lays the foundation for a comprehensive compilation of indicators and is intended as a framework from which to proceed in data acquisition efforts. In that sense, the potentially considerable task of assembling, formatting, and interpreting multidisciplinary information about climate change vulnerability is focused by a conceptual foundation.

## 6. Conclusion

The intention of this study was to provide an assortment of indicators and assessment techniques that would enable regional mapping of vulnerability. The indicators were chosen with regard to known data sources and may not be representative of the best or most up to date information available. However, the probabilistic foundation on which the study is based is a framework that can be used to interpret any number of other indicators. The method and approach for the compilation of indicators, geographic allocation and synthesis is valid for other sets of data as well. Of course, the better the data used to derive the indicator in the first place, the more confidence can be had in its descriptive power.

One potential shortcoming of the probabilistic approach is that vulnerability is scaled between 0 and 1. While this may be useful in defined regions of interest, it may obfuscate differences between regions, especially internationally. Thus, areas that receive vulnerability ratings close to one (extremely vulnerable) may experience vastly different magnitudes of social and environmental impacts from climate change, depending on their geographic and international context.

The method proposed here is intended to benefit future studies that aim to compile regional estimates of vulnerability. The types of data required, the linkages between sectors, and some mathematical approaches to the formulation of indicators are merely presented as a guide for the establishment of a vulnerability geographic information system. Some of the methods may not be appropriate at local or national scales. This consideration of scale will be important in the determination of what indicators are necessary and feasible for the inclusion in any potential study of vulnerability. Additional research is needed to test the approaches presented in this study.

## 7. Acknowledgments

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