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Spatial mapping of socio-ecological vulnerability to environmental change in Southern Africa

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Abstract

Aggregate measures that capture multiple aspects of socio-ecological vulnerability in a single or small number of vulnerability indices can be used to produce vulnerability maps that act as powerful visual tools to identify those areas most susceptible to future environmental changes. Such indices are easily communicable and offer valuable guidance to policymakers and investors, providing insights as to where more targeted research or policy interventions can address current challenges and reduce future risks. However, such aggregation inevitably reduces the richness of information provided by the suites of individual vulnerability indicators on which the maps are based. This trade-off between information richness and information communicability is a constant challenge in the quantification and communication of complex phenomena such as socio-ecological vulnerability. This paper presents an exploratory analysis using Principal Component Analysis (PCA) techniques as a means of creating and comparing spatially-explicit aggregate indices of socio-ecological vulnerability. Vulnerability indices are produced for the Southern Africa Development Community region based on published biophysical and socio-economic data and mapped at a 10 arc minute resolution. The resulting vulnerability maps are particularly informative as they indicate the regional spatial variability of four statistically independent components of socio-ecological vulnerability. Such information-rich vulnerability indices represent a potentially useful policy tool for identifying areas of greatest concern in terms of both the relative level, and the underlying causes and impacts of, socio-ecological vulnerability to environmental changes across broad spatial scales.

Keywords: vulnerability indices; PCA; climate change; SADC; trade-offs, socio-ecological data.

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1. Introduction

The academic literature generally conceptualizes vulnerability as a function of exposure, sensitivity and adaptive capacity (Eakin and Luers, 2006, Gallopin, 2006, Yohe and Tol, 2002). Exposure is defined as the degree to which a system experiences internal or external system perturbations and sensitivity is defined as the degree to which a system is affected by those system perturbations (McCarthy et al., 2001). Adaptive capacity is defined as the ability of a system to adjust its behaviour and characteristics in order to enhance its ability to cope with external stress (Brooks, 2003). Spatially-explicit vulnerability assessments (vulnerability maps) are an increasingly important consideration in environmental policy formulation and in climate change and development debates (Metzger and Schröter, 2006, Stelzenmüller et al., 2010). They can act as powerful visual tools that help identify those groups and areas most susceptible to harm at a particular point in time, allowing more targeted policy and investments that both mitigate current challenges and reduce future risks (e.g. Davies et al., 2010; Ericksen et al., 2011). The literature on socio-ecological systems provides a useful theoretical framing to underpin the development of vulnerability maps, in that it ties together both the socio-economic and biophysical components of vulnerability, allowing a more comprehensive approach to vulnerability assessment (Eakin and Luers, 2006, Berkes and Folke, 2000). Such holistic approaches have been applied to vulnerability assessments across a range of socio-ecological systems at a variety of scales (e.g. Antwi-Agyei et al., 2012, Fraser and Stringer, 2009, Simelton et al., 2009).

Identifying and quantifying the multiple sources and drivers of vulnerability can nevertheless be problematic, particularly when seeking to identify and map vulnerability across broad spatial scales (Eakin and Luers, 2006, Füssel, 2009, Van Velthuizen et al., 2007). Many spatially explicit indicators of sensitivity, exposure and adaptive capacity are available, encompassing a wide range of social, biophysical and economic aspects of vulnerability. However, these indicators are not necessarily directly comparable when attempting to represent multiple sources of vulnerability in a manner that is useful for policy formulation and decision making (Adger, 2006). While each individual indicator may be of interest to policy makers seeking to reduce a specific aspect of vulnerability, in isolation they do not provide a clear understanding of composite (or aggregate) socio-ecological vulnerability. For example, population density in agrarian communities may either increase or decrease vulnerability (Meyer et al., 1998). High population density in agrarian communities may result in a dependence on marginal land for food production. These lands can rapidly become unproductive and therefore increase vulnerability to food insecurity (Reycraft and Bawden, 2000). Conversely, high population density in similar communities in locations with high quality agricultural land may allow intensified production and investment in infrastructure to increase food supplies (Boserup, 1965). If population density alone is considered as the key vulnerability indicator, the interaction with the environmental system and its capacity for agricultural production remains unassessed (uncontextualized) and could lead to the development of inappropriate policy. To gain a more holistic insight requires an understanding of how multiple, often interdependent, indicators of vulnerability, vary in space and time in relation to each other.

Combining suites of often interdependent indicators into aggregate vulnerability indices—where the term index is taken to mean a unitless aggregation of multiple indicators of related phenomena—can provide a potentially useful overview of aggregate socio-ecological vulnerability (Füssel, 2009). However, there is an unavoidable trade-off between richness of information and usefulness of that information in policy formulation in moving from a large suite of individual indicators to a small number of composite, unitless indices (Braat, 1991, Campbell, 1996). The choice of the trade-offs between communicability and comprehensiveness largely depends on whether the priority is to guide policy in a particular direction or to present results that utilise indicators strictly and yield results that are more comprehensively correct and complex but perhaps less straightforward to communicate.

In the context of broad scale vulnerability mapping, we argue that it is difficult for policy makers to act on the basis of large numbers of discrete indicators that may be mutually contradictory in terms of the areas in which they indicate that vulnerability occurs. Therefore, despite complexities that include the large number of possible drivers of vulnerability in complex socio-ecological systems and the imperfect data related to the indicators of vulnerability, there is still considerably utility in generating spatially-explicit measures that capture multiple aspects of socio-ecological vulnerability in a single or small number of aggregate indices. Such aggregate indices, imperfect as they will be, can offer valuable guidance to policymakers and donor agencies, and provide insights as to where more detailed vulnerability assessments should be undertaken.

The combination of multiple indicators of vulnerability into aggregate vulnerability indices is challenging, due to the incommensurability of both the values that these indicators represent and the units in which they are measured (Sullivan and Meigh, 2005). For example, it is impossible to directly compare infant mortality and soil degradation as these two indicators have different units of measurement, although both provide indications of vulnerability in agrarian societies. Standardisation of data to a common (comparable) unitless scale is generally used to overcome issues of incommensurability when combining multiple indicators. Aggregate indices based on standardised and summed indicators of socio-ecological vulnerability (e.g. Davies and Midgley, 2010) are useful in identifying hotspots where multiple aspects of vulnerability occur. However, the generation of a single composite vulnerability index using a standardisation/summation approach, is problematic because potentially important information regarding the relations between the original variables are obscured in the resulting unitless, aggregated index.

When mapping socio-ecological vulnerability across large spatial extents (and therefore across diverse socio-ecological systems) it is likely that drivers of vulnerability will vary considerably across space (Eakin and Luers, 2006). Vulnerability assessments are therefore highly context specific (Füssel, 2009, Yohe and Tol, 2002). A standardisation/summation based vulnerability index may return similar scores in two locations where vulnerability is driven by very different processes (for example, forest loss or drought). Therefore policymakers viewing aggregate vulnerability maps have to rapidly return to the original indicators to understand and interpret the aggregate vulnerability indices. From a policy perspective it is therefore questionable as to whether aggregate vulnerability indices convey information in a more useful way than the multiple indicators of vulnerability on which they are based.

The potential for confusion linked to lack of clarity in the communication of information regarding the underlying relations between different drivers of vulnerability is important. We suggest that when multiple indicators are used to generate aggregated indices of socio-ecological vulnerability at broad spatial scales it would be useful if the relations between the original indicators (for example, how they co-vary across space) could be communicated in the resulting vulnerability indices, thus striking a balance between information richness and communicability. Retention of clearly communicable information regarding the relations of the underlying variables to the resultant aggregate vulnerability indices provides vital contextual information regarding the specific sources of vulnerability for a given point in space. The contextualization of spatially explicit, aggregate vulnerability indices should increase their interpretability and usefulness for policy makers.

This paper presents an exploratory attempt to use Principal Component Analysis (PCA) as a means of creating spatially-explicit aggregate indices of socio-ecological vulnerability for the Southern Africa Development Community (SADC) region. A PCA approach to the generation of aggregate socio-ecological vulnerability indices utilises a purely descriptive, statistical approach to data transformation as a means of overcoming incommensurability. In this sense it does not differ greatly from the more common approach to overcoming incommensurability of variables through data standardisation. However, we argue that PCA-based aggregate vulnerability indices are more informative than those derived from standardisation/summation. They can provide both relative vulnerability "scores" for a small number of statistically uncorrelated indices, as well as easily interpreted and communicated insights into which specific underlying indicators of vulnerability most influence those aggregate indices.

2. Methods

Principal Component Analysis (PCA) is an analytical tool that uses orthogonal linear transformation to reduce the number of variables in statistical analysis by identifying a smaller number of uncorrelated proxy variables (principal components) that capture the variability in the underlying data. The first principal component (PC) accounts for as much of the total variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible (Jolliffe, 2002), where the total variability within the data is simply the sum of the variances of the observed variables, when each variable has been transformed so that it has a mean of zero and a variance of one (Hatcher, 1997). For each PC a proxy variable (score) is provided for each data point that represents the relative values of the underlying variables associated with that principal component. 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. Here we conceptualise these PC scores as unitless aggregated measures of multiple aspects of socio-ecological vulnerability—vulnerability indices. PCA is a non-parametric analysis and is independent of any hypothesis about data probability distribution (Abdi and Williams, 2010).

By retaining only those principal components that account for more of the variability in the original data than any of the original individual variables, a smaller number of independent indices of socio-ecological vulnerability can be generated. The factor loadings of the original vulnerability indicators on the retained principal components—the extent to which the variables influence the resulting principal component—can shed light on the aspects of socio-ecological vulnerability each principal component index represents. Taken together, the PC scores and factor loadings provide information pertaining to the relative levels of vulnerability (scores) and the underlying drivers of that vulnerability (factor loadings). The indices produced by PCA are unitless measures that can be used to compare the relative vulnerability of different regions and for spatially-explicit mapping of multiple aspects of socio-ecological vulnerability across broad spatial extents. In this paper, we do not assign arithmetic relationships between multiple indicators of sensitivity, adaptive capacity and exposure in order to develop aggregate vulnerability indices. Rather we use PCA to identify where there may be correlations or spatial discontinuities between these different aspects of socio-ecological vulnerability in the SADC region. As with other investigations of socio-ecological vulnerability we differentiate between biophysical and socio-economic indicators (Füssel, 2009, Yohe and Tol, 2002).

The mapping of PCA based vulnerability indices can highlight the spatial patterns of different aggregated aspects of socio-ecological vulnerability. The SADC region contains a wide range of agro-ecological zones and socio-economic conditions (Stringer et al., 2012) allowing us to test the utility of using a PCA approach to vulnerability mapping across diverse socio-ecological systems and implying that the methods explored here will be of wider value for future up-scaling of such assessments. By studying this region using PCA, we aim to develop initial vulnerability indices that can guide more detailed research, as well as informing policy development and donor investment.

The Southern African Development Community (SADC) study area includes: Angola, Botswana, Democratic Republic of Congo (DRC), Lesotho, Madagascar, Malawi, Mozambique, Namibia, South Africa, Swaziland, United Republic of Tanzania, Zambia and Zimbabwe (see Figure 1). Mauritius and the Seychelles were excluded from the analysis due to their small size and the lack of availability of good quality spatially explicit data. The SADC region covers four broadly defined ecoregions[1], based on Olson et al's (2001) classification: 1) tropical and sub-tropical moist broadleaf forests, 2) tropical and subtropical grassland savannah and dry forests, 3) montane grasslands and shrubland and 4) drylands—desert, xeric shrubland and Mediterranean woodland and shrubland. In addition to a SADC-wide analysis, a separate PCA analysis was conducted for the drylands ecoregion covering much of eastern South Africa, southern Namibia Botswana and Madagascar (see Figure 1). Undertaking SADC region-wide and ecoregion specific PCAs allows comparison of the relative vulnerability indices that are produced when comparing vulnerability both across several different ecoregions and within a single ecoregion.

[Insert Figure 1 here]

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[1] An ecoregion is defined as a large area of land or water that contains a geographically distinct assemblage of natural communities that share a large majority of their species and ecological dynamics, similar environmental conditions, and interact ecologically in ways that are critical for their long-term persistence. Ecoregions are sub-categorisations within the broader categorisation of biomes.

3. Data

The data used here is mapped at a spatial resolution of 10 arc minutes (approximately 18.5 km at the equator). The majority of data covers a time period of 2000-2009, with the exceptions of the land degradation data (1990), the aridity index (average from 1960-1990) and precipitation indicator average from 1950-2000). The main criteria for inclusion of vulnerability indicators in this analysis were that the data should be of high quality, from a reputable source, and should have a relatively fine spatial resolution. Much of the available biophysical data (e.g. disaster events, water withdrawals) and socioeconomic data (e.g. educational and health indexes) are only reported at the national scale, hiding considerable spatial variability within nations. The use of such data can be argued to have distorted previous attempts at regional vulnerability mapping for the SADC region (Davies et al., 2010). For example, rural/urban divides and centres of development based on historical precedents or comparative competitive advantages create spatially heterogeneous socio-economic structures within nations, while geology, climate and typography can vary considerably within small spatial extents creating very different environmental patterns. The inclusion of national statistics is problematic for the spatially explicit mapping of socio-economic vulnerability. It would be necessary to assume an even distribution of those nationally reported indicators in the absence of evidence that it is satisfactory to do so.

While some available indicators of aspects of socio-ecological vulnerability were both of good quality and at a fine spatial resolution, they were excluded from the analysis as they were not equally useful across the different ecoregions present within the SADC study area. For example, forest loss may be a good indicator of environmental sensitivity in forest ecoregions, yet is of little value in desert ecoregions, where there are no forests to be lost. The effect of including ecoregion-specific indicators is to prejudice the resultant relative vulnerability indices towards ecoregions in which the indicator is relevant. In addition, many of the spatially-explicit variables available represent different aspects of the same indicator. For example, there are high quality, spatially-explicit datasets for length of growing season, soil quality and climate variability and topological factors such as slope. All these variables influence the suitability of land for agricultural production (an important potential source of vulnerability in the largely agrarian societies of the SADC). However, these variables interact with each other, often in complicated ways, influencing vulnerability in such a way that cannot be captured through a simple arithmetic combination of individual factors. Rather than treat these variables as individual indicators, an aggregate indicator of agricultural constraints/suitability provided by van Velthuizen et al (2007) was included instead (see section 3.1 for details) .

Two aspects of socio-ecological vulnerability were considered in our analysis. First, environmental indicators of vulnerability were selected that represented biophysical resource scarcity or pressures on natural resources utilised in maintaining the wellbeing of SADC populations. Second, socio-economic indicators of vulnerability based on monetary and infrastructure poverty and health were considered important as these act as both indicators of the current vulnerability of SADC populations to resource scarcity and disease, and as indicators of the socio-economic capacity of SADC populations to cope with future perturbations or shocks to socio-ecological systems. In both cases, focus was largely on rural vulnerability. The indicators of vulnerability included in the analysis are detailed below and summarised in Table 1.

3.1 Environmental and Biophysical indicators

1) AGRICULTURAL CONSTRAINTS: this dataset represents constraints on agricultural production at a 10 arc minutes resolution. It combines terrain slope constraints, global agro-ecological zones, and other biophysical factors that influence agricultural production such as soil quality, length of growing period, soil type, climate variability (Van Velthuizen et al., 2007). This agricultural constraints indicator represents an important source of vulnerability for the agrarian dominated ecoregions under investigation. While this aggregate indicator includes aspects of climate variability (see indicators 11 and 12 below) the climate variables only account for a small proportion of the calculation of agricultural constrains and we believe the importance of including this indicator outweighs any potential double counting.

2) SOIL DEGRADATION: the Global Assessment of Human-induced Soil Degradation (GLASOD dataset was used as an indicator of soil degradation based on multiple measures

of degradation severity (combining the degree and extent of degradation) within four categories: 1 = light, 2 = moderate, 3 = strong, 4 = extreme. The data was in vector format. The status of soil degradation was mapped within loosely defined physiographic units based on expert judgement for the period 1987-1990 (GLASOD, 1990).

3) HANPP (human appropriation of net primary production). HANPP is an indicator of the pressure of human activity on ecosystems and reports the percentage of primary vegetative production within an ecosystem that is appropriated by humans. These data were obtained from a recent and comprehensive assessment of global appropriation conducted by Haberl et al. (2007) with a resolution of 5 arc minutes. The authors used the Lund–Potsdam–Jena (LPJ) dynamic global vegetation model (Gerten et al., 2005, Sitch et al., 2003) to calculate NPP0 (potential net primary production), and a combination of vegetation modelling, agriculture and forestry statistics, alongside GIS data on land use, land cover and soil degradation, to calculate NPPact (actual net primary production) and HANPP (see Haberl et al., 2007 for details). Note that only HANPP was used directly in the PCA; NPPact was used to create the POPNPP dataset (see below).

4) POPNPP: this dataset was based on NPPact (see above) and the Gridded Population of the World (GPWv3) land area grid for the year 2000. The GPWv3 dataset has a resolution of 2.5 arc-minutes. A proportional allocation gridding algorithm, utilizing more than 300,000 national and sub-national administrative units, is used to assign population values to grid cells (CIESIN et al., 2005). GPWv3 is produced by the Columbia University Center for International Earth Science Information Network (CIESIN) in collaboration with the United Nations Food and Agriculture Programme (FAO) and the Centro Internacional de Agricultura Tropical (CIAT). NPPact was divided by population density to give an indicator of the available net primary production per capita for the year 2000. As such, POPNPP differs from HANPP as it is an indicator of one aspect of the per capita carrying capacity of ecosystems (the productivity of the system) rather than an indicator of the current pressure on that aspect of carrying capacity.

5) ARIDITY: This uses the global aridity map produced by Zomer et al (2008) for the year 2000, with a spatial resolution of 30 arc seconds. The data represents deficit over

atmospheric water demand through a standardized Aridity Index of mean annual precipitation divided by mean annual evapotranspiration. The Aridity Index was based on data from 1960–1990, at a resolution of 30 arc seconds Water availability was seen as a key limitation to agricultural production and areas of water scarcity are likely to be disproportionally vulnerably to changes in climate.

6) PRECIPITATION CV: the coefficient of variation of annual rainfall was taken from the Global Historical Climatology Network (GHCN), the FAO, and CIAT. This dataset provides an indicator of the annual variability in rainfall at a resolution of 5 arc minutes based on data for the years 1950-2000 (Hijmans et al., 2005).

3.2 Socio-economic indicators

7) INFANT MORTALITY: Global Sub-national Infant Mortality Rates consist of estimates of infant mortality rates for the year 2000 with a nominal resolution of 2.5 arc minutes. The infant mortality rate is defined as the number of children who die before their first birthday for every 1,000 live births. This dataset is produced by the Columbia University Center for International Earth Science Information Network (CIESIN, 2005a).

8) MALNUTRITION: The Global Sub-national Prevalence of Child Malnutrition dataset consists of estimates of the percentage of children under the age of 5, who are underweight based on weight-for-age z-scores that are more than two standard deviations below the median of the NCHS/CDC/WHO International Reference Population (CIESIN, 2005b). Data are reported for the most recent year with sub-national information available at the time of development (1990-2002) with a resolution of 5 arc minutes.

9) IRRIGATION: Grid with percentage of area equipped for irrigation with a spatial resolution of 5 arc minutes for the year 2000. This dataset is developed in the framework of the AQUASTAT programme of the Land and Water Development Division of the Food and Agriculture Organization of the United Nations and the Johann Wolfgang Goethe Universität, Frankfurt am Main, Germany (Siebert et al., 2007). The map resolution was 10 arc minutes and the values were transformed so that high values represent areas that are not equipped for irrigation.

10) INFRASTUCTURE POVERTY: This dataset combines the LandScan 2004 population dataset (Oakridge National Laboratory, 2004) and the Night Time Lights dataset (Elvidge et al., 1997) to present a high resolution (30 arc seconds) poverty map (Elvidge et al., 2009) . The infrastructure poverty index is calculated by dividing the LandScan 2004 population count by the average visible band digital number from the lights. In areas where population is present but no lights were detected the full population count is passed to the index. The concept of the poverty index is to create a grey-scale image that is adjusted to lower values in abundantly lit areas where economic activity is high. High poverty index values occur in areas with high LandScan population count and dim (or no) lighting (Elvidge et al., 2009).

11) POVERTY: This dataset was developed as a part of the "Geographic Domain Analysis to Support the Targeting, Prioritization, and Design of a CGIAR Mega-Project (MP) Portfolio". It was constructed by the Center for Tropical Agriculture (CIAT), the Center for International Earth Science Information Network (CIESIN), the International Food Policy Research Institute (IFPRI), and the World Bank. The global poverty map was constructed using more than 24,000 sub-national data points for the developing world, creating the first ever sub-national poverty map of the developing world (the percentage of people with incomes of less than $2.00 (PPP) per day). The data represents the year 2005 and had a spatial resolution of 10 arc minutes (Wood et al., 2010).

12) TRAVEL TIME: Travel Time to Major Cities is a dataset developed by the European Commission and the World Bank in creates an urban/rural population gradient around large cities. The data has a resolution of 30 arc seconds and provides and indicator of the remoteness/connectivity to markets and infrastructure based on minutes of land based travel necessary to reach cites of greater than 50,000 inhabitants for the year 2000. (World Bank, 2009) The map was produced for the World Bank's Development report 2009: Reshaping Economic Geography.

[Insert table 1 here]

Where necessary, all spatially-explicit data sets were re-projected in ArcGIS (ESRI, 2006) from their original coordinate systems to World Geodetic System (WGS) 1984 global projection system. Vector/polygon data was converted to raster data at the same spatial resolution as the original data sets (all the original data, with the exception of country boundaries and ecoregions were, provided as gridded datasets). Hawth's tools (Beyer, 2004) was used in ArcGIS to create 10 arc minute vector grid squares (approximately 18.5 km at the equator) across the entire SADC study area. A 10 arc minute spatial resolution for the PCA analysis was chosen as it represented the maximum spatial resolution of datasets utilised in the analysis. A finer spatial resolution would have resulted in relative vulnerability indices implying a greater resolution than could be provided from the original spatial data. A coarser resolution (to match the 20 arc minute resolution of the coarsest dataset utilised in the analysis) would have resulted in a loss of spatial detail provided by many of the datasets that had a resolution of 5 arc minutes.

The Zonal Statistic Tool within ArcGIS's Spatial Analyst was then used to calculate the mean values for each spatially-explicit vulnerability indicator for each of the 10 arc minute analysis grid squares. When the resolution of the vulnerability indicator is finer than 10 arc minutes and a PCA analysis grid square falls on the border between terrestrial land masses and water bodies, the zonal statistics tool can distort the reported value of vulnerability by averaging the value from the terrestrial and water based cells. This "edge effect" reduces the indicator scores returned for costal grid squares. To avoid this, edge analysis grid squares that crossed coastal boundaries and large water bodies were removed from the analysis, reducing the number of grid squares from 30,942 to 30,677.

3.3. PCA analysis

All PCAs were undertaken using the Minitab statistical program (Minitab, 2010) Pairwise correlation tests were applied in an attempt to reduce the initial set of metrics to a smaller subset of non-highly correlated metrics (Lausch and Herzog, 2002, Schindler et al., 2008). As none of the twelve vulnerability metrics were highly correlated (for all pairwise Spearman's correlations $p < 0.80$) all twelve vulnerability metrics were retained in the PCA analysis. The Kaiser-Mayer-Olkin (KMO) sampling adequacy test values were > 0.5 and Bartlett's sphericity tests returned $P \leq 0.05$ for all PCA analyses, suggesting that the variables were suitable for PCA analysis (Hair et al. 2006).

The choice of principal components to be retained from the PCAs was in part based on subjective judgment and interpretability of the components (Srivastava, 2002). Additional retention criteria were based on Kaiser's rule of thumb that the Eigenvalues of the component should be > 1.0, the proportion of the variation in the original variables explained by the component and the shape of the scree and loading plots (Griffith et al., 2000). The scores from the retained principal components were used as unitless indicators of aspects of the relative socio-ecological vulnerability of each 10 arc minute analysis grid square. The aspect of socio-ecological vulnerability represented by each principal component was defined by the relative loadings of each individual vulnerability indicator on that component. For example, if a principal component was heavily positively loaded on indicators of infrastructure poverty (irrigation, travel time night time lights) then the resulting vulnerability index based on the scores associated with that principal component would be regarded as an indicator of infrastructure poverty. For ease of comparison, the principal component scores (and therefore vulnerability indices) were standardised to values between 0-1, where 0 represents the least vulnerable and 1 the most vulnerable grid square.

4. Results

Section 4.1 presents the PCA results for the whole SADC region, covering all four broad ecoregions, while section 4.2 presents the PCA results from the SADC dryland ecoregion analysis. Section 4.3 combines the multiple relative socio-ecological vulnerability indices presented in 4.1 and 4.2 into single socio-ecological vulnerability indices for both the SADC-wide and dryland specific analyses.

4.1 SADC analysis

Four principal components were retained in PCA for the whole of the SADC region. Each had an eigenvalue > 1 and together these first four principal components accounted for 64% of the variation in the original 12 variables included in the analysis. The loading of each variable for the retained principal components are detailed in Table 2, with the heaviest loadings highlighted.

[Insert table 2 around here]

The first principal component was heavily loaded on INFANT MORTALITY, POVERTY, AGRICULTURAL CONSTRAINTS and MALNUTRITION. The second component was loaded heavily on HANPP (human appropriated net primary productivity), SOIL DEGRADATION and IRRIGATION. The third component was loaded on POPNPP, INFRASTRUCTURE POVERTY and TRAVEL TIME and the fourth component on PRECIPITATION CV, MALNUTRITION AND ARIDITY. (Note, MALNUTRITION is mentioned twice as one variable can load on several principal components). The loadings of the 12 indicators allowed identification of four spatially discrete aspects of socio-ecological vulnerability based on the way in which the indicators co-varied across space. For ease of interpretability we termed these spatially-discrete aspects of socio-ecological vulnerability "Poverty and health vulnerability" (PC1), "biophysical pressure vulnerability" (PC2), "infrastructure poverty and population pressure vulnerability" (PC3) and "climate and malnourishment vulnerability" (PC4). It should be noted that these do not represent precise categories, rather they show the dominant indicators that define each of the four retained principal components and therefore the 4 discrete indices of relative socio-ecological vulnerability found in this research. The spatial distributions of these for proxy indicators of aspects of socio-ecological vulnerability for the SADC region are shown in Figure 2.

[Insert figure 2 around here]

Figure 2 indicates that there are strong regional differences in the sources of socio-ecological vulnerability across the SADC region. Poverty and health vulnerability (PC1) dominate in the DRC, Angola, Mozambique and Tanzania, while biophysical pressures (PC2) are highest in the eastern and southern coastal regions of South Africa and the afforested eastern side of Madagascar. Infrastructure poverty and population pressure vulnerability (PC3) is highest in the urbanized area of South Africa and the desert regions of Namibia and Botswana. Climate and malnourishment vulnerability (PC4) dominates in the eastern states of Malawi, Mozambique, and Tanzania as well as the dryland regions of western Angola and the dry western side of Madagascar. PC4 also indicates high climate and malnourishment vulnerability in the densely populated region of South Africa encompassing Johannesburg and Pretoria.

4.2 SADC drylands ecoregion analysis

For the PCA limited to the SADC drylands ecoregion four principal components were also retained. Each of the retained components had an eigenvalue > 1 and again these first 4 principal components accounted for 64% of the variation in the original 12 variables included in the analysis. However, the loading on each of the four retained PCAs was different from those found for the SADC analysis. The loading of each variable for the retained principal components for the SADC drylands ecoregion is detailed in Table 3, with the heaviest loadings highlighted. The four retained principal components can broadly be described as: poverty and primary productivity vulnerability (PC1); health, malnourishment and climate vulnerability (PC2); infrastructure poverty and soil degradation vulnerability (PC3) and biophysical pressure vulnerability (PC4). In the SADC drylands ecoregion, poverty and primary productivity vulnerability was highest on the western coast of South Africa and southern Botswana. Health, malnourishment and climate vulnerability was highest in Madagascar and Botswana. While infrastructure poverty and soil degradation (PC3) and biophysical pressure (PC4) vulnerability was highest in the central regions of South Africa and Namibia, only the coastal Cape region of South Africa had consistently low measures across all four aspects of relative vulnerability.

[Insert table 3 around here]

4.3 Combined vulnerability indices

Because the scores associated with the retained principal components produced in the PCA are unitless, it becomes possible to combine the resulting vulnerability indices into a single relative vulnerability index. As there are no *a priori* assumptions regarding the relative importance of the different aspects of vulnerability captured by the retained PCA scores, a simple average value for each 10 arc minute grid was taken to create a single relative vulnerability indices that capture approximately 64% of the variation in the original 12 indicators of vulnerability for both the SADC wide and SADC drylands ecoregion analysis (Figure 3).

The combined relative vulnerability index for the SADC region suggests that socio-ecological vulnerability is relatively low in western South Africa, Botswana and Namibia and is highest in the more densely populated areas of eastern South Africa, Malawi, Angola, Mozambique, Madagascar and DRC. In general, relative vulnerability was highest in areas of, or surrounding areas of, relative high population density. However, a quite different pattern of relative vulnerability can be seen when comparing the results for the drylands ecoregion in the ecoregion only and the region-wide analysis. The analysis suggests higher relative vulnerability in the central western Namibia and South Africa in the drylands analysis than in the region-wide analysis. Given that the PCA based indicators of socio-ecological vulnerability are relative measures, the spatial extent over which the analysis is undertaken is likely to have a considerable influence on the resulting indices. In particular, an analysis across ecoregions tends to identify differences between ecoregions while minimising the difference in relative vulnerability within ecoregions.

5. Discussion and Conclusion

All spatially-explicit vulnerability assessment maps yield outputs that reflect the datasets and methods underpinning the analysis, and are contingent upon considerations such as the choice of indicators retained, the aggregation of datasets, the spatial resolution of the data and analysis, and any weighting of indicators that is employed in the analysis. Moreover, there are significant normative assumptions inherent in any attempt to identify aggregate socio-ecological vulnerability, not least in the initial choice of the suite of individual indicators of vulnerability that are selected for aggregation and the interpretation of individual indicators (Eakin and Luers, 2006, Füssel, 2009).

The choice of indicators used in this exploratory research was in a large part determined by the limited availability of high resolution, spatially explicit datasets for southern Africa. There are important indicators of socio-ecological vulnerability (such as civil unrest, inequality, local governance issues) for which data were not available. It should also be noted that vulnerability is often regarded as a context-specific term defined in regard to specific exogenous or endogenous perturbations/threats (Dilley and Boudreau, 2001, Smit and Wandel, 2006b) whereas here socio-ecological vulnerability has been defined in a more generalised form. Finally vulnerability is a dynamic concept and spatial mapping of vulnerability provides a static "snapshot" description of vulnerability at a particular point in time. Therefore as socio-ecological conditions change, new vulnerability maps will be required to reflect changes. For these reasons considerable care must be taken when interpreting the maps presented here and when comparing these maps to other created using different data and methods. Nevertheless, despite the caveats noted above we argue that given the data that were available and given the difficulty in modelling future socio-ecological conditions, these maps provide a useful "first pass" in assessing broad scale socio-ecological vulnerability.

Although our results share some similarities with other recent regional vulnerability assessments (e.g. Davies et al., 2010), they also exhibit some important differences to these and other assessments (e.g. Simelton et al., 2012, Ericksen et al., 2011). For example, the Regional Climate Change Programme's (RCCP) vulnerability mapping for Southern Africa (Davies et al., 2010) and our combined socio-ecological vulnerability indices (Figure 4) both indicate relatively low levels of vulnerability in western South Africa and Namibia and high levels of relative vulnerability in northern Mozambique, Angola and eastern and southern DRC. However, the RCCP analysis indicates considerably higher vulnerability in Zambia and Zimbabwe than indicated in the analysis presented here. This discrepancy is in part due to the different modelling approaches and data used in the two mapping exercises. For example, the RCCP considered indicators of adaptive capacity, sensitivity and exposure to climate variability and extremes separately and produced projected vulnerability maps looking forward up to the year 2050, whereas we identified 12 key variables and assessed current vulnerability. Nevertheless both sets of maps can be useful to policymakers and development aid donors, particularly when it comes to identifying hotspots of high vulnerability at a glance (Liu et al., 2008). Such indications can illuminate those locations where there is a need for further, urgent, in-depth case study based research to supplement and understand the detail of relationships between different indicators of vulnerability at smaller scales. Regional vulnerability maps should thus be considered a starting point for further analysis: they can contribute towards and inform policy, but should not be considered prescriptive or end points of vulnerability assessment in themselves.

Using a Principal Components Analysis technique based on high resolution spatial datasets helps to highlight the spatial arrangement of different aspects of socio-ecological vulnerability. Our PCA based assessment of the socio-ecological vulnerability of the SADC region indicates that different aspects of vulnerability are spatially discrete, with different regions characterised by different types of vulnerability. From a policy perspective such relatively contextualised, "information rich" vulnerability indices may prove useful as they provide a compromise between the rich, often potentially confusing, and difficult to interpret detailed information provided by a large suite of individual vulnerability indicators and easy to visualize but potentially "information poor" aggregate vulnerability indices. Our analysis also suggests that there is a need to carefully consider scale when using PCA to generate aggregate vulnerability indices. Analyses at multiple spatial scales are likely to reveal different patterns of vulnerability. Multiple scale PCA analyses of socio-ecological vulnerability represent a useful policy tool for identifying areas of concern in terms of both the relative level, and the underlying causes and impacts of socio-ecological vulnerability across broad spatial scales.

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Figures

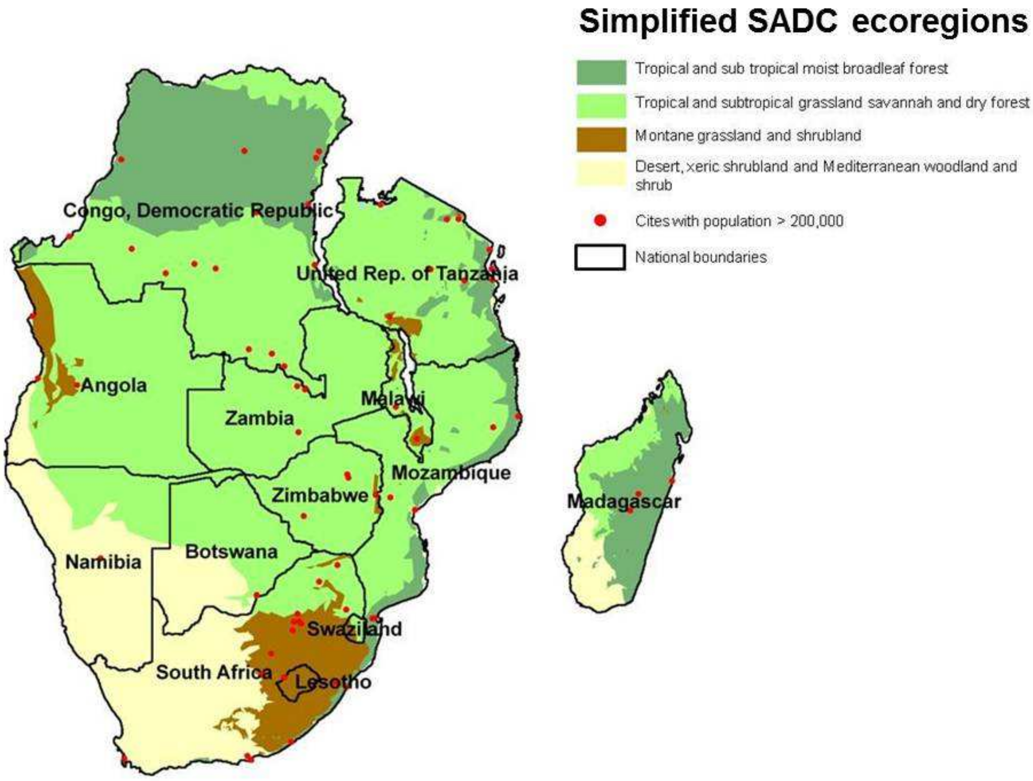

Figure 1. SADC study area (ecoregions based on Olson et al (2001))

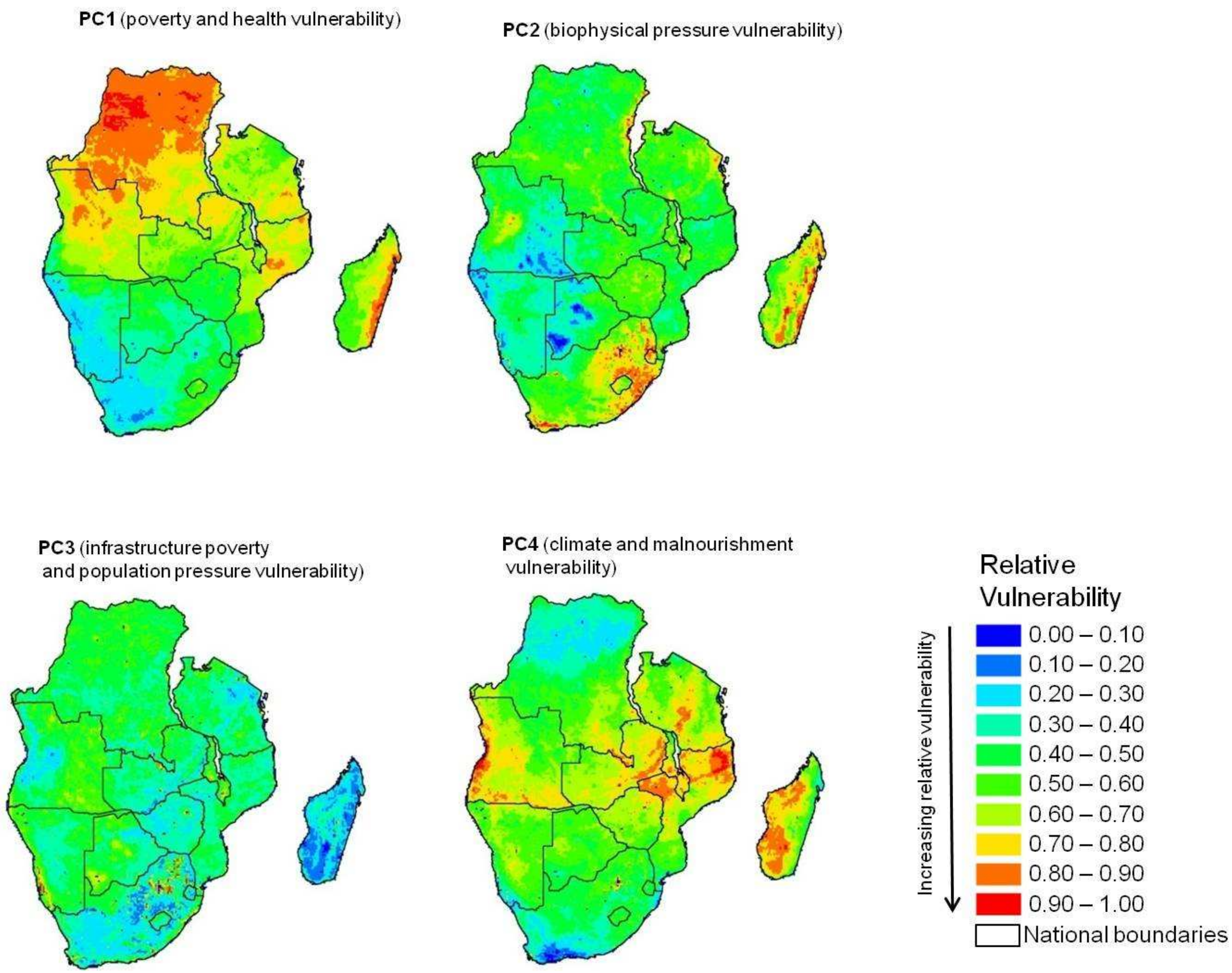

Figure 2. Principal components of relative socio-ecological vulnerability for the SADC region

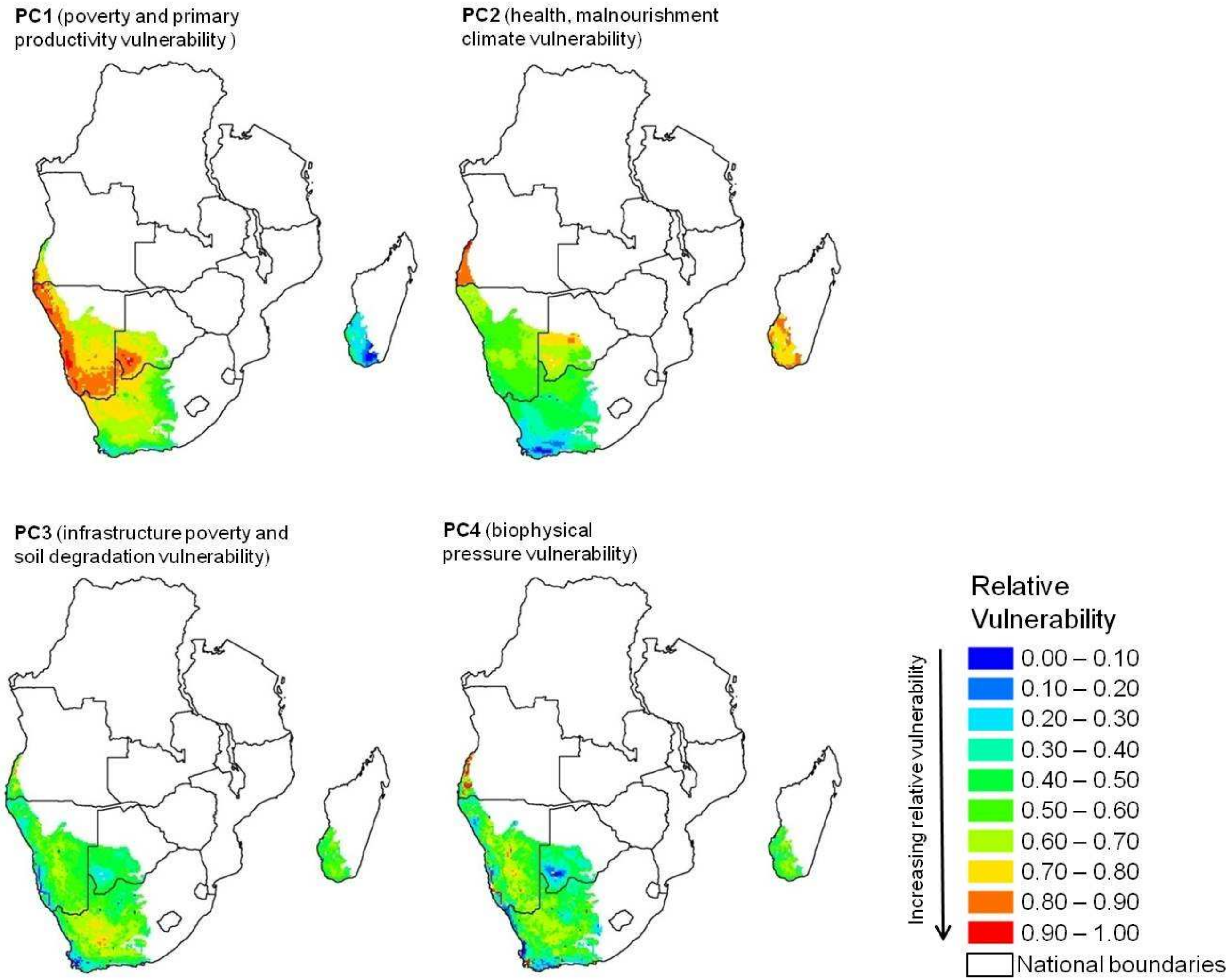

Figure 3. Principal components of relative socio-ecological vulnerability for the SADC desert ecoregion

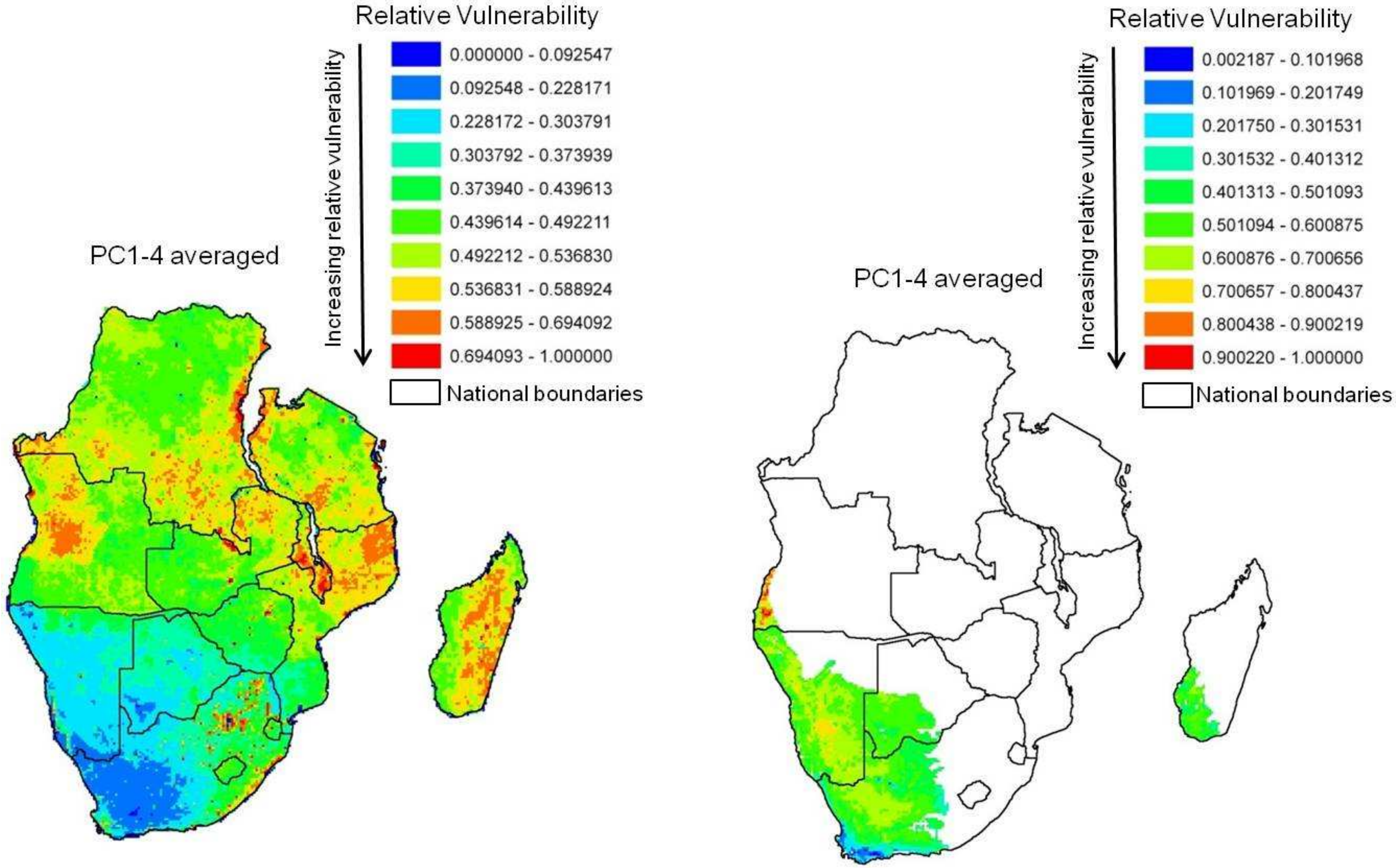

Figure 4. Combined indices of relative socio-ecological vulnerability for the SADC region and SADC drylands ecoregion

Tables

Table 1. Summary of spatially explicit datasets used in PCA of socio-ecological vulnerability

Dataset name	Data description	Year dataset represents	Data source
INFANT MORTALITY	Infant mortality rate	2000	(CIESIN, 2005a)
POVERTY	Percentage of the population living in poverty	2005	(Wood et al., 2010)
AGRICULTURAL CONSTRAINTS	Constraints on agricultural production	2000	
HANPP	Human appropriation of net primary production	2000	(Haberl et al., 2007)
SOIL DEGRADATION	Severity of soil degradation	1987-1990	(GLASOD, 1990)
IRRIGATION	Percentage of land not equipped for irrigation	1990-2002	(Siebert et al., 2007)
POPNPP	Available net primary production per capita	2000	(Haberl et al., 2007) and (CIESIN et al., 2005)
INFRASTRUCTURE POVERTY	Infrastructure poverty, based on night-time lights per capita	2000	(Elvidge et al., 2009)
TRAVELTIME	Travel time to nearest city with a population greater than 50,000	2000	(World Bank, 2009)
PRECIPITATION CV	Annual coefficient of variation in precipitation	1950-2000	(Hijmans et al., 2005)
MALNOURISH	Percentage of children under 5 suffering from malnutrition	2000	(CIESIN, 2005b)
ARIDITY	Index of aridity	2000	(Zomer et al., 2008)

Table 2. Retained principal components for the spatial analysis of socio-ecological vulnerability in SADC

	PC1	**PC2**	**PC3**	**PC4**
INFANT MORTALITY	0.409	-0.178	0.041	0.257
POVERTY	0.341	0.243	-0.143	0.187
AGRICULTURAL CONSTRAINTS	0.29	-0.13	0.104	-0.28
HANPP	0.037	0.512	-0.079	0.104
SOIL DEGRADATION	-0.164	0.388	-0.266	0.062
IRRIGATION	-0.077	0.321	-0.088	0.102
POPNPP	-0.044	0.192	0.667	0.093
INFRASTRUCTURE POVERTY	-0.012	0.248	0.632	0.161
TRAVELTIME	0.038	-0.45	0.165	-0.113
PRECIPITATION CV	-0.167	-0.168	-0.077	0.754
MALNOURISH	0.382	-0.072	-0.067	0.388
ARIDITY	-0.448	-0.183	0.005	0.155
Eigenvalue	3.7108	2.0596	1.3216	1.1691
Proportion	0.285	0.158	0.102	0.09
Cumulative	0.285	0.444	0.546	0.635

Table 3. Retained principal components for the spatial analysis of socio-ecological vulnerability in the SADC drylands ecoregion

	PC1	**PC2**	**PC3**	**PC4**
ARIDITY	0.452	-0.03	0.127	0.124
POVERTY	0.406	-0.047	0.066	0.094
TRAVELTIME	0.277	0.212	-0.231	-0.286
AGRICULTURAL CONSTRAINTS	0.049	-0.039	-0.484	-0.658
INFANT MORTALITY	-0.054	0.52	-0.025	-0.049
MALNOURISH	-0.174	0.513	0.067	0.127
PRECIPITATION CV	0.095	0.477	0.003	0.121
IRRIGATION	0.204	0.284	0.151	0.137
INFRASTRUCTURE POVERTY	-0.086	0.076	0.531	-0.444
SOIL DEGRADATION	-0.24	-0.252	0.31	0.083
POPNPP	0.043	-0.047	-0.529	0.444
HANPP	-0.438	-0.026	0.008	0.014
Eigenvalue	3.5378	2.3911	1.3949	1.032
Proportion	0.272	0.184	0.107	0.079
Cumulative	0.272	0.456	0.563	0.643