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Using Principal Component Analysis for information-rich socio-ecological vulnerability mapping in Southern Africa

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A B S T R A C T

Aggregate measures that capture multiple aspects of socio-ecological vulnerability in a single or small number of vulnerability indices can 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 challenge in the quantification and communication of complex phenomena such as socio-ecological vulnerability. This paper investigates the use of Principal Component Analysis (PCA) techniques as a means of creating information-rich spatially-explicit aggregate indices of socio-ecological vulnerability.

We present a 'proof of concept' analysis of socio-ecological vulnerability for the Southern Africa Development Community (SADC) region using both PCA and traditional normalization based techniques for generating spatially explicit, aggregated socio-ecological vulnerability indices. The vulnerability indices are based on published biophysical and socio-economic data and mapped at a 10 arc minute resolution. The resulting PCA based vulnerability maps indicate the regional spatial variability of four statistically independent, unique components of socio-ecological vulnerability, providing more information than the single index produced using a normalization/summation approach. Such uncorrelated, 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.

Introduction

This paper examines spatial mapping techniques for assessing vulnerability of human well-being in dynamic, integrated and complex socio-ecological systems. We conceptualize socio-ecological vulnerability as a function of exposure, sensitivity and adaptive capacity (e.g. Eakin & Luers, 2006; Gallopin, 2006; Yohe & Tol, 2002). Where exposure is defined as the degree to which a system experiences internal or external system perturbations. Sensitivity is defined as the degree to which a system is affected by those system perturbations (McCarthy, Canziani, Leary, Dokken, & White, 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).

Vulnerability is a highly complex phenomenon with both biophysical and socio-economic factors affecting exposure and sensitivity (Adger, 2006). The literature on socio-ecological systems, therefore, 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 (Berkes & Folke, 2000; Eakin & Luers, 2006). 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, Fraser, Dougill, Stringer, & Simelton, 2012; Fraser & Stringer, 2009; Simelton, Fraser, Termansen, Forster, & Dougill, 2009). Using data on multiple

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socio-economic and biophysical indicators potentially results in a richer more robust elucidation of vulnerability (Johnson, Stanforth, Lulla, & Luber, 2012).

Spatially-explicit vulnerability assessments are increasingly important instruments in environmental policy formulation and in informing environmental and development debates (Metzger & Schröter, 2006; Stelzenmüller, Ellis, & Rogers, 2010), because vulnerability maps can act as powerful visual tools. Such maps can 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 & Midgley, 2010; Ericksen et al., 2011). Recently institutions such as the United Nations Environmental Programme (UNEP, 2006) and the UK's Department of International Development (Thornton et al., 2008) have undertaking broad-scale (multinational to continental scale) vulnerability mapping exercises. Nevertheless, quantifying and communicating the multiple drivers of socio-ecological vulnerability is problematic, particularly when seeking to explicitly map vulnerability across broad spatial scales (Eakin & 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 biophysical and socio-economic aspects of vulnerability. These indicators are not necessarily directly comparable when attempting to represent multiple sources of vulnerability (Adger, 2006). While each individual indicator may be of interest to policymakers, 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 may result in a dependence on degraded or marginal land for food production. These lands can rapidly become unproductive and therefore increase vulnerability to food insecurity (Reycraft & Bawden, 2000). Conversely, high population density 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 could lead to the development of inappropriate policy. Therefore, to gain a more holistic insight requires an understanding of how multiple, often interdependent indicators of vulnerability vary in relation to each other.

A common approach to holistic vulnerability mapping is to aggregate the multiple biophysical and socio-ecological indicators of vulnerability is to produce spatially explicit vulnerability indices—where the term index is taken to mean a unitless aggregation of multiple indicators of related phenomena. Such indices reduce 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'.

Aggregation of vulnerability indicators

Combining suites of often interdependent indicators into aggregate vulnerability indices can provide a useful overview of aggregate socio-ecological vulnerability (Füssel, 2009; Norman et al., 2012). 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 are less straightforward to communicate (see Fig. 1).

In the context of broad scale vulnerability mapping, we argue that it is difficult for policymakers 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. 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 smaller number of aggregate indices. Such aggregate indices 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 must overcome the incommensurability of the units in which the individual indicators are measured (Sullivan & 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.

Normalization of data to a common (comparable) unitless scale and subsequent summation of the normalized data is generally used to overcome issues of incommensurability when combining multiple indicators. Normalization of individual variables provides a linear transformation that preserves the ranking and correlation structure of the original data and allows for variables with different scales to be summed (Tran, O'Neill, & Smith, 2010).

Aggregate indices based on normalized and summed indicators of socio-ecological vulnerability are useful in identifying hotspots where multiple aspects of vulnerability occur. However, the generation of a single composite vulnerability index using a normalization/summation approach, is problematic because potentially important information regarding the relations between the original variables are obscured in the resulting unitless, aggregated index (from many indicators to a single index). Moreover, 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 & Luers, 2006). Vulnerability assessments are therefore highly context specific (Füssel, 2009; Yohe &

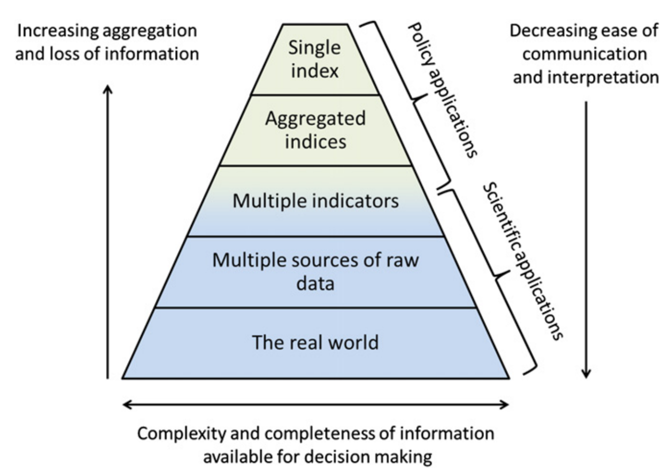

Fig. 1. Trade-offs between communicability, and information richness in the description of complex systems (adapted from Braat (1991)).

Tol, 2002). A normalization 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 a single aggregate vulnerability index conveys information in a more useful way than the multiple indicators of vulnerability on which it is 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 policymakers.

This paper proposes the use of Principal Component Analysis (PCA) as a means of creating spatially-explicit aggregate indices of socio-ecological vulnerability across broad spatial scales. After discussing the potential advantages of PCA over the dominant normalization approach to indices production, we present a "proof of concept" analysis by producing and comparing spatially-explicit aggregate indices of socio-ecological vulnerability for the Southern Africa Development Community (SADC) region using both PCA and normalization approaches.

PCA

PCA is an ordination based statistic data exploration tool that converts a number of potentially correlated variables (with some shared attribute, such as points in space or time) into a set of uncorrelated variables that capture the variability in the underlying data. As such, PCA can be used to highlight patterns within multi-variable data. PCA is a non-parametric analysis and is independent of any hypothesis about data probability distribution (Abdi & Williams, 2010).

PCA uses orthogonal linear transformation to identify a vector in N-dimensional space that accounts for as much of the total variability in a set of N variables as possible—the first principal component (PC)—where the total variability within the data is 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). A second vector (second PC), orthogonal to the first, is then sought that accounts for as much of the remaining variability as possible in the original variables. Each succeeding PC is linearly uncorrelated to the others and accounts for as much of the remaining variability as possible (Jolliffe, 2002).

PCA can therefore be used as descriptive, statistical approach to data transformation as a means of overcoming variable incommensurability. The ranking of the PCs in order of their significance (based on how much of the variability in the data they capture) is denoted by the eigenvalues associated with the vector for each PC. In the case of a spatially explicit analysis each data point for each variable is related to a specific point in space and the PCs derived from a PCA can be assigned scores (synthetic variable values) for each of these points in space.

A PCA approach provides several potential advantages in the aggregation of spatially explicit, potentially incommensurable variables. When the original variables are correlated then the higher order PCs will capture more of the total variability in the data than any individual original variable. Excluding the lower order PCs reduces the dimensionality (number of variables) of the data while minimising the loss of information (Smith, 2002). As such PCA provides an approach to move from a large suite of individual indicators to a small number of composite, unitless indices (PCs) while reducing the trade-off between richness of information and is communicability. Here it should be noted that the choice of the number of dimensions (PCs) to be retained is subjective and is generally based on the interpretability of the retained components (Srivastava, 2002), the proportion of the variation in the original variables explained by the retained components and the shape of the scree and loading plots (Griffith, Martinko, & Price, 2000). PCA provides flexibility in the data reduction process through the subjective choice of the number of PCs, and therefore indices, that are retained. As many indices as usefully express important patterns in the multivariate data can be retained. In contrast, a normalization approach to data aggregation collapses all indicators into a single index. Finally, and perhaps most importantly, each PC can be related to the original variables that the PC is most influenced by through the reported principal component loading factors. The PCA loading factors associated with each retained PC allow the original variables to be readily associated with the resulting 'indices', thus retaining important information regarding the underlying drivers of the retained indices.

PCA and socio-ecological vulnerability indices

In this paper we conceptualise the PC scores associated with the multiple variables of vulnerability as a vulnerability indices. By retaining only those PCs that account for a substantial proportion of the variability in the original data 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 shed light on the aspects of socio-ecological vulnerability each PC index represents. The indices produced by the PCA highlight spatial patterns of different aspects of socio-ecological vulnerability across space and are used to map these multiple aspects of socio-ecological vulnerability across broad spatial extents. Rather than assigning arithmetic relationships between multiple indicators of sensitivity, adaptive capacity and exposure in order to develop aggregate vulnerability indices the PCA is used to identify correlations or spatial discontinuities between these different components of socio-ecological vulnerability.

There are likely to be multiple types of vulnerability occurring simultaneously within a complex socio-ecological system. In response to this complexity it is often argued that in order to provide policy relevant research one should quantify vulnerability in relation to a single, clearly identified issue (e.g. Preston, Yuen, & Westawa, 2011). However, such a 'focused' approach to assessment ("vulnerability to…") presupposes that the most important sources of socio-ecological vulnerability within the system are already known. In the absence of such *a priori* knowledge there is a danger that important, but unacknowledged, aspects of vulnerability will go unassessed. We argue that the mapping of an 'unfocused' notion of socio-ecological vulnerability—aggregate vulnerability resulting from multiple interconnected perturbations and socio-ecological conditions—is valuable because it can provide clear empirical evidence to answer the question "vulnerability to what?". Once the key types of vulnerability are identified more focused vulnerability assessment can be undertaken. While in this paper we undertake an ‘unfocused’ vulnerability assessment we would nevertheless argue that the novel methods presented here are equally applicable to any form of vulnerability mapping based on multivariate data.

Application of PCA to the mapping of socio-ecological vulnerability indices for the SADC

We analyse and compare the resulting socio-ecological vulnerability indices produced through PCA and normalization approaches for the SADC. 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. We aim to show that the use of PCA based vulnerability indices across broad spatial extents can guide more detailed and context specific research efforts, at finer spatial resolutions, as well as informing more targeted policy development and donor investments that can inform transitions towards reduced vulnerability (Foxon, Reed, & Stringer, 2009).

It is important to note that the quality of vulnerability indices is ultimately dependent on the choice and quality of the indicators on which the index is based. We do not claim to produce a definitive map of socio-ecological vulnerability for the SADC region; rather we seek to assess the utility of a PCA approach to data aggregation for vulnerability mapping.

The SADC study region

The 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 Fig. 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 (Fig. 2). 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 (Olson et al., 2001). Our ecoregions are, 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 (Fig. 2). 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. The same indicators of vulnerability used in the PCA were aggregated using a simple normalization approach to allow a comparison between the two approaches.

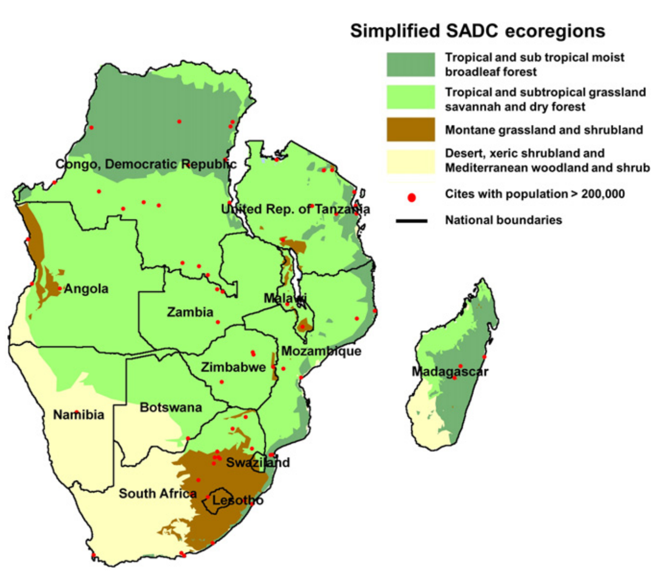

Fig. 2. SADC study area (ecoregions based on Olson et al. (2001)).

Data and methods

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 to 1990) and precipitation indicator (average from 1950 to 2000). Given the large temporal frame of the data used, that the resultant indices should not be considered as authoritative measures of the current socio-ecological vulnerability in the SADC region.

As noted previously, the choice of indicators of vulnerability is the primary determinant of the outcomes of any aggregate indices of vulnerability. However, issues related to the quality, and spatial scale at which the individual vulnerability indicators also influence the resulting indices. To avoid introducing bias into the analysis (other than unavoidable bias related to data availability and selection), we required 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 national scale data will have distorted previous attempts at regional vulnerability mapping for the region (Davies & Midgley, 2010). Inclusion of variables reported at a national scale is particularly problematic in a PCA approach as it introduces spatial autocorrelation into the statistical analysis based on artificially constructed features (national boundaries). For these reasons, national reports of vulnerability indicators were excluded from the analysis.

A further issue is that 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 intra-annual climate variability and topographic factors such as slope. All these variables influence the suitability (or potential productivity) of land for agricultural production, which in turn is 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 manner 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 Environmental and Biophysical indicators section).

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 well-being of 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 and do not differentiate between exposure, sensitivity and adaptive capacity. The indicators of vulnerability included in the analysis are detailed below and summarised in Table 1.

Environmental and biophysical indicators

Agricultural constraints

This dataset 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). It represents an important source of vulnerability for the agriculture dominated ecoregions under investigation. While this aggregate indicator includes aspects of climate variability 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 with the climate variables detailed below.

Soil degradation

The Global Assessment of Human-induced Soil Degradation (GLASOD, 1990) 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 status of soil degradation was mapped within loosely defined physiographic units based on expert judgement.

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). 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 HANPP.

Available NPP per capita (POPNPP)

This dataset was based on NPPact (Haberl et al., 2007) and the Gridded Population of the World (GPWv3). A proportional allocation gridding algorithm, utilizing more than 3,00,000 national and sub-national administrative units, is used to assign population values to grid cells (CIESIN, FAO, & CIAT, 2005). NPPact was divided by population density to give an indicator of the available NPP 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.

Aridity

This uses the global aridity map produced by Zomer, Trabucco, Bossio, van Straaten, and Verchot (2008). These data represent deficit over atmospheric water demand through a standardized Aridity Index of mean annual precipitation divided by mean annual evapotranspiration. Water availability was seen as a key limitation to agricultural production and areas of water scarcity are likely to be disproportionally vulnerable to climate changes.

Precipitation CV

The coefficient of variation of annual rainfall was taken from the Global Historical Climatology Network (GHCN), the FAO, and CIAT (Hijmans, Cameron, Parra, Jones, & Jarvis, 2005). This dataset provides an indicator of the annual variability in rainfall and is an important indicator of the vulnerability in the largely subsistence farming agro-ecosystems of southern Africa.

Socio-economic indicators

Infant mortality

Global Sub-national Infant Mortality Rates consist of estimates of infant mortality rates, where infant mortality rate is defined as the number of children who die before their first birthday for every 1000 live births. This dataset is produced by the Columbia University Center for International Earth Science Information Network (CIESIN, 2005a).

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).

Irrigation

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, Döll, Feick, Hoogeveen, & Frenken, 2007). Values were transformed so that high values represent areas that are not equipped for irrigation.

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	Van Velthuizen et al. (2007)
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	CIESIN et al. (2005) and Haberl et al. (2007)
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)

Infrastructure poverty

This dataset combines the LandScan 2004 population dataset (Oakridge National Laboratory, 2004) and the Night Time Lights dataset (Elvidge, Baugh, Kihn, Kroehl, & Davis, 1997) to present a high resolution 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. High poverty index values occur in areas with high LandScan population count and dim (or no) lighting (Elvidge et al., 2009).

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, creating the first ever sub-national poverty map of the developing world, spatially depicting the percentage of people with incomes of less than $2.00 (PPP) per day (Wood et al., 2010).

Travel time

Travel Time to Major Cities is a dataset developed by the European Commission and the World Bank. It creates an urban/rural population gradient around large cities 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).

Methods

Where necessary, all spatially-explicit datasets were re-projected in ArcGIS (ESRI, 2006) from their original coordinate systems to World Geodetic System (WGS) 1984 global coordinate system. Vector/polygon data was converted to raster data at the same spatial resolution as the original datasets (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 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 finer spatial resolution.

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 analysis grid square. When the original 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 analysed from 30,942 to 30,677.

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 & Herzog, 2002; Schindler, Poirazidis, & Wrbka, 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, Black, Babin, Anderson, & Tatham, 2006). A correlation matrix was used for the PCA analyses as this standardizes the data and avoids potential bias resulting from the inclusion of data with different scales and data ranges.

The choice of PCs to be retained from the PCAs was in part based on subjective judgement 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 aspect of socio-ecological vulnerability represented by each PC 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 and 1, where 0 represents the least vulnerable and 1 the most vulnerable grid square.

Normalization analysis

The same data, projections and spatial extents were uses as described in the previous sections. The 12 variables were normalized to a scale of 0–1 using the following formula: $\delta = (\chi - \chi_{min})/(\chi_{max} - \chi_{min})$ where δ is the normalized value, χ the original value and χ_{min} and χ_{max} the minimum and maximum values in the dataset. The normalized variables were then summed and the results normalized again to provide a final vulnerability index with a range of 0–1 to allow direct comparison with the PCA based vulnerability indices.

Results

SADC PCA analysis

Four principal components were retained in PCA for the whole SADC regional analysis. Together these first four principal components accounted for 63.5% of the variation in the original 12 variables included in the analysis. The 5th principal component captured only an additional 5.6% of the total data variability and the factor loading was dominated by Precipitation CV and POPNPP. The loading of each variable for the retained principal components are detailed in Table 2, with the heaviest loadings shaded in grey.

The first PC 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

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

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. The spatial distributions of these vulnerability indices for the SADC region are shown in Fig. 3. The Normalized vulnerability index (Fig. 3) reflects some of the patterns found in the PCA indices, but the ‘trade-offs’ between different components of vulnerability appear to have evened out the extremes. For example, the poverty and health vulnerability in the Democratic Republic of Congo (north west region in Fig. 3) indicated in PC1 is hidden in the normalized vulnerability index by relatively low levels of vulnerability in the other 3 PCA based indices.

Fig. 3 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 carrying capacity vulnerability (PC3) is highest in the urbanized area of South Africa and the desert regions of Namibia and Botswana, where relatively high populations in areas with low net primary production dominate. 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. In contrast the Normalized vulnerability index provides a less spatially heterogeneous picture of vulnerability, with Namibia, Botswana and western South Africa all having low vulnerability index scores and only the eastern coast of Madagascar indicated as having high levels of vulnerability.

Looking at the vulnerability indices in terms of ecoregions rather than nations provides interesting insights. The normalized index indicates low relative vulnerability in dryland ecoregion (desert,

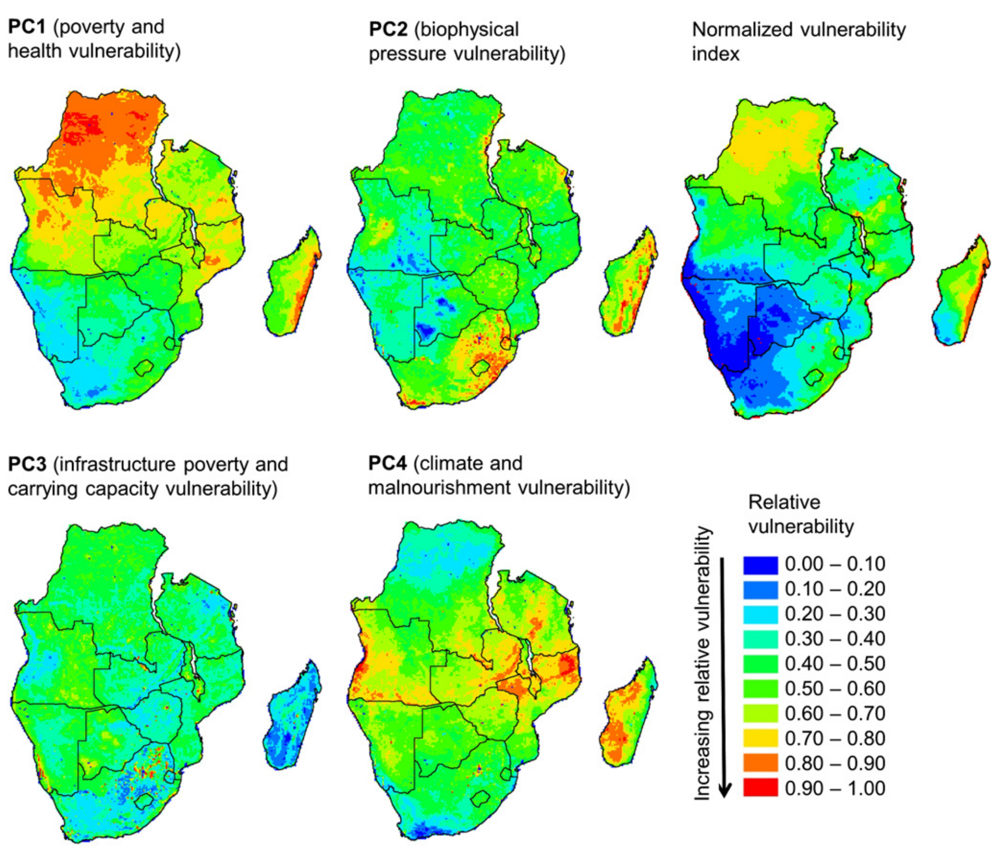

Fig. 3. PCA based and normalized maps of relative socio-ecological vulnerability for the SADC region.

xeric shrubland and Mediterranean woodland) average levels of vulnerability in the montane and tropical grasslands ecoregions and highest vulnerability in the tropical and sub-tropical broadleaf forest ecoregion. The normalized index shows little variation in vulnerability within each ecoregion. In contrast, the different PCA indices indicate both differences within and between ecoregions. For example, the poverty and human health index (PC1) is high in the tropical forest ecoregion and low in the drylands regions. Whereas the climate and malnourishment index PC4 shows significant variation within ecoregions, with montane grassland in Angola and northern Mozambique indicated as having high relative vulnerability and the same ecoregion in South Africa and indicated as having only average vulnerability. Where the normalized vulnerability index identifies different relative levels of aggregate vulnerability between ecoregions, the PCA based indices highlights both the aspects of vulnerability most associated with different ecoregions and differences in aspects of vulnerability within ecoregions.

SADC drylands ecoregion analysis

For the PCA limited to the SADC drylands ecoregion four principal components were also retained. The retained 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 for the SADC drylands ecoregion is detailed in Table 3, with the heaviest loadings highlighted in grey, the loading on each of the four retained PCAs for the drylands analysis differed from those found for the SADC analysis (Table 2).

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 (Fig. 4). 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. The normalized vulnerability index for the dryland ecoregion can be more easily related to the vulnerability indices from the PCA than for the SADC wide analysis, with the normalized index looking like a combination of PC1 and PC2, with relatively little influence form the more evenly distributed PC3 and PC4 scores.

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

Discussion

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 & Luers, 2006; Füssel, 2009).

The choice of indicators used in this exploratory research was 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. Vulnerability is a dynamic concept and spatial mapping 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, care must be taken when interpreting the maps presented here and when comparing these maps to others created using different data and methods.

Here it should also be noted that a potential disadvantage of a PCA approach is that it is not possible to provide weightings regarding the relative importance of individual indicators in the resulting aggregate indices. Each indicator is treated as equally important as a driver of vulnerability. As such a PCA based approach to vulnerability mapping does not provide absolute measures of vulnerability; rather it indicates the different spatial patterns of relative vulnerability relating to spatially co-occurrences of individual drivers of vulnerability. It could therefore be argued that in systems where particular driver of vulnerability are known to be of paramount importance the application of PCA may not be appropriate in creating aggregate vulnerability indices. However, given that the individual drivers of vulnerability can be associated with one or more of the retained vulnerability indices it is still possible for the policymakers to subsequently weigh the resulting indices based on their knowledge of which drivers or types of vulnerability are most important. For example, in the SADC analysis climate and malnourishment vulnerability (PC4) may be judged a more pressing issue than biophysical pressure vulnerability (PC2) and funding and support focused appropriately based on this assessment.

The results presented here do suggest that the use of PCA to derive multiple independent indices of vulnerability from a suite of biophysical and socio-economic indicators of sensitivity, exposure and adaptive capacity will be of considerable use in the broad scale mapping of socio-ecological vulnerability. Such PCA based maps may provide a useful “first pass” in assessing broad scale socio-ecological vulnerability, indicating not just which areas are vulnerable, but also to what is driving that vulnerability. Both the normalization and PCA approaches to vulnerability mapping could 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). Our analysis suggests that a PCA approach provides a smaller trade-off between communicability and the information richness than is provided by the normalization approach to index development. The utility of a PCA approach to vulnerability mapping is not limited to mapping of broadly defined ‘unfocused’ socio-ecological vulnerability. PCA can also be applied to enhance understanding of focused aspects of vulnerability.

PCA based vulnerability maps can illuminate those locations where there is a need for further, urgent, in-depth case study based

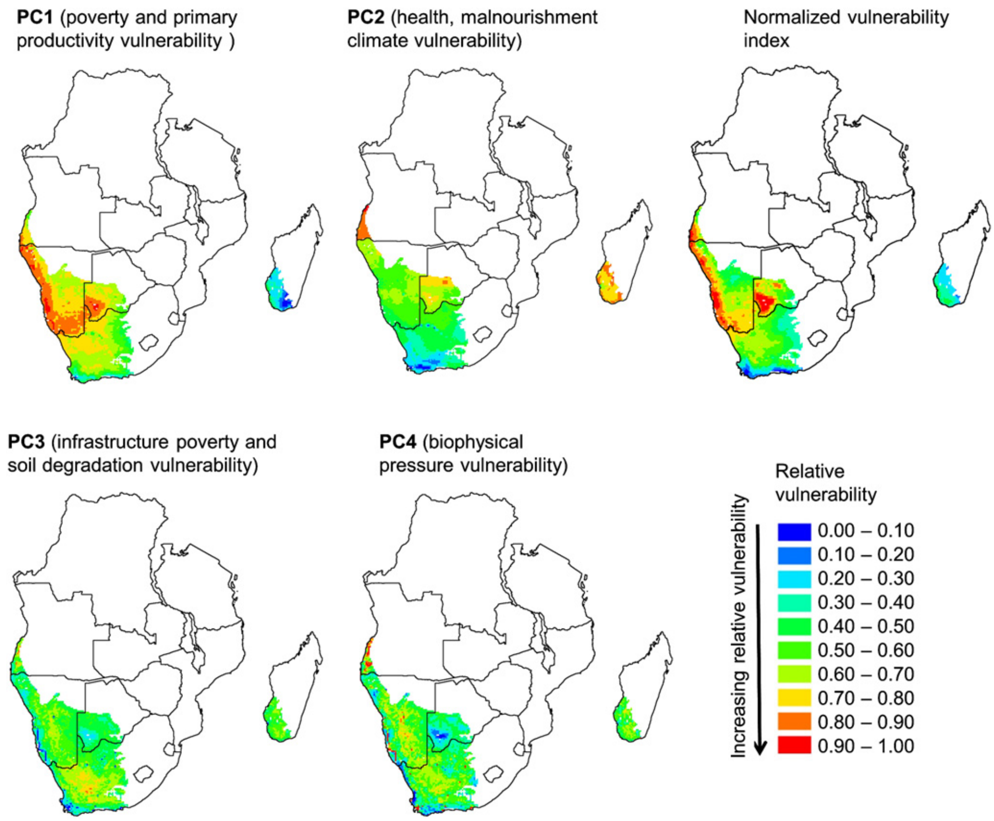

Fig. 4. PCA based and normalized maps of relative socio-ecological vulnerability for the SADC desert ecoregion.

research to supplement and understand the detail of relationships between different indicators of vulnerability at smaller scales. Regional PCA based vulnerability maps should be considered a starting point for further analysis as they can contribute towards and inform policy. Nevertheless, challenges remain, in the initial choices of indicators, the best spatial scale at which to undertake such assessments. Here too a PCA approach has some potential advantages. With a more traditional normalization approach the use of context specific indicators of vulnerability at broad spatial scales can prove problematic. For example, inclusion of data on forest loss in a study area that contains both forest and non-forest ecosystems will tend to result in higher vulnerability scores in forest ecosystems simply because only these areas are affected by this driver of vulnerability. In a PCA based assessment the PC the factor loadings would indicate in which areas the context specific drivers are important factors in the aggregate vulnerability indices. This allows 'unfocused' vulnerability assessment to be carried out across large spatial extents without resulting in potentially misleading aggregated indicators across different socio-ecological systems. A PCA approach that provides a small number of independent, easily interpreted and spatially explicit indices may help regional or national institutions and organisations to define context specific aspects of socio-ecological vulnerability that are of concern in specific geographical locations or socio-ecological systems.

Conclusions

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 demonstrates that different aspects of vulnerability are spatially discrete, with different regions characterised by different types of vulnerability. From a policy perspective such contextualised, "information rich" vulnerability indices will prove useful as they provide a compromise between the rich 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 suggests that there is a need to carefully consider scale when using PCA to generate aggregate vulnerability indices. Analyses at multiple spatial scales will 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 underlying causes and impacts of, socio-ecological vulnerability across broad spatial scales.

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