Farmers' vulnerability in African drylands

A quantitative and spatially-explicit typology based on clustering

Sietz, D.[1], Ordoñez, JC.[1], Kok, M.[2], Janssen, P.[2], Hilderink, H.[2], Lüdeke, M.[3], Walther, C.[3], Sterzel, T.,[3] and Van Dijk, H.[1]

Contact: diana.sietz@wur.nl

[1] Wageningen University, The Netherlands; [2] Environmental Assessment Agency, The Netherlands; [3] Potsdam Institute for Climate Impact Research, Germany

Background: The recurrence of specific processes that shape farmers' vulnerability to environmental and socio-economic perturbations in various regions has inspired research on archetypical patterns of vulnerability. This study investigates farmers' vulnerability to climate variability, market impacts and demographic perturbations in the drylands of Sub-Sahara Africa at a sub-national resolution.

Aim: The aim of this study is to identify relevant and valid patterns of farmers' vulnerability including their spatial distribution.

Methodology: This study employs cluster-based pattern recognition relying on well-defined and formalised mechanisms that generate vulnerability. Four methodological steps serve to identify typical vulnerability patterns as outlined below.

Step 1: Mechanism hypotheses

- Hypotheses about mechanisms that generate vulnerability are formulated based on the „Dryland Development Paradigm" (Reynolds et al. 2007) and its refinements proposed in the „Dryland Livelihood Paradigm" (Safriel and Adeel 2008). The hypotheses are adequate when **the clusters** identified are **interpretable** in the light of the mechanisms elicited.

Step 2: Quantitative indication

- Based on the hypotheses derived from Step 1, **quantitative data** are chosen to indicate vulnerability. Data used for indication need to be **well-resolved both spatially and temporally**.
- Indicators that contribute significantly to the **variance** of the data space and are **least correlated** are most suitable for clustering. We selected nine indicators as shown below.

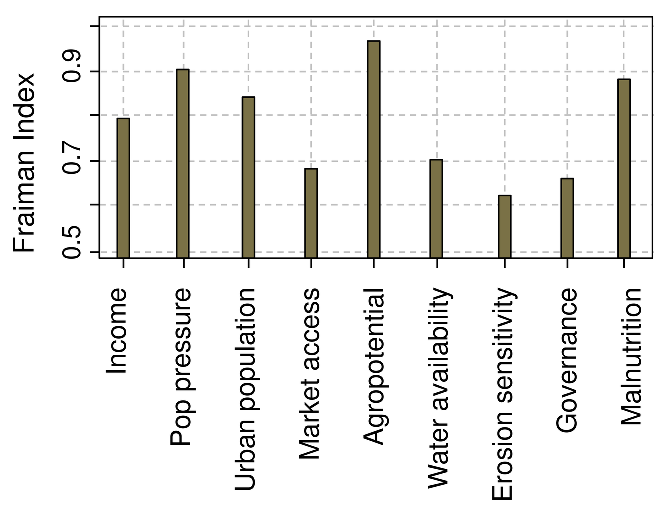
Step 3: Cluster analysis

- Cluster analysis is performed in the nine-dimensional data space using a **sequence of hclust and k-means algorithms** (Janssen et al. 2012, Sietz et al. 2011). First, hclust is **initialised based on a random subset** of 100 grid cells. Second, the resulting cluster centres serve as **starting point for k-means** applied to the full dataset. Clustering is performed in a pairwise way and repeated 200 times. Pairwise comparison yields the reproducibility of cluster partitions, expressed as consistency measure. It is calculated for a given cluster number to indicate cluster stability. Partitions with nine clusters show a local maximum.
- To assess the sensitivity of cluster results, variables are iteratively fixed at their mean value ("blinding" of variables). A comparison of "blinded" clustering with the original partition with all variables fully included leads to the Fraiman Index.

Consistency measure

Consistency measure: Number of grid cells with an identical cluster allocation in repeated cluster runs. Green and red dotted lines: Standard deviation (50 repetitions of 200 pairwise comparisons). The small standard deviation shows the good convergence of the stochastic approach.

Cluster sensitivity



Sensitivity of cluster results to omission of variables. Values: 0 (most important) to 1 (least important)

Step 4: Ground-truthing

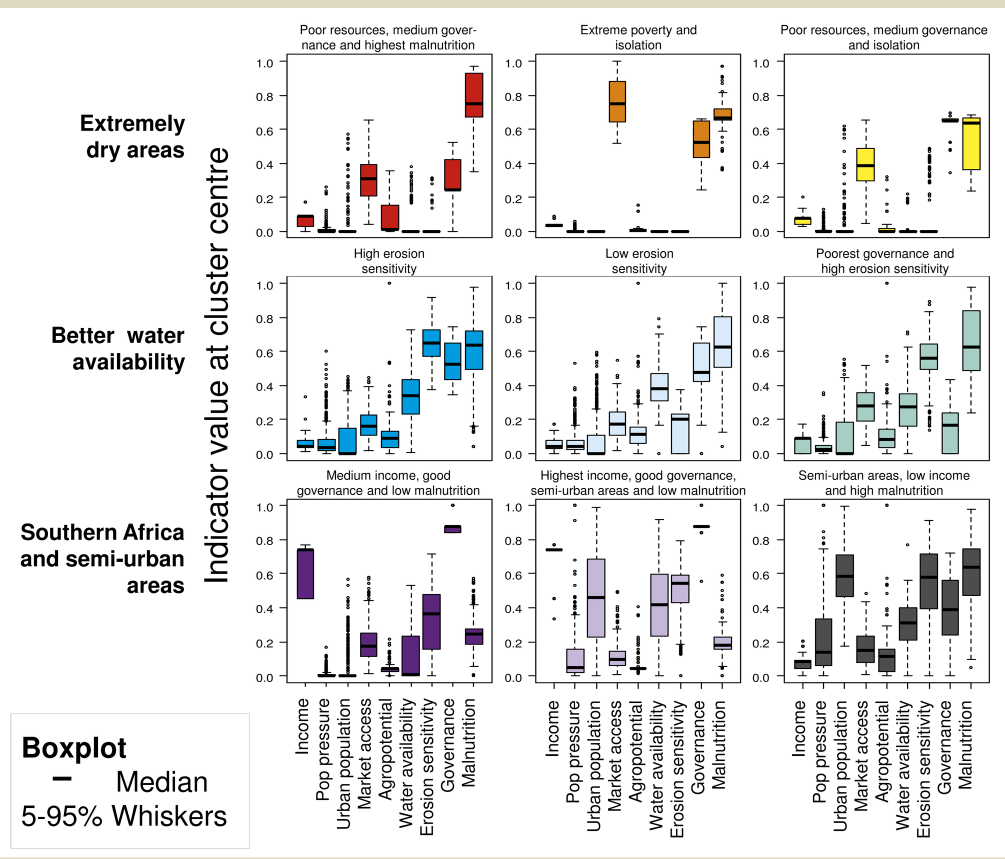
- To ground-truth our results, we used **independent case studies** to confirm cluster-specific mechanisms (see Step 1) and their spatial distribution. Working at the continental level largely restricts a more rigorous outcome-oriented validation, such as that applied by Sietz et al. (2012) at the household level, due to spatial variations in exposure and limitations in independent observational data.
- **Ample empirical evidence** describes determinants and outcomes of famers' vulnerability in regions with high levels of malnutrition, but better water availability as well as in regions with good governance, higher income and low malnutrition in southern Africa (e.g., dark blue, light blue and dark purple clusters). In contrast, other regions such as the extremely dry areas in western Africa and regions with highest levels of malnutrition and poor natural resources in northern Sudan are **less well documented** (e.g., orange and red clusters).

Vulnerability indicators

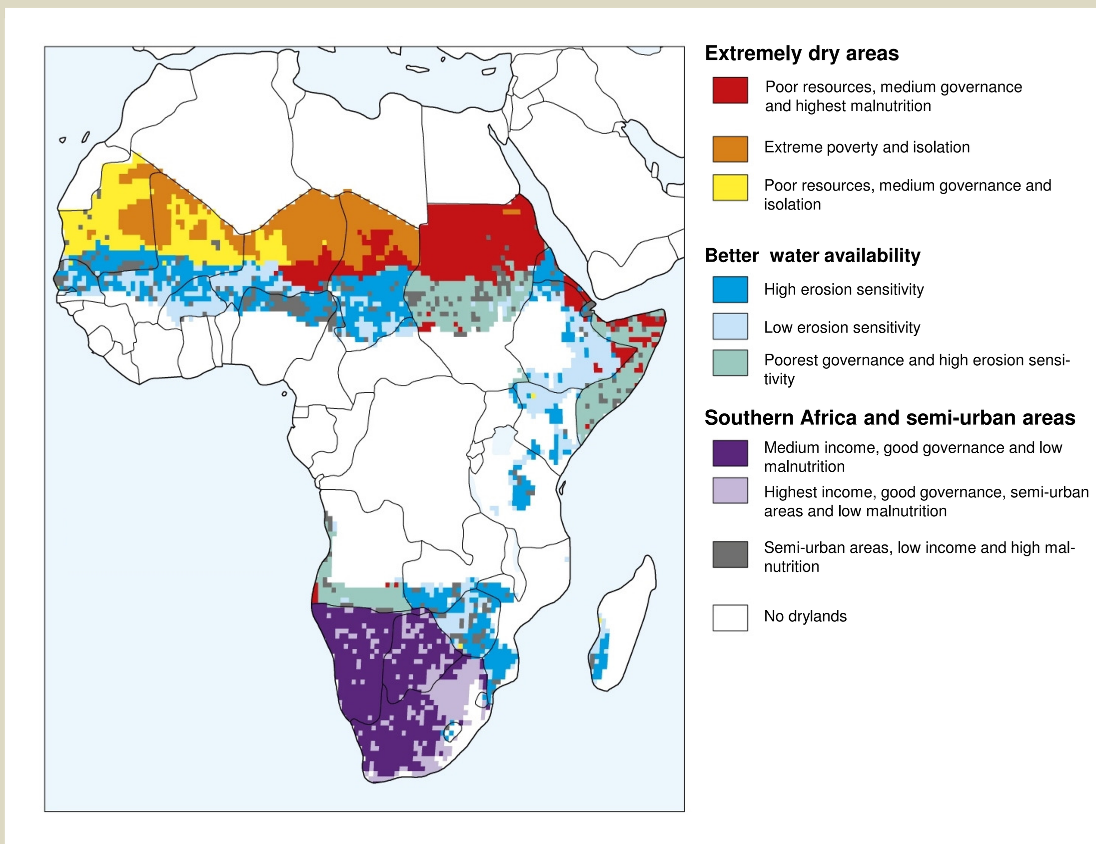
- Spatial resolution: 0.5° grid cells
- Time reference: 2000
- Min-max normalisation: 0-1

Dimension	Indicator	Source
Malnutrition	Prevalence of child under weight	CIESIN (2005)
Water availability	Water runoff per river basin	Alcamo et al. (2003)
Erosion sensitivity	Water erosion sensitivity of soil	Hootsman et al. (2001)
Agropotential	Ratio of grassland productivity to maximum productivity	MNP (2006)
Income	GDP/capita	UNSTAT (2005), World Bank (2006)
Population pressure	Population density	Klein Goldewijk et al. (2010)
Dependence on land resources	Urban population	Klein Goldewijk et al. (2010)
Market access	Market distance	Letourneau et al. (2010)
Governance	Governance	Kaufmann et al. (2008)

Vulnerability clusters



Spatial distribution



Conclusions: The cluster-based approach reveals similarities between heterogeneous vulnerability situations. Thus, the typology allows the essence of farmers' vulnerability to be grasped beyond individual cases, while at the same time representing the spatial and functional heterogeneity at an aggregate level. Identifying similarities enables the evaluation of key determinants and opportunities for transferring vulnerability reduction measures.

Methodological refinements: A novel methodology was developed to **refining global insights into vulnerability at a regional scale** (Sietz 2014). It is based on a spatially explicit link between broad patterns of vulnerability and modelled regional smallholder development in Northeast Brazil. Feeding back to case study research, regionalised mechanisms such as those identified by Sietz (2014) may stimulate investigations to further elaborate our knowledge. Finally extending the methodology outlined in this study, **dynamics in vulnerability patterns** and the **linkages between vulnerability patterns and violent conflicts** have been assessed in drylands worldwide (Lüdeke et al. 2014, Sterzel et al. 2014).

References:

Janssen, P., Walther, C. and Lüdeke, MKB. (2012)) Cluster analysis to understand socio-ecological systems: A guideline. PIK Report 126.
Lüdeke, MKB., Walther, C., Sterzel, T., Kok, M., Lucas, P., Janssen, P. and Hilderink, H. (2014) Understanding change in patterns of vulnerability. PIK Report 127.
Sietz, D. (2014) Regionalisation of global insights into dryland vulnerability: Better reflecting smallholders' vulnerability in Northeast Brazil. Glob. Environ. Change 25(1): 173-185.
Sietz, D., Mamani Choque, SE. and Lüdeke, MKB. (2012) Typical patterns of smallholder vulnerability to weather extremes with regard to food security in the Peruvian Altiplano. Reg. Environ. Change 12(3): 489-505.
Sietz, D., Lüdeke, MKB. and Walther, C. (2011) Categorisation of typical vulnerability patterns in global drylands. Glob. Environ. Change 21(2): 431-440.
Sterzel, T., Lüdeke, MKB. et al. (2014) Armed conflict distribution in global drylands through the lens of a typology of socio-ecological vulnerability. Reg. Environ. Change, Published online: 23 January 2014.