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Valerie Graw, Christine Ladenburger

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Geographical Targeting for Poverty Reduction

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Authors' addresses

Valerie Graw
Center for Development Research (ZEF), University of Bonn,
Walter-Flex-Str. 3
53113 Bonn, Germany
Tel. 0049 (0)228-73 1913
E-mail: valerie.graw@uni-bonn.de

Christine Ladenburger
Center for Development Research (ZEF), University of Bonn,
Walter-Flex-Str. 3
53113 Bonn, Germany
Tel. 0049 (0)228-73 1913
E-mail: ladenburger@uni-bonn.de

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Valerie Graw, Christine Ladenburger

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Abstract

This mapping approach aims to make the marginalized and poor visible by identifying areas with difficult biophysical and socio-economic conditions. Mapping using different data sources and data types gives deeper insight into possible causal interlinkages and offers the opportunity for comprehensive analysis. The maps highlight areas where different dimensions of marginality overlap – the marginality hotspots – based on proxies for marginality dimensions representing different spheres of life. Furthermore, overlaying the marginality hotspots with the number of poor shows where most of the poor could be reached to help them to escape the spiral of poverty. Marginality hotspots can be found in particular in India and Nepal as well as in several countries in Central and Eastern Africa, such as Eritrea, Mozambique, Central African Republic, the Democratic Republic of Congo, Northern Sudan and large parts of Niger. Maps showing the overlap between marginality and poverty highlight that the largest number of marginalized poor are located in India and Bangladesh, as well as in Ethiopia, Southeastern Africa and some parts of Western Africa.

Keywords: GIS, Marginality, Poverty Mapping, Hotspot Mapping, Spheres of Life

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1. Introduction: Why do we map marginality?

"Maps are a powerful tool for presenting information in a way that is easily comprehensible by a non-specialist audience. Maps encourage visual comparison and make it easier to look for spatial trends, clusters or other patterns. Maps are therefore useful not only to governments and decision makers, but also to the local communities." (Deichmann 1999, p.3)

Historically, the first and still one of the most famous examples of using geospatial analysis for mapping causal linkages, is the cholera map of London in 1854. By mapping information about drinking water, pumps and the number of cholera victims, John Snow, an English physician, could identify a positive relationship between drinking water and the spread of cholera (Kriz 2010). Today, technologies and the development of Geo Information Systems (GIS) allow us to demonstrate simple relationships and to analyze the more complex ones.

Mapping and GIS are applied here to illustrate dimensions of marginality around the world. We thereby seek to make the marginalized and poor visible by identifying areas where many poor people live under difficult biophysical and socio-economic conditions. For this purpose a broad set of variables covering ecological, social and economic dimensions were identified and analyzed in this first marginality mapping approach. The focus is on Sub-Saharan Africa (SSA) and South Asia (SA) where most of the poor and in particular the poorest live (Ahmed et al. 2007, von Braun et al. 2009).

Mapping and spatial analysis have become useful tools to reduce poverty and vulnerability (Gauci 2005, see also chapter 2). They allow us to identify and analyze different combinations of *proximate causes*, e.g. belonging to an ethnic minority, living in remote areas, having no job and income, and *underlying causes*, e.g. being socially excluded because of specific cultural beliefs, having no access to water or transportation which causes marginality (Gatzweiler et al. 2011). By combining different data sources and types, we are able to identify areas which are lagging behind in different dimensions. Additionally, spatial relationships between variables can be analyzed and made comparable between regions (Davis 2003).

The number of extreme poor and hungry people remains unacceptably high. Being excluded from growth and other dimensions of development is an indication of the extreme poor being at the margin of society and triggers the downward spiral of poverty (Gatzweiler et al. 2011). **Marginality**, frequently cited as a root cause of poverty (von Braun et al. 2009), is a complex issue not amenable to simple solutions or answers. It is defined "***as an involuntary position and condition of an individual or group at the margins of social, political, economic, ecological and biophysical systems, preventing them from access to resources, assets, services, restraining freedom of choice, preventing the development of capabilities, and eventually causing extreme poverty.***" (Gatzweiler et al. 2011, p.3). Marginality thus explains why individuals or groups are excluded from or do not have access to processes or resources, which otherwise would free them from extreme poverty.

The concept of marginality overlaps partly with Sen's definition of poverty as capability deprivation (Sen 1981; Sen 1999) but also takes spatial and environmental aspects into consideration. Marginality refers to the constraints that need to be removed in order to recognize capabilities and transform them into functionings (Gatzweiler et al. 2011, p.3).

Single causal factors alone are not sufficient to explain marginality which should be seen as a network of causal factors which together lead to extreme poverty. "Having a low income alone, for instance, is not a sufficient cause for qualifying as marginalized, as someone with no income could be cared for within a family or social group. That means, in combination with underlying causes of being excluded, experiencing discrimination or not having access to services and facilities, causality crystalizes to specific causal networks of marginality and explains extreme poverty." (Gatzweiler et al. 2011, p.7) Thus, marginality is not only multidimensional with regards to the determining causes of poverty but also multi-relational with regards to the network character of the causal relations.

Causal relationships cannot be mapped. However, what we try to do here is to identify areas where many dimensions of marginality overlap and could thus cause extreme poverty. Furthermore, if the reasoning of marginality causing poverty is true, areas where many dimensions of marginality overlap should also be areas where many people are poor.

Following an overview of several mapping approaches used for poverty, vulnerability and marginality mapping (chapter 2), chapter 3 will describe a new approach to marginality mapping, developed in the context of the MARGIP (Marginality Reduction for Enhanced Investments for and with the Poorest) project of the Center for Development Research (ZEF) at the University of Bonn.[1] Moreover hotspots of both marginality and poverty were mapped via overlay analysis in GIS (chapter 3). We conclude by outlining a number of limitations and providing an outlook on further work in chapter 4.

2. State of the art: poverty and marginality mapping

2.1 Poverty mapping

In general poverty mapping and assessment can help to

- Define poverty
- Describe the situation and problem,
- Identify and understanding causes of poverty,
- Develop programs and formulating policies, and
- Select interventions and guiding allocation of resources (Henninger 1998 p. 2).

Understanding the distribution, characteristics and causes of poverty through maps requires a careful selection of indicators. Maps are defined and based on these indicators and depict what mappers identify as the 'right' indicators. The choice of indicators will also have important implications for the design of poverty reduction strategies.

Poverty mapping based on socio-economic data

The majority of poverty mapping approaches, in particular those undertaken at the national level, use household expenditure or income as proxies for poverty (Fujii 2003, Hentschel et al. 2000 and others). The advantage of this approach is the general availability of data. However, the maps only illustrate the complex phenomenon of poverty from a single perspective, i.e. through monetary data. Some national maps also use nutritional data, especially measures of child under- and malnutrition or a nutrition-based poverty line. One example is provided by Amarasinghe, Samad, and Anputhas (2005) who used a nutrition-based poverty line to map poverty in Sri Lanka. These mapping exercises can draw on publicly available data, for instance the Demographic and Health Survey (DHS).[2]

An interesting example of global poverty mapping that is based on more comprehensive socio-economic data was developed by the **Socioeconomic Data and Applications Center (SEDAC) of the Center for International Earth Science Information Network (CIESIN)** (Storeygard et al. 2008).[3] In addition to national data on GDP and number of people living on less than $1 per day, the maps also use indicators such as child malnutrition and infant mortality rates as proxies for

[1] See http://www.zef.de/margip.html for further information about the project.
[2] Available at http://www.measuredhs.com/
[3] The maps can be found at http://sedac.ciesin.org/maps/gallery/browse

poverty. SEDAC also provides maps on national scales which show the distribution of poverty or inequality within a country, based on household surveys and census data and prepared with small area estimation techniques (see also Box 1).

Box 1: Most frequently used methods for poverty mapping

Small Area estimation method

The small area estimation (SAE) "offers a powerful approach to produce statistically reliable poverty estimates for small areas" and is the most widespread method for mapping on national scales (WB et al. 2009). Via SAE statistically reliable poverty estimates for small areas can be calculated. The method combines detailed household survey information with population census data. The idea is to use survey data to create a predictive model for a dependent variable that is available in the survey but not in the census. The independent variables included in the model are common to both the survey and the census data. Various methods have evolved, in which different data sources such as data on household units or community level are used to develop the predictive model, which is then applied to the census data (Chris Elbers, Jean O. Lanjouw, and Peter Lanjouw 2003; C. Elbers, J. O Lanjouw, and P. Lanjouw 2000). The assumption is that relationships defined by the model resulting out of the survey data also hold true for the larger population. Therewith the measured spatial area can be relatively ´small` compared to only using census data (C. Elbers, J. O Lanjouw, and P. Lanjouw 2000).

Principal component analysis

Principal component analysis is a statistical technique that reduces a given number of variables using an orthogonal transformation to convert a set of observations of correlated variables into a set of values of uncorrelated variables, i.e. principal components. The number of principal components is less than or equal to the number of original variables. This transformation ensures that the first principal component accounts for as much of the variability in the data as possible, and each succeeding component in turn captures the highest possible variance under the constraint that it is orthogonal to the preceding components (Bahrenberg, Giese, and Nipper 2003).

Thus, principal component analysis can be used to reduce the number of variables or to calculate weights for variables that shall be summarized in one overall index. Since the principal components are linear combinations of the standardized variables of the data set, the coefficients of the variables in these linear combinations can be used as weights.

Factor analysis

Similar to principal component analysis, factor analysis is a statistical method to reduce the number of variables. The method is used to describe the variability among observed variables in terms of a lower number of unobserved variables, the factors. Joint variation among observed variables is assumed to be caused by unobserved underlying factors. The observed variables are modeled as linear function of these factors and their error terms. Either the factors as such can be mapped or the factors are used to group variables into indices (see the example of the South African Development Indicator; Bahrenberg et al. 2003).

Interpretation of satellite data

Remote Sensing is a good tool to map changes happening on the land surface. This could be land cover change which also includes the conversion of arable land to urban settlements or the monitoring of night lights to identify populated places with electricity (Sobrino & Raissouni 2000, Elvidge et al. 2009). Remote sensing imagery allows for mapping on very small scales depending on the resolution available from different sensors. This technique does not depend on national or district boundaries but on good data, i.e. remote sensing imagery without atmospherics such as a heavy cloud cover.

Another advantage of this approach is that the data is globally collected at the same time, unlike the comparison of survey and/or census data (e.g. used in SAE) which are usually gathered in different years and using different definitions of or proxies for poverty, thus making global comparisons difficult. In contrast satellite data is globally consistent and could be used for repeatable observations (Elvidge et al. 2009).

Cost-distance calculation is usually based on a combination of data on infrastructure, slope, exposition and land cover and locations of interest such as schools, hospitals etc. (Reusing & Becker 2003, Nelson 2008)

Another example is the poverty mapping of **Harvest Choice** which focuses on SSA and SA.[4] This dataset will also be of further interest for the mapping of marginality hotspots (chapter 3). The Harvest Choice methodology is under revision and data for some countries is still missing. An interesting aspect of their approach is to focus not only on rates or percentages of poor but also to include the number of poor which is relevant for poverty alleviation that aims to reach as many people as possible to help them overcome poverty and marginality.

The maps by Harvest Choice draw on two datasets (Wood et al. 2009):

1. Poverty prevalence as a share of the reference population living below the international reference poverty lines of $1,25 and $2 per day in $PPP 2005 currency units
2. Estimates of the actual number of poor *(still under revision)*

The focus is on SSA, but surveys were also conducted in South and Southeast Asia which extended the dataset.

To make the data of different countries comparable, Wood et al. (2009) developed the following methodology: In the cases where household level data was available, the 2005 $PPP exchange rate was applied to derive the 2005 local currency equivalent which was then converted into the equivalent amount for the survey year using national consumer price indices. Finally, the national poverty lines were replaced by the $1.25 and $2 ($PPP 2005) poverty lines in nominal local currency to get the comparable poverty rates. In the cases where only poverty rates were available but not the underlying household data, a national scale poverty rate headcount ratio for each country was newly calculated using sub-national poverty rates which were weighted by the population of the respective unit. Then, these poverty rates based on national poverty lines were rescaled to the 2005 PPP poverty line with the help of the 2008 World Development Indicators data. The respective national scaling factor was then used to convert the sub-national poverty rates of the original datasets into the poverty rates according to the $PPP 2005 poverty line (Wood et al. 2009). The second dataset, showing the number of poor, was derived by including population data for 2005 provided by CIESIN´s Global Rural-Urban Mapping Project (GRUMP).

Another approach is presented by Elvidge et al. (2009) who developed a disaggregated global poverty map using remote sensing data on **population count[5] and nighttime lights[6]**. Light was used as a proxy for wealth, assuming that areas with a higher amount of poor people can be detected by scarce light use during the night. A poverty index was calculated dividing the population count obtained from LandScan by the average visible band digital number from the

[4] See also: http://harvestchoice.org/households/povertyhunger and http://labs.harvestchoice.org/2010/08/poverty-maps/

[5] LandScan 2004 data of the US Department of Energy

[6] US Air Force Defense Meteorological Satellite Program's Operational Linescan System

lights. Where no light was detected, the light data was set to one so that the LandScan population count fully enters into the poverty index (Elvidge et al. 2009).

However, Elvidge et al. 2009 also acknowledge some drawbacks of this approach. Since data on nighttime light is only available for the range between 65° North and South, the analysis is restricted to countries inside this area. There are also cultural variations in using lightning, which are not taken into account in the poverty index. States putting emphasis on sustainable development reduce nighttime light leading to erroneously high poverty rates, as illustrated by the US states of Vermont and Maine. Moreover, the inclusion of lights from gas flares, for instance in coastal Nigeria, causes downward biases of poverty estimates.

Combining socio-economic and environmental data

Robinson, Emwanu, and Rogers (2007) explore a novel approach to poverty mapping in Uganda, combining 2002/2003 household survey data with environmental variables that are either "direct measures of key climatic variables (such as temperature), descriptor variables of key ingredients of poverty-generating processes (such as agricultural production systems) or proxies for constraints on the health and well-being of the human populations (such as disease-causing pathogens)." (p. 205)

The environmental data used in the model was mostly derived from satellite imagery which allows for mapping on very small scales (30 arc seconds, i.e. approximately 1km). The model included data on natural habitats (capturing seasonal processes) as well as data on elevation, human population density, access to markets, cattle, sheep, goat and pig densities, and the probability of major tsetse species being present (Robinson, Emwanu, and Rogers 2007). By using a discriminant analytical method, Robinson, Emwanu, and Rogers (2007) can explain more than 50 percent of the variance in the poverty data at a spatial scale of 20km or more.

2.2 Marginality Mapping

Though only few, a number of approaches to marginality mapping have been developed. The **Mexican marginalization index** for example is composed of nine variables representing four dimensions of marginality, i.e. education, housing, income and size of the city or village a person is living in. After the classification into five 'degrees of marginality', the index was crossed with other spatially based criteria such as geographical location, distance between localities and accessibility of institutions of health, education and other infrastructure (Anzaldo & Prado 2005). Poverty maps were then produced with a combination of SAE for household expenditure and the marginalization index (López-Calva et al. 2007).

Another example of maps that draw on the concept of marginality is the approach developed by Reusing, and Becker (2003) for the GTZ (now GIZ, Gesellschaft für internationale Zusammenarbeit) which combines topographic, land cover and infrastructure information to develop **cost-distance maps**. The map shows marginalized areas identified by calculating cost-distances to places of interest, such as markets or hospitals (Reusing & Becker 2003).

The **Enumeration District Marginality Index** (EDMI) is one of two indices[7] that were constructed for a comprehensive poverty mapping exercise in Guyana. The index consists of various socio-economic variables such as school attendance, access to water and electricity and number of people per bedroom. Using the 2002 Population and Housing Census and the 2005/6 Household

[7] The second index is the Living Conditions Index. For more information, see Skoufias 2005.

Budget Survey the marginality index was produced to check for the sensitivity of the poverty estimates (Skoufias 2005).

Another related approach is **vulnerability mapping**. Vulnerability is defined as "the condition resulting from physical, social, economic and environmental factors or processes that increases the susceptibility of a community to the impact of a hazard" (Birkmann 2006). Different systems can be vulnerable, including social systems, ecosystems or markets, which need to be defined at the outset and require different approaches and sources and types. Ecosystem vulnerability maps, for instance, tend to focus on land degradation, respective land degradation vulnerability, or loss of biodiversity, and are often based on remote sensing imagery (Eswaran, Lal & Reich 2001). The World Risk Report of 2011 (UNU-EHS 2011) provides a good overview of indicators used for vulnerability (and risk) mapping at both global and national scales.

Different approaches have also been combined to explore causal linkages. A study by Thornton et al. 2006, for instance, applies a **combination of vulnerability and poverty assessments** based on mapping approaches. Several databases on climate, precipitation and agriculture were used to obtain information about climate change scenarios and how they could affect the population of SSA. This study highlights how vulnerability and poverty and therefore also marginality as a root cause of poverty are connected.

3. Marginality Hotspots

The mapping approaches discussed in the previous chapter and presented in the Annex make considerable contributions to localizing poor people. However, most of the poverty maps focus on socio-economic and in particular income-related data. Only a few of the above-mentioned examples have started to add environmental indicators, e.g. the mapping in Uganda and the methodology developed by Reusing, and Becker (2003). In the mapping approach presented in this chapter, we covered a wide variety of important spheres of life representing different dimensions in which marginalization can occur and eventually cause poverty.

3.1 Finding Proxies for Marginality Indicators on the global scale

Given that marginality is a complex and multifaceted phenomenon, we include a broad set of variables covering ecological, social and economic aspects. The **marginality dimensions** are derived from the spheres of life defined in Gatzweiler et al. (2011) and outlined in Table 1. For the purpose of the mapping exercise, single indicators were identified for each of the spheres. Spheres C and F are both captured by the single indicator of "accessibility", sphere B and D are both represented by "stunting" (explained in more detail below). Maps for the individual marginality dimensions are presented in Figure 1.

For each dimension, represented by one indicator, a **cut-off point** defines the threshold below which an area is considered to be marginalized in the respective dimension. Indicators for the different dimensions of marginality are overlaid to find the areas where bad performances in the single indicators overlap – the **marginality hotspots**. We define a marginality hotspot as an area in which at least three dimensions of marginality overlap.

The maps draw on national and sub-national data published by the World Bank, the United Nations Food and Agriculture Organization (FAO), Harvest Choice and others. Table 2 provides a detailed overview of the data used, the sources from which it was taken and which cut-off points were chosen.

Table 1: Spheres of Life

Sphere of Life	Description
A. Economy	Production, consumption, different types of income, income inequality, assets, ownership of land or other property, social- and network capital, access to social transfer systems, prices, labor supply/demand, resource flows, investments, trade
B. Demography	Population size, -density, birth/death rates, migration, ethnicity
C. Landscape design, land use and location (spatial variables)	Urban/rural space, agricultural/forest use, proportion of land used for recreation, traffic (roads), settlement, protected areas, areas for water retention, distance from urban centers, remoteness
D. Behavior and quality of life	Health, security, human rights, education, social connectedness, exclusion, social segregation/integration, crime, ethnic tensions, civil war; Aspirations, happiness, mutual support, alienation, gender equality.
E. Ecosystems, natural resources and climate	Precipitation, soil fertility, soil erosion, biodiversity, ecosystem intactness, goods and services
F. Infrastructure	Communication, transport (e.g. road, rail), market places, hospitals, schools, universities, power supply system, water supply system, sanitation
G. Public domain and institutions	Regulations, laws, contract, contract enforcement, conflict resolution mechanisms, formal and informal institutions

Source: Gatzweiler et al. (2011, p.8)

I. Economic dimension

Gross National Income (GNI) per capita (in current US$) is used to represent the **economic sphere**, rather than Gross Domestic Product (GDP) per capita which is more commonly used (Syrquin 2011). This approach follows the most recent Human Development Report (HDR) (UNDP 2010b) where GDP is replaced by GNI as a more representative indicator for standard of living. In contrast to GDP per capita – which only gives information on the monetary value of goods and services produced in a country, but excludes information on how much is retained within the country – GNI also includes international flows such as remittances and aid and thereby represents "a more accurate measure of a country´s economic welfare" (UNDP 2010b[8]). The World Bank[9] also uses GNI per capita as a key indicator for classifying economies into high-, middle- and low-income countries.

The World Bank divides GNI per capita into different income groups using the World Bank Atlas method[10]. The groups are: low income, $1,005 or less; lower middle income, $1,006 - $3,975; upper middle income, $3,976 - $12,275; and high income, $12,276 or more. For the purpose of the marginality mapping, the cut-off point for the economic dimension was set at **1,005$ per capita** or less which is the World Bank threshold for "low income" countries.

[8] See also: http://hdr.undp.org/en/statistics/hdi/
[9] http://data.worldbank.org/about/country-classifications
[10] The World Bank Atlas Method includes the use of an Atlas conversion factor which should reduce the impact of exchange rate fluctuations in the cross-country comparison of national incomes (http://econ.worldbank.org/WBSITE/EXTERNAL/DATASTATISTICS/0,,contentMDK:20452009~pagePK:64133150~piPK:64133175~theSitePK:239419,00.html).

II. *Demography and quality of life dimension*

Stunting, i.e. low height for a particular age (de Onis et al. 2011), represents the **demography and quality of life sphere**. Children are defined as stunted if their height is below the fifth percentile of the reference population in height for age (Lewit & Kerrebrock 1997). Stunting is also a measure for chronic undernutrition and thus a good overall indicator for health and hunger, as it reflects long-term cumulative effects of nutrition deficiency (Yohannes et al. 2010; Syrquin 2011).

The subnational dataset on "Prevalence of stunting among children under five by lowest available sub-national administrative unit, varying years" was produced by the FAO in 2007 within the Food Insecurity, Poverty and Environment (FGGD) project[11]. The data was compiled by the FAO from different sources such as Demographic and Health Surveys (DHS), the Multiple Indicator Cluster Survey of United Nations International Children´s Fund UNICEF MICS, World Health Organization (WHO), Global Database on Child Growth and Malnutrition as well as national surveys.

According to the FGGD dataset stunting is rated as 'very high' when the **prevalence of stunting among children under five is more than 50%**. We use this threshold for the quality of life and health dimension of marginality.

III. *Landscape design and infrastructure dimension*

An interesting approach developed by A. Nelson (2008), which measures accessibility via the **travel time to major cities**, is used to represent the **sphere of landscape design and infrastructure.** Accessibility is defined as "the travel time to a location of interest using land (road/off road) or water (navigable river, lake an ocean) based travel" (JRC, 2010[12]). To calculate the travel time, a friction surface has to be developed, including any geographic features which could be of interest for the analysis. The key indicators of this approach are sources of agglomeration economics and also include population size, population density and travel time as well as land-cover and elevation (Hirotsugu & Andrew Nelson 2010). An enumeration of all input variables is shown in Table 2.

The cut-off point for this dimension is set at the point where **more than 10 hours travelling is required to reach the next city with 50,000 or more people**. The number of 50,000 was chosen by P. J. Nelson (2007) based on the World Development Report 2009 which defines settlement with 50,000 inhabitants as 'large' (WorldBank 2008, p.54). We chose 10 hours travelling time – a relatively high value – as the cut-off-point since we assume that on the way to a 'large settlement' there might be smaller agglomerations that already satisfy a part of the demand that leads people to large cities.

IV. *Ecological dimension*

To represent the **ecological sphere** we use the dataset on "**Global land area with soil constraints**", which was developed within the FGGD[13] project. Especially the rural poor depend on natural resources and the land they live on. The chosen dataset includes information on soil depth, soil chemical status and natural fertility, drainage, texture and miscellaneous land, i.e. land, which is not suitable for agriculture such as salt flats, deserts or glaciers (van Velthuizen et al. 2007). The information is derived from various datasets, including several GIS layers on soil, elevation or land cover, climate databases, and remote sensing imageries to get e.g. data on slopes. The *digital soil information* dataset obtained by the FAO gives a broad set of information

[11] The Food Insecurity, Poverty and Environment Global GIS Database (FGGD) was also implemented by FAO (as FIVIMS) as an initiative to improve the use of disaggregated spatial information on different scales, global and national level (Huddleston et al. 2006)(see also: http://geonetwork3.fao.org/fggd/)

[12] Joint Research Centre: http://bioval.jrc.ec.europa.eu/products/gam/description.htm

[13] For more information: http://geonetwork3.fao.org/fggd/

on soils in the resolution of 5 minutes grid-cells. The *elevation* data, which can be used to get information on slopes, was taken from the GTOPO 30 dataset of the Earth Observation and Science (EROS) Data Center which represents a digital elevation model (DEM) and has a resolution of ca. 1km (30arc seconds). It was compiled by the use of different raster sources and remote sensing imagery[14].

Based on the classification developed by the FAO, we define marginalized soils as those falling in the categories **'frequent severe' and 'very frequent severe' soil constraints as well as soils 'unsuitable for agriculture'** (van Velthuizen et al. 2007).

V. The public domain dimension

For the **sphere of public domain** we take into account the Worldwide Governance Indicators (WGI) developed by the World Bank[15]. Kaufmann, Kraay, and Mastruzzi (2010) define governance as "*the traditions and institutions by which authority in a country is exercised. This includes (a) the process by which governments are selected, monitored and replaced; (b) the capacity of the government to effectively formulate and implement sound policies; and (c) the respect of citizens and the state for the institutions that govern economic and social interactions among them.*" (p. 4) Following this definition, the WGI are based on six indicators, with two measures of governance for each of the three areas:

(a) Voice and Accountability and Political Stability and Absence of Violence/Terrorism,
(b) Government Effectiveness, and Regulatory Quality and
(c) Rule of Law and Control of Corruption.

All indicators are based on subjective or perception-based measures of governance, gathered through surveys of households and firms as well as expert assessments produced by various organizations (Kaufmann et al. 2010).

The indicators cover data from 1996 to 2010 and include 212 countries (in 2010), compiled from several hundred individual variables which measure perceptions of governance according to 35 separate data sources conducted by 33 different organizations globally (Kaufmann et al. 2009).

We assessed the correlation between all six governance indicators and found that they are all highly correlated.

Among the six indicators, **political stability** was chosen to represent this sphere. Political stability is one of the indicators "measuring perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including political violence or terrorism" (Thomas 2009, p.5). Referring to Collier (2002), civil wars (political instability) in a country is one of the three main causes for a developing country being a developing country. Political stability or even more instability gives information about the ability of the government to lead its population. It is linked to economic growth, as it decreases growth, regarding per capita GDP especially in low income countries (Polachek & Sevastianova 2010, The Economist 2011). Political stability is also an important issue with regard to the socio-economic development of Africa as a result of the establishment of an institutional and legislative framework (Ong´ayo 2008). The cut-off point for this dimension was chosen by quantiles. For this approach we chose the 3-quantile.

As we are interested in the number of people that are affected by different marginality dimensions, we included **population data**, particularly data on the number of poor by Harvest Choice, which is using the population data base provided by SEDAC and CIESIN. The Gridded Population of the World and the Global Rural-Urban Mapping Project provide 2.5 arc-minutes resolution data on population densities based on a population layer compatible with datasets from social, economic, and earth science fields (Kaufmann et al. 2010).

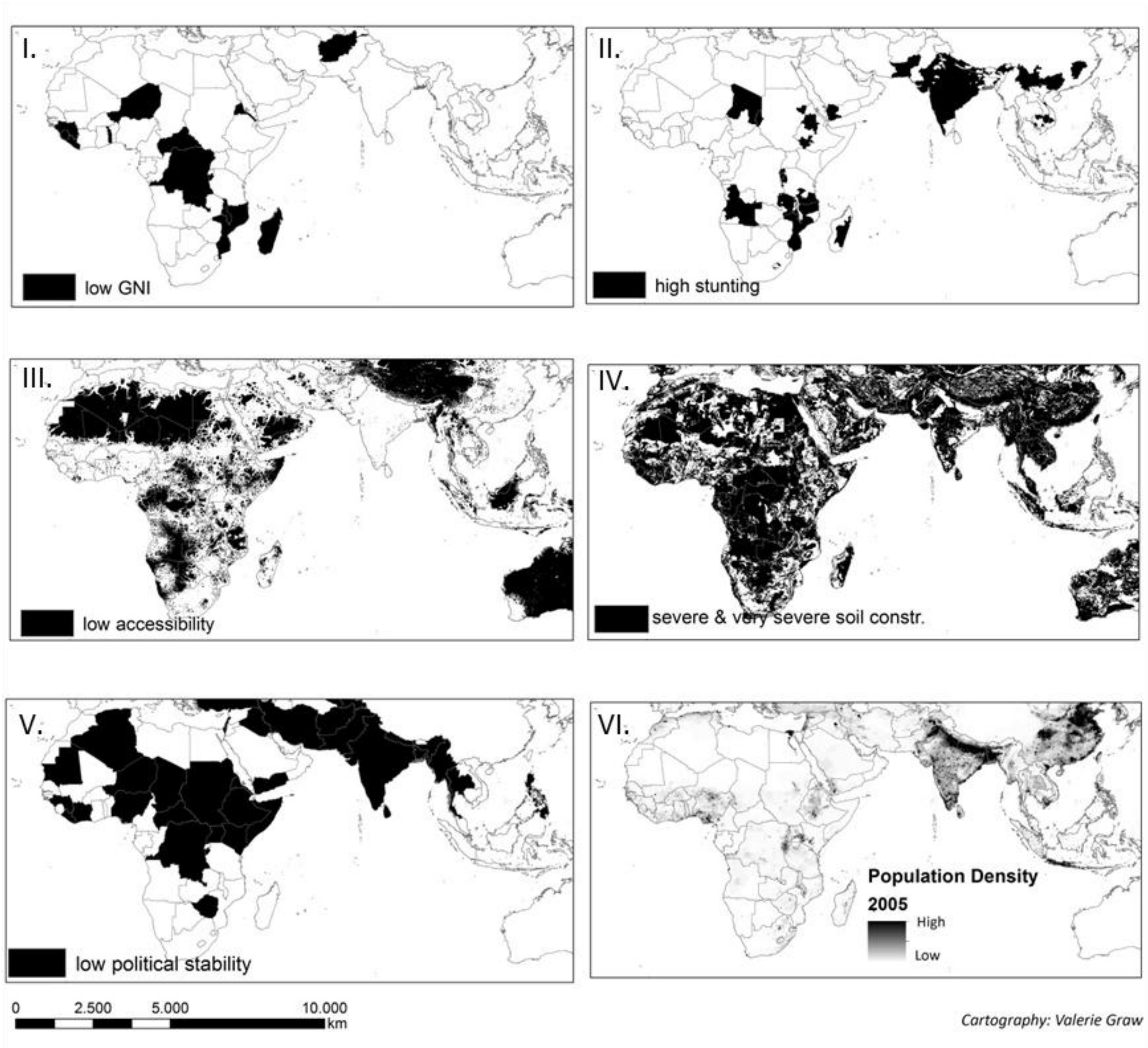
[14] For more information: http://eros.usgs.gov/#/Find_Data/Products_and_Data_Available/gtopo30_info
[15] See also: http://info.worldbank.org/governance/wgi/index.asp

Table 2: Identified Proxies for mapping Marginality Hotpots

	Dimension of marginality / Sphere of life	Indicator	Input	Cut-off point	Source
I	Economy (variables which define the economy or livelihood activities)	***Gross national income (GNI) per capita PPP (current US$)***	World Bank Data 2010, visualized and geo-processed in ArcGIS	1,005$ GNI per capita World Bank definition for "low income country" (<$1,005)	World Bank (compiled by data of the years 2008-2010).
II	Quality of life	***Prevalence of stunting among children under five,*** *by lowest available subnational administrative unit, varying years (FGGD)*	Global raster data layer with 5 arc-minutes resolution. Data compilation by FAO including the prevalence of stunting, LandScan global population database and the percentage of children under five.	Prevalence of stunting among children under five >50% FGGD definition for "very high" stunting prevalence	FAO, 2007 http://www.fao.org/geonetwork/srv/en/metadata.show?id=14055&currTab=simple The data is based on sources according to UNICEF. The map was created within the FGGD Digital Atlas
III	Landscape design and infrastructure	***Travel time to major cities****: A global map of accessibility*	Infrastructural data (based on data of: populated places, cities, road network, travel speeds, railway network, navigable rivers, major waterbodies, shipping lanes, borders, urban areas, elevation and slope)	More than 10 hours travelling to the next agglomeration with more than 50,000 people.	Nelson, A. 2000 http://bioval.jrc.ec.europa.eu/products/gam/sources.htm
IV	Ecosystems, natural resources and climate	***Global land area with soil constraints***	Depth, soil chemical status and natural, fertility, drainage, texture, miscellaneous land	Soils that are „frequent severe" and „very frequent severe" soil constraints as well as "unsuitable for agriculture" according to FAO 2007 (FGGD) definition	FGGD, IIASA 2000 GAEZ study (van Velthuizen et al. 2007)
V	Public domain and institutions (variables which define how the system is regulated, the inner order)	***Political stability*** *Governance indicator*	"measuring perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including political violence or terrorism" (Thomas 2009: 5).	Last 3-quantile	World Bank, 2009
	Demography (variables which define the actors/stakeholders)	*Gridded population of the world; population density of 2005*	30 arc-second land area grid showing urban areal extents worldwide, and a database of human settlements, their spatial coordinates , and population	--	CIESIN/SEDAC (http://sedac.ciesin.columbia.edu/gpw/) CIESIN et al. 2004

Figure 1 shows individual maps for the different marginality dimensions based on the spheres of life as well as for population densities using different spatial resolutions depending on the available data sets. As one can see, the economic and the governance indicator are on national level and provide thus less detailed information than the other indicators. It is important to bear that in mind when interpreting the marginality hotspot maps.

Figure 1: Overview of Single Marginality Dimensions (I.-V.) and Population Density (VI.)

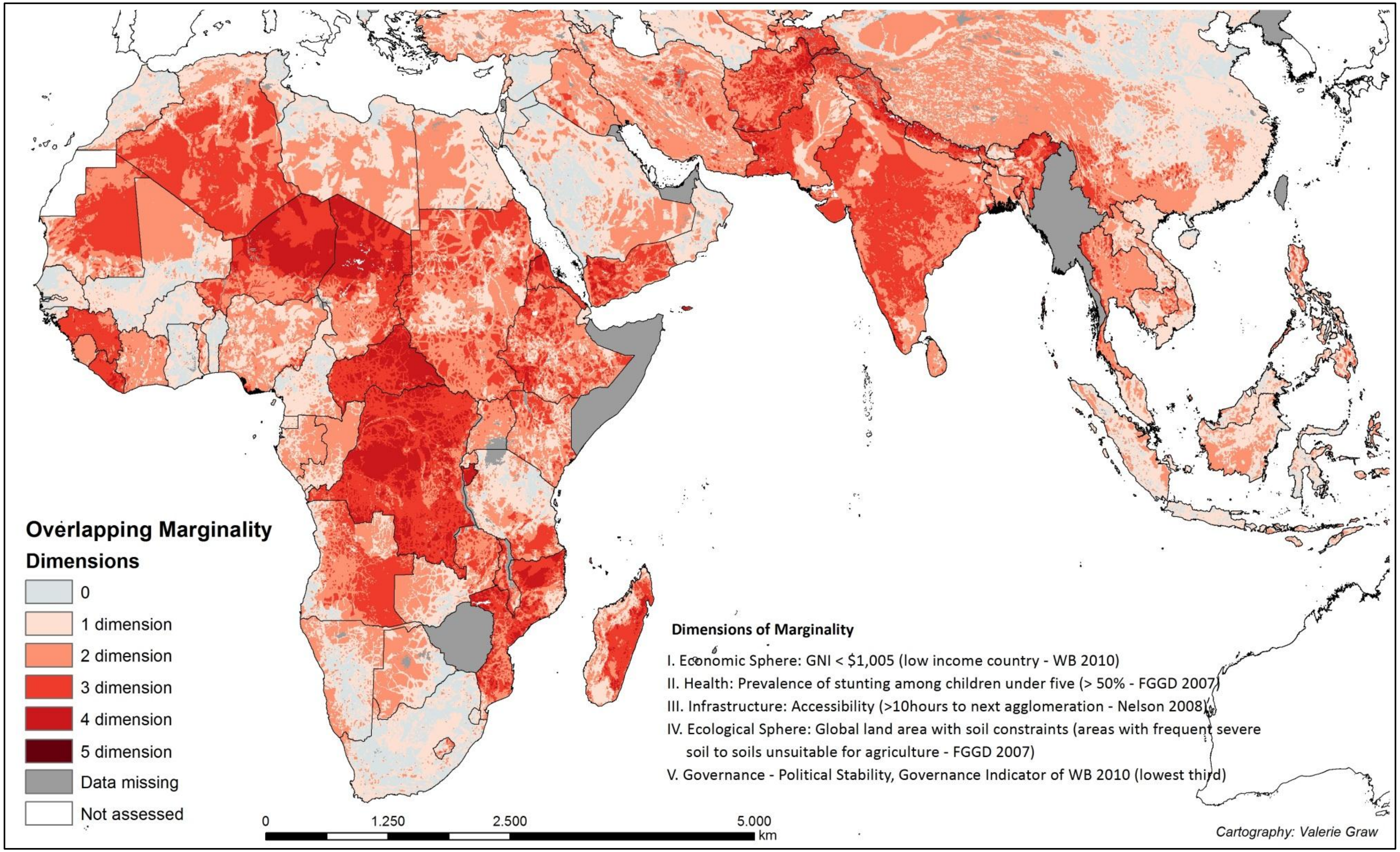


data sources: WB 2010, Nelson 2008, FAO 2007 and CIESIN et al. 2004

3.2 The Marginality Hotspots

Using classification techniques and geoprocessing in ArcGIS (the most commonly used GIS-Software by the Environmental Systems Research Institute (ESRI)), a marginality hotspot map was produced showing areas where several dimensions of marginality overlap (Map 1). The subset including Sub-Saharan Africa and South Asia was chosen as these two regions suffer most from poverty and hunger (Ahmed et al. 2007, von Braun et al. 2009).

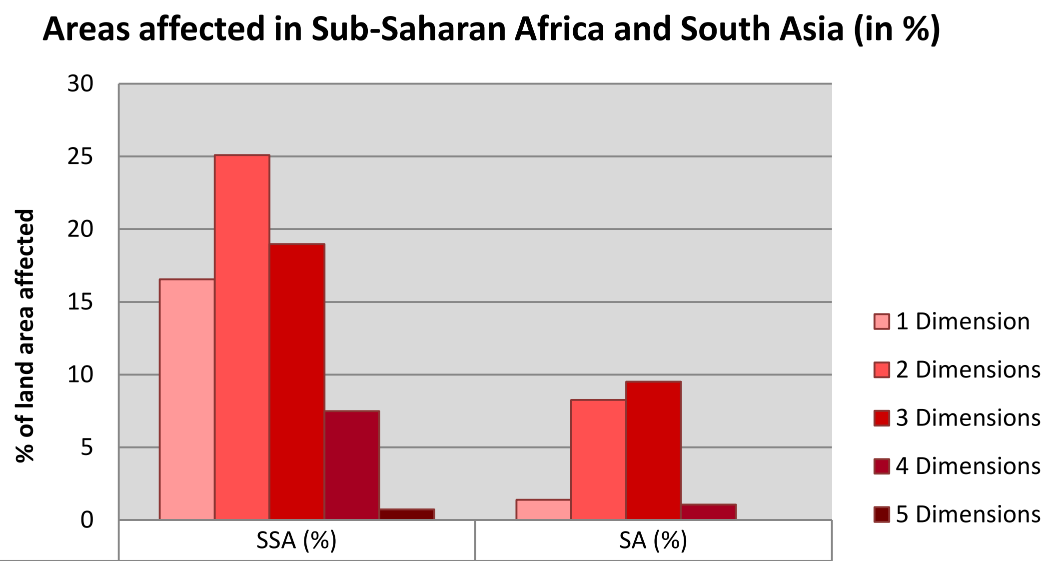
Map 1: Dimensions of marginality - where do negative values in different dimensions of marginality overlap?



In terms of marginality hotspots, we can identify heavily affected areas in South Asia (India and Nepal in particular) and SSA, especially Central and Eastern Africa, such as Eritrea, Mozambique, Central African Republic, the Democratic Republic of the Congo, Northern Sudan and large parts of Niger.

Comparing the two regions, in SSA the value of at least one dimension lies below the cut-off in nearly 70% of the total area compared to 20% for South Asia (Figure 2). Marginality hotspots, i.e. areas where the values of at least three overlapping dimensions are below the respective cut-off points, affect 27% of the area in SSA and 11% of South Asia. Moreover, in South Asia there is no area with five overlapping dimensions.

Figure 2: Comparison of marginality dimensions in Sub-Saharan Africa and South Asia (in %)



	SSA (%)	SA (%)
1 Dimension	16,56	1,38
2 Dimensions	25,09	8,26
3 Dimensions	18,98	9,51
4 Dimensions	7,48	1,05
5 Dimensions	0,73	0

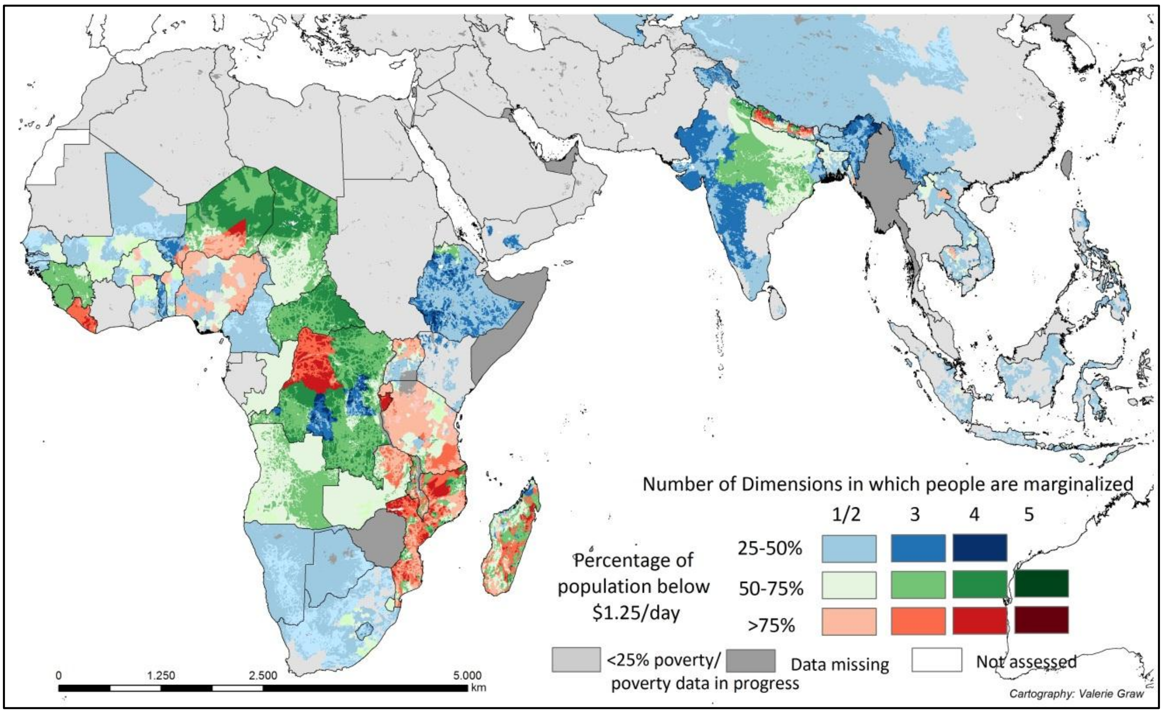
3.3 Poverty and Marginality Hotspots – where do they overlap?

After identifying the marginality hotspots based on the five dimensions of marginality, two additional maps were generated to assess how these dimensions overlap with poverty. To this end, marginality hotspots (i.e. areas which are marginal in at least three dimensions) were overlaid with subnational poverty data provided by Harvest Choice showing the proportion of the population and total number of people whose consumption level is below the poverty line (see also chapter 2.1). It is important to bear in mind that the poverty data set is still under development and data for some countries is missing, in particular outside Sub-Saharan Africa, thus making it difficult to draw final conclusions. Nevertheless, a number of areas can be identified that are marginal in several dimensions and are strongly affected by poverty.

Map 2 shows the overlay of the number of dimensions in which people are marginalized and the **percentage of the population living below $1.25 per day**. We can identify coherences of marginality and poverty in large areas of Sub-Saharan Africa as well as South Asia. Map 2 shows that areas where a high percentage of poor people coincide with marginality hotspots can be found in Central and South East Africa, especially the northern parts of Niger and in Chad, in the Central African Republic, in the Democratic Republic of the Congo (especially the western part of the country) as well as in Mozambique, Malawi and Burundi. In South Asia, marginality hotspots coincide with poverty rates particularly in Bangladesh and Nepal.

The case of Ethiopia highlights the difficulties of using national official poverty data: In Map 2, parts of the country appear in dark blue color, indicating marginality hotspots, but since official poverty rates for the country are astonishingly low (see Ahmed et al. 2007), there is no overlap of high poverty rates with marginality hotspots shown in the map.

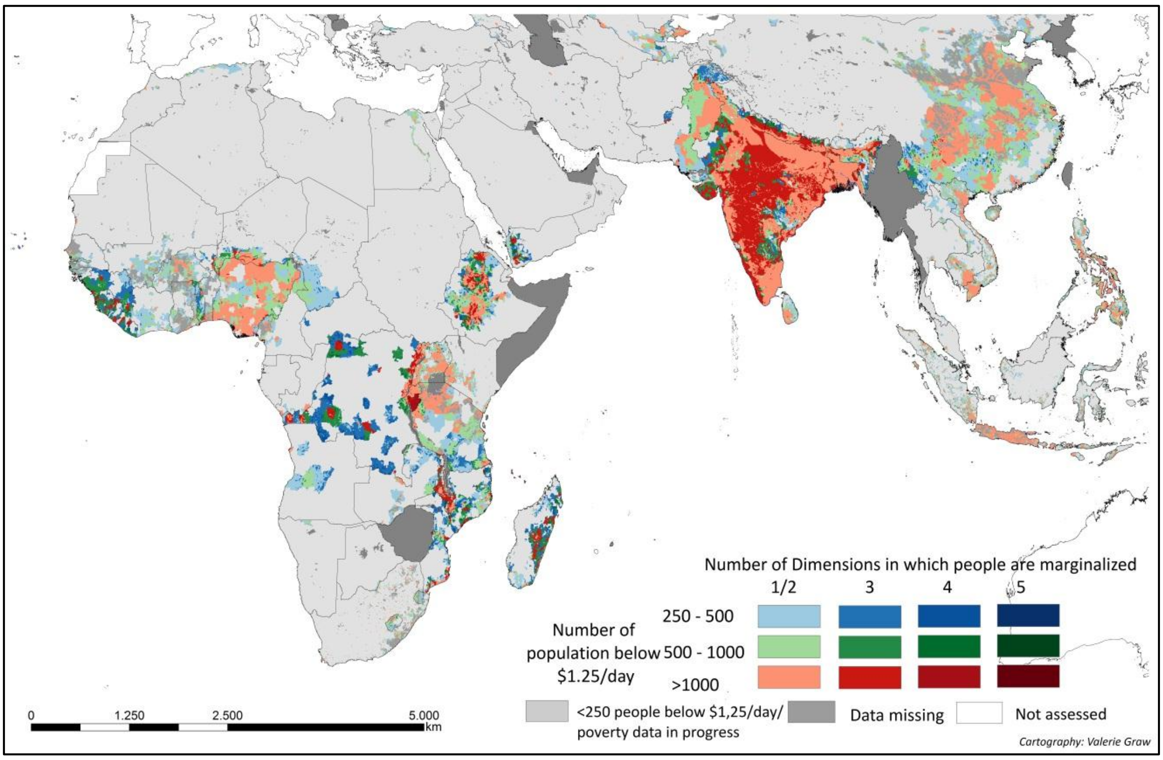
Map 2: Overlay: number of marginality dimensions with percentage of people living below 1,25$/day (Poverty data source: HarvestChoice, see also Wood et al. 2009)



A second map shows the overlay of marginality hotspots with the **number of people living below $1.25 per day** (Map 3). The map highlights that the largest number of marginalized poor can be reached in India and Bangladesh, as well as in Ethiopia, Southeastern Africa and some parts of Western Africa. While poverty rates in India are generally not as high as in other regions, high population numbers and densities mean that a large number of people are affected, particularly in central and western parts of India.

Comparing Maps 2 and 3 shows that Eastern Africa is always a hotspot of poor and marginalized people. In contrast, Africa's central regions no longer stand out as clearly on the map when the number of poor people (rather than poverty rates) is taken into account. Nevertheless, small spots in the Democratic Republic of the Congo, Ethiopia, Uganda, Burundi, Mozambique and Malawi as well as the coastal parts of several West African countries appear to be marginality hotspots where a large number of poor people live. Map 3 confirms that in Asia the sheer number of poor people is still extremely high while in Africa the percentage of poor and extreme poor people is particularly high.

Map 3: Overlay: number of marginality dimensions with number of people living on less than 1.25$ / day. (Poverty data source: HarvestChoice; see also Wood et al. 2009)



For a more detailed analysis, national and subnational maps are needed that can benefit from data on regional and local level. Moreover the pixel-scale (8km * 8km) needs to be lowered to the household level. Additional ground-truthing is an important aspect which should be a clear objective in local mapping approaches.

4. Limitations and Outlook

Marginality is a complex issue that often lies at the root of poverty. To reflect the different dimensions that influence marginality we undertook a mapping exercise that makes a first attempt at taking into account different spheres of life instead of focusing on subsets of social, economic or ecological aspects.

The most important limitation of this approach relates to the scale of the data. In the absence of comprehensive subnational data, we used GNI and political stability data at a national scale. In contrast, data on stunting were on sub-national scale and soil constraints on pixel-scale. These different scales make comparisons difficult. Therefore further work is needed to find representative datasets on local scales. Our mapping approach uses a pixel size of 8km by 8km, which is already a small scale for the purpose of global mapping. However, 64km² is still a relatively large area compared to the number of people living there and interpretations need to be made carefully.

We also acknowledge that the definition of the cut-off points below which an area is considered 'marginal' in a certain dimension can be difficult and often debatable. Further research is needed to assess how different cut-off points influence the hotspot map. One of these assumptions was the definition of 'far' using the accessibility dataset of Nelson (2008) which is based on infrastructure and a cost-distance model. The extreme poor mainly live in rural areas, particularly remote areas (Sachs 2005). Even available public transport might be unaffordable for them. Thus, while the distances in the map are the minimum time needed to get to the next agglomeration by the help of transportation, the time expenditure might be much higher for poor people as they have to first cover a distance on foot. For further research, the accessibility methodology could be applied on a more local scale to include walking distances to roads (e.g. 1hour per 5km).

The use of satellite imagery should also be explored further. The advantage of remote sensing is the low costs (except for very high resolution data) compared to other possible methods to identify marginal areas. It is much more time consuming to conduct a large survey than processing e.g. land use data out of several remote sensing imageries if available. Satellite imagery also provides pixel-level data instead of national or regional data which can generate misleading results.

It is a challenge to map coupled human-environment systems as represented also by the ecosystem sphere. Climate data, soils and potential for agricultural productivity have to be included equal to land use and suitability to obtain more precise information on environmental aspects. Finding a good indicator that represents complex ecosystems is therefore challenging. Several mapping approaches, especially those undertaken by the FAO, are working on this issue. Some difficulties already arise from a lack of data such as rainfall data in developing countries (Hughes 2006). Progress is being made to increase the amount of rainfall stations in remote areas to monitor rainfall variability, but in many cases these data are checked only rarely and therefore data is not always accurate. As a result, monitoring and assessment of ecological variables is increasingly based on remote sensing imagery which offers a good tool for monitoring changes on the land surface, whether human or natural. Nevertheless, this data, even if very high-resolution, must also be ground-truthed to validate results.

The limitations of mapping approaches are manifold and especially on the global scale the limits are reached fast if data is on a large scale. Also, lack of data in some areas makes comparisons between countries and regions more difficult. At the same time, it is important to bear in mind that the maps presented here are mainly meant to provide a general indication of particularly disadvantaged areas which should then be analyzed further through more detailed data analysis at smaller scales.

The next step will involve optimization of the indicators for identifying marginality hotspots on the global scale, while developing more reliable and representative approaches on the national scale. After hotspots are identified at the global level, further studies at national and subnational levels are necessary. Follow-up research will also include scenario modeling to understand causal interlinkages and identify possibilities for poverty and marginality alleviation.

References

Agostini, C. & Brown, P., 2007. Spatial inequality in Chile. *ILADES-Georgetown University Working Papers*.

Ahmed, A.U., Hill, R.V., Smith, .C., Wiesmann, D.M., Frankenberger, T., Gulati, K., Quabili, W. & Yohannes, Y.., 2007. *The world's most deprived: Characteristics and causes of extreme poverty and hunger*, Washington: IFPRI.

Alderman, H., Babita, M., Demombynes, G., Makhatha, N. & Özler, B., 2002. How low can you go? Combining census and survey data for mapping poverty in South Africa. *Journal of African Economies*, 11(2), 169.

Amarasinghe, U., Samad, M. & Anputhas, M., 2005. Spatial clustering of rural poverty and food insecurity in Sri Lanka. *Food Policy*, 30(5-6), 493-509.

Anzaldo, C. & Prado, M., 2005. *Índices de marginación* Consejo Nacional de Población, ed., Ciudad de México: CONAPO.

Baschieri, A. et al., 2005. Creating a Poverty Map for Azerbaijan. *SSRN eLibrary*. Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=874817 [Accessed October 4, 2011].

Benson, T., 2002. *Malawi: an atlas of social statistics* Malawi National Statistical Office & International Food Policy Research Institute, eds., Washington D.C.: International Food Policy Research Institute.

Bigman, D., Dercon, S., Guillaume, D. & Lambotte, M.., 2000. Community targeting for poverty reduction in Burkina Faso. *The World Bank Economic Review*, 14(1), 167-193.

Birkmann, 2006. *Measuring Vulnerability To Natural Hazards*, TERI Press.

von Braun, J., Vargas Hill, R. & Pandya-Lorch, R., 2009. The Poorest and Hungry: A Synthesis of Analyses and Actions. In *The Poorest and Hungry. Assessment, Analyses, and Actions*. IFPRI 2020. Washington: IFPRI, pp. 1-61.

Center for International Earth Science Information Network (CIESIN), Columbia University; International Food Policy Research Institute (IFPRI); The World Bank; and Centro Internacional de Agricultura Tropical (CIAT). 2004. Global Rural-Urban Mapping Project, Version 1 (GRUMPv1): Population Density Grid. Palisades, NY: Socioeconomic Data and Applications Center (SEDAC), Columbia University. Available at http://sedac.ciesin.columbia.edu/gpw [Accessed January 5, 2012]

Collier, P., 2002. On the Incidence of Civil War in Africa. *Journal of Conflict Resolution*, 46(1), 13 - 28.

Coulombe, H. & Otter, T., 2008. *Botswana Census-based Poverty Map: District level results* Botswana Central Statistics Office, ed., Gaborone: Botswana Central Statistics Office.

Davis, B., 2003. *Choosing a method for poverty mapping*, Rome: FAO. Available at: ftp://ftp.fao.org/docrep/fao/005/y4597e/y4597e00.pdf [Accessed January 5, 2012].

Deichmann, U., 1999. Geographic aspects of inequality and poverty. Available at: http://siteresources.worldbank.org/INTPGI/Resources/Pro-Poor-Growth/5319_povmap.pdf [Accessed January 5, 2012]

Elbers, C. & Lanjouw, J., 2004. Poverty and Inequality in Brazil: New Estimates from Combined PPV-PNAD Data. *Inequality and economic development in Brazil*, 81.

Elbers, C., Fujii, T., Lanjouw, P. Özler, B. & Yin, W., 2007. Poverty alleviation through geographic targeting: How much does disaggregation help? *Journal of Development Economics*, 83(1), 198-213.

Elvidge, C.D., Sutton, P.S., Baugh, K.E., Tuttle, B.T., Howard, A.T., Erwin, E.H., Bhaduri, B. & Bright, E.., 2009. A global poverty map derived from satellite data. *Computers & Geosciences*, 35, 1652-1660.

Fofack, H., 2000. Combining light monitoring surveys with integrated surveys to improve targeting for poverty reduction: The case of Ghana. *The World Bank Economic Review*, 14(1), 195-219.

Fujii, T., 2003. Commune-level estimation of poverty measures and its application in Cambodia. *Unpublished manuscript, Dept. of Agriculture and Resource Economics, UC Berkeley*.

Gatzweiler, F., Baumüller, H., Ladenburger, C. & von Braun, J., 2011. Marginality: Addressing the Root Causes of Extreme Poverty. Bonn: *ZEF Working Paper Series*, (77).

Gauci, A., 2005. Spatial maps. Targeting & mapping poverty. Available at: http://www.uneca.org/espd/publications/spatial_maps_targeting_mapping_poverty.pdf [Accessed January 5, 2012].

Haslett, S. & Jones, G., 2005. Local Estimation of Poverty in the Philippines. *Report prepared for the World Bank in cooperation with the National Statistics Coordination Board of the Philippines*. Available at: http://www.nscb.gov.ph/poverty/sae/NSCB_LocalPovertyPhilippines.pdf [Accessed January 5, 2012].

Healy, A., Hitsuchon, S. & Vajaragupta, Y., 2003. Spatially disaggregated estimates of poverty and inequality in Thailand. *Massachusetts Institute of Technology and Thailand Development Research Institute*.

Henninger, N., 1998. Mapping and Geographic Analysis of Human Welfare and Poverty - Review and Assessment.

Hentschel, J., Lanjouw, J.O., Lanjouw, P & Poggi, J., 2000. Combining census and survey data to trace the spatial dimensions of poverty: A case study of Ecuador. *The World Bank Economic Review*, 14(1), 147-165.

Hirotsugu, U. & Nelson, A., 2010. Agglomeration Index. Towards a New Measure of Urban Concentration. Available at: http://www.wider.unu.edu/stc/repec/pdfs/wp2010/wp2010-29.pdf [Accessed January 5, 2012].

Hirschowitz, R., Orkin, M. & Alberts, P., 2000. Key baseline statistics for poverty measurement. *Measuring Poverty in South Africa*, 53–81.

Hoogeveen, J., 2005. Measuring welfare for small but vulnerable groups: Poverty and disability in Uganda. *Journal of African Economies*, 14(4), 603.

Hughes, D., 2006. Comparison of satellite rainfall data with observations from gauging station networks. *Journal of Hydrology*, 327(3-4), 399-410.

Instituto nacional de estadística Guatemala, 2002. Mapas de pobreza de Guatemala 2002. *Secretaría Planificación y Programación, SEGEPLAN, Gobierno de Guatemala*.

Ivaschenko, O., 2004. Poverty and inequality mapping in Bulgaria. *World Bank.* Available at: http://siteresources. worldbank. org/INTPGI/Resources/342674-1092157888460/Ivaschenko. MappingBulgaria. pdf) [Accessed January 5, 2012].

Jones, G. & Haslett, S., 2004. *Local Estimation of Poverty and Malnutrition in Bangladesh* Bangladesh Bureau of Statistics & United Nations World Food Programme, eds., Dhaka: Government of Bangladesh & UN World Food Programme.

Kaufmann, D., Kraay, A. & Mastruzzi, M., 2009. Governance Matters VIII: Aggregate and Individual Governance Indicators, 1996-2008. *SSRN eLibrary*. Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1424591 [Accessed November 11, 2011].

Kaufmann, D., Kraay, A. & Mastruzzi, M., 2010. The Worldwide Governance Indicators: Methodology and Analytical Issues. *World Bank Policy Research Working Paper*, No. 5430.

Kijima, Y. & Lanjouw, P., 2003. Poverty in India During the 1990s: A Regional Perspective. *World Bank Policy Research Working Paper No. 3141*.

Kriz, K., 2010. *Mapping Different Geographies*, Berlin Heidelberg: Springer.

Lewit, E. & Kerrebrock, N., 1997. Population-Based Growth Stunting. *The Future of Children. Children and Poverty*, 7(2), 149-156.

López-Calva, L.F., Rodríguez-Chamussy, L. & Székely, M., 2007. Poverty Maps and Public Policy in Mexico. In T. Bedi, A. Coudouel, & K. Simler, eds. *More Than A Pretty Picture. Using Poverty Maps to Design Better Policies and Interventions*. Washington D.C.: WorldBank, pp. 188-207.

Minot, N. & Baulch, B., 2005. Spatial patterns of poverty in Vietnam and their implications for policy. *Food Policy*, 30(5-6), 461-475.

Mistiaen, J., Özler, B., Razafimanantena, T., Razafindravonoma, J., 2002. Putting welfare on the map in Madagascar. *The World Bank: African Region Working Paper Series*, 34.

Ndeng'e, G., Opiyo, C., Mistiaen, J. & Kristjanson, P., 2003. *Geographic Dimensions of Well-being in Kenya: Where are the Poor?: from Districts to Locations.* Kenya Central Bureau of Statistics, ed., Nairobi: Kenya. Ministry of Planning and National Development.

Nelson, A., 2008. Travel time to major cities: A global map of Accessibility. *European Commission*.

Nelson, P.J., 2007. Human Rights, the Millennium Development Goals, and the Future of Development Cooperation. *World Development*, 35(12), 2041-2055.

Ong´ayo, A.O., 2008. Political instability in Africa. Where the problem lies and alternative perspectives. Available at: http://www.diaspora-centre.org/DOCS/Political_Instabil.pdf [Accessed January 5, 2012].

de Onis, M., Blössner, M. & Borghi, E., 2011. Prevalence and trends of stunting among pre-school children, 1990–2020. *Public Health Nutrition*, (April).

Polachek, S.W. & Sevastianova, D., 2010. Does Conflict Disrupt Growth? Evidence of the Relationship Between Political Instability and National Economic Performance. *SSRN eLibrary*. Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1556550&http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1556550 [Accessed November 29, 2011].

República de Panamá Ministerio de Economía y Finanzas, 1999. *Mapa de Pobreza: Metodología para su Elaboracíon*, Panamá: República de Panamá Ministerio de Economía y Finanzas.

Reusing, M. & Becker, M., 2003. Practitioner's Guide: Mapping central and marginal areas. Available at: http://www.methodfinder.net/pdfmethods/lupo/lupo_method48.pdf [Accessed January 5, 2012].

Robinson, T., Emwanu, T. & Rogers, D., 2007. Environmental Approaches to Poverty Mapping: an example from Uganda. *Information Development*, 23(2-3), 205 -215.

Sachs, J., 2005. *The End of Poverty: How We Can Make it Happen in Our Lifetime*, Penguin.

Sen, A., 1999. *Development as freedom*, Oxford: Oxford University Press.

Sen, A., 1981. *Poverty and famines: an essay on entitlement and deprivation*, Oxford: Oxford University Press.

Simler, K. & Nhate, V., 2005. Poverty, inequality, and geographic targeting: Evidence from small-area estimates in Mozambique. *International Food Policy Research Institute, FCND Discussion Paper*, 192.

Skoufias, E., 2005. A poverty map for Guyana: Based on the 2002 population and housing census. Available at: http://www.statisticsguyana.gov.gy/pubs/Marginality_Index_brief_notes%28Region%29.pdf [Accessed January 5, 2012].

Storeygard, A., Balk, D., Levy, M. & Deane, G., 2008. The global distribution of infant mortality: a subnational spatial view. *Population, Space and Place*, 14(3), 209–229.

Syrquin, M., 2011. GDP as a Measure of Economic Welfare. *ICER Working Papers*.

The Economist 2011. Africa's hopeful economies: The sun shines bright. *The Economist*. Available at: http://www.economist.com/node/21541008 [Accessed December 6, 2011].

Thomas, M.A., 2009. What Do the Worldwide Governance Indicators Measure? *European Journal of Development Research*, 22(1), 31-54.

Thornton, P., Jones, P.G., Owiyo T., Kruska, R.L., Herrero, M., Kristijanson, P., Notenbaert, A., Bekele, N. & Omolo, A., 2006. *Mapping Climate Vulnerability and Poverty in Africa: Report to the Department for International Development*, ILRI (aka ILCA and ILRAD).

UNDP, Human Development Report 2010. The Real Wealth of Nations: Patways to Human Development. Human Development Index (HDI). Frequently Asked Questions (FAQs).

UNU-EHS, 2011. World Risk Report 2011. Available at: http://www.ehs.unu.edu/file/get/9018 [Accessed January 5, 2012].

Van der Weide, R., 2004. How poverty came on the map in Lao PDR. *World Bank mimeo*.

van Velthuizen, H., B. Huddleston, G. Fischer, M. Salvatore, E. Ataman, F.O. Nachtergaele, M. Zanetti & M. Bloise, 2007. *Mapping biophysical factors that influence agricultural production and rural vulnerability.*, Rome, Italy, FAO.

Wood, S. Z. Guo, J. Koo, G. Hyman, M. Herrero, R. Tenorio, O. Williams, U. Wood-Sichra & K. Sebastian, 2009. Geographic Domain Analysis. To Support the Targeting, Prioritization & Design of a CGIAR Mega-Project (MP) Portfolio. Available at: http://docs.google.com/viewer?a=v&pid=sites&srcid=Y2d4Y2hhbmdlLm9yZ3xhbGxpYW5jZXxneDoyZmJhZTVhNzBjY2Q3Y2Iw [Accessed January 5, 2012].

WorldBank, 2008. *World Development Report 2009: Reshaping Economic Geography*, Washington D.C.: World Bank.

WorldBank & Department of Census and Statistics, Sri Lanka, 2005. *A Poverty Map for Sri Lanka—Findings and Lessons*, WorldBank and Department of Statistics, Sri Lanka.

Yohannes, Y., Fritschel, H., Olofinbiyi, T., Nestorova, B., Menon, P., Ruel, M.T., von Grebmer, K., von Oppeln, C., Towey, O. & Golden, K.,, 2010. *2010 Global Hunger Index : The Challenge of Hunger : Focus on the Crisis of Child Undernutrition*, Washington D.C.: International Food Policy Research Institute.

Annex

This table focuses on the national poverty and marginality mapping aspect of each approach. Some of the listed publications also map other aspects. These aspects are not included in the table for the sake of shortness and focus on the issue of poverty.[16]

Table 3: Overview of national poverty and marginality mapping approaches

What is mapped	**Country**	**Method**	**Indicator(s)**	**Data input**	**Source**
Creating a Poverty Map for Azerbaijan	Azerbaijan	'imputed welfare' method [**small area estimation]** Mapping the asset index	Asset index and household consumption	2002 Household Budget Survey (HBS), 1999 Census data	Baschieri et al. (2005)
Local Estimation of Poverty and Malnutrition in Bangladesh	Bangladesh	**Small area estimation**	poverty & children malnutrition **Poverty** *Poverty*: per capita expenditure *Food poverty*: calorie intake <1805 kcal/day **Children malnutrition**: *stunting* (low height-for-age) children under five *underweight* (low weight-for-age) children under five	2001 population census, 2000 Household Income and Expenditure Survey, 2000 Child Nutrition Survey Update with: 2005 Household Income and Expenditure Survey, 2001 Population Census	Jones and Haslett (2004)
Botswana Census-based Poverty Map: District level results	Botswana	**Small area estimation**	household expenditure	2002/03 Household Income and Expenditure Survey (HIES), 2001 Population and Housing Census	Coulombe & Otter (2008)
Poverty and Inequality in Brazil: New Estimates from Combined PPV-PNAD Data	Brazil	**Small area estimation** (different models for each of the ten regions in the PPV)	household per-capita measure of consumption expenditure	1996/7 Pesquisa Nacional por Amostra de Domicílios household survey, 1996 Pesquisa sobre Padrões de Vida	C. Elbers and Lanjouw (2004)
Poverty and inequality mapping in Bulgaria	Bulgaria	**Small area estimation**	household per capita consumption	Population and Housing Census 2001 Bulgaria Integrated Household Survey 2001	Ivaschenko (2004)
Community targeting for poverty reduction in Burkina Faso	Burkina Faso	Econometric analysis **similar to small area estimation**: first a prediction model for household consumption is estimated, using the household data of the Priority Survey and the	Household consumption	• Priority Survey 1994, • census 1985, • data on health and water infrastructure, distances to provinces infrastructure, public administration, and social groupings (1995, Ministry of Water	Bigman et al. (2000)

[16] The table exclusively focuses on poverty mapping approaches. Hunger mapping approaches are not included. Other aspects covered in the listed publications such as inequality are also not included for the sake of shortness and precision.

		community data from all other sources using only variables for which there is data for all villages outside the Priority Survey sample. Second, the prediction model and the village-level data from the GIS database are used to predict welfare at the village level for villages outside the Priority Survey sample.		Management and Infrastructure), • data on primary school, infrastructure and teacher-pupil ratios (1995, Ministry of Education), data on various indicators ranging from average literacy rates to vegetation indexes (1993, Department Ministry of Agriculture), • data on temperature , evapotranspiration and rainfall (1961-95, Department Directorate of Meteorology), • data on cattle per household (1993, Province Ministry of Agriculture)	
Commune-Level Estimation of Poverty Measures and its Application in Cambodia	Cambodia	**Small area estimation**	Per capita household consumption	1997 and 1999 Cambodia Socio-Economic Survey (CSES), 1998 Cambodian national population census	Fujii (2003)
Spatial inequality in Chile	Chile	**Small area estimation**	total per capita income of the household	2003 National Survey of Socioeconomic Characterization, 2002 census	Agostini and Brown (2007)
Combining census and survey data to trace the spatial dimensions of poverty: A case study of Ecuador	Ecuador	**Small area estimation**	household consumption expenditure	Ecuador Encuesta sobre las Condiciones de Vida (ECV) 1994 and 1990 census	Hentschel et al. (2000)
Poverty alleviation through geographic targeting: How much does disaggregation help?	Ecuador, Madagascar, Cambodia	**Small area estimation**	household-level per-capita consumption	1994 Encuesta de Condiciones de Vida & 1990 census, 1993/4 Enquête Permanente Auprès des Ménages & 1993 census, 1997 Cambodia Socio-Economic Survey & 1998 census	Chris Elbers et al. (2007)
Mapping central and marginal areas	Ethiopia	Calculation of a cost-distance map	Central and marginal areas	Topographic map of Ethiopia 1:50000 (Ethiopian Mapping Authority 1984) Digital elevation model, land cover map, spatial dataset of selected infrastructure	Reusing and Becker (2003)
Combining Light Monitoring Surveys with Integrated	Ghana	Comparison and combination of household expenditure estimates based on Integrated	Household-level per capita expenditure	Ghana Living Standards Surveys 1991, Priority Survey	Fofack (2000)

Surveys to Improve Targeting for Poverty Reduction: The Case of Ghana		Surveys (Ghana Living Standards Survey) vs. light monitoring surveys (Priority Survey)			
A global poverty map derived from satellite data	Global (45° N – 45°S)	Combining different satellite data (on population count and nightlight), using nighttime light as proxy for wealth	poverty index: dividing the population by the average visible band digital number from the lights	satellite data on population count (LandScan 2004 data of the US Department of Energy), nighttime lights (US Air Force Defense Meteorological Satellite Program's Operational Linescan System)	Elvidge et al. (2009)
Mapas de Pobreza de Guatemala	Guatemala	**Small area estimation**	Poverty (household consumption) and inequality (Theil index)	2000 Encuesta Nacional de Condiciones de Vida, 2002 Censo Nacional de Población y Vivienda	Instituto nacional de estadística Guatemala (2002)
Poverty in India during the 1990s. A Regional Perspective	India	**Small area estimation**	Log per-capita household expenditure	1993/94 and 1999/00 National Sample Survey Organization household survey	Kijima and Lanjouw (2003)
Geographic Dimensions of Well-Being in Kenya: Where are the Poor? From Districts to Locations	Kenya	**Small area estimation**	per capita consumption and expenditure of a household	1997 Welfare Monitoring Survey (WMS III), 1999 Population and Housing Census	Ndeng'{}e, Opiyo, et al. (2003)
How poverty came on the map in Lao PDR	Lao PDR	**Small area estimation**	Household level consumption (for North, Center, South and rural/urban respectively)	1997/8 Lao Expenditure and Consumption Survey (LECS II), 2005 population survey	Van der Weide (2004)
Putting Welfare on the Map in Madagascar	Madagascar	**Small area estimation**	Per capital expenditure for every household (urban rural)	1993 household survey (Enquête Permanente auprès des Ménages - EPM), 1993 population census	Mistiaen et al. (2002)
Malawi. An atlas of social statistics	Malawi	**Small area estimation**	daily per capita consumption and expenditure of a household	1997-98 Integrated Household Survey (IHS), 1998 Malawi Population and Housing Census	Benson (2002)
Poverty Maps and Public Policy in Mexico	Mexico	**Small area estimation**, separate model for each strata of marginalization according to the marginalization index, which is calculated using **principal component analysis**	Household expenditure; Marginality index is composed of the coefficients of the first principal component of the variables: education, housing, income and size of the city or village a person is living in	2005Conteo de Población y Vivienda, 2005 Encuesta Nacional de Ocupación y Empleo	Ló{}pez-Calva, Rodrí{}guez-Chamussy, and Szé{}kely (2007)

Poverty, inequality, and geographic targeting: Evidence from small-area estimates in Mozambique	Mozambique	**Small area estimation** Overlay with road infrastructure	welfare (poverty) and inequality **welfare**: consumption per capita for every household, adjusted for spatial and temporal variation in prices **inequality**: generalized entropy (GE) indices [GE(0) and GE(1)]	1996–97 Mozambique National Household Survey of Living Conditions, 1997 National Population and Housing Census	K. R. Simler and Nhate (2005)
Mapa de Pobreza: Metodología para su Elaboracíon	Panama	**Small area estimation**	Consumption per capita for each household	1997 Encuesta de Niveles de Vida, 1990 Censos Nacionales de Población y Vivienda	República de Panamá Ministerio de Economía y Finanzas (1999)
Local Estimation of Poverty in the Philippines	Philippines	**Small area estimation** (separately for rural, urban and different regions)	log average per capita household income and log per capita household expenditure	2000Family Income and Expenditure Survey (FIES), 2000 Labour Force Survey (LFS), 2000 Census of Population and Housing	Haslett and Jones (2005)
How low can you go? Combining census and survey data for mapping poverty in South Africa	South Africa	**Small area estimation**	Household expenditure	1996 South African census, October Household Survey (OHS) and Income Expenditure Survey (IES) in 1995	Alderman et al. (2002)
Key baseline statistics for poverty measurement	South Africa	**Small area estimation** Factor analysis	monthly household expenditure quintiles Household Infrastructure index Household circumstances index	1995 October household survey, 1995 income and expenditure survey, 1996 population census	Hirschowitz, Orkin, and Alberts (2000)
Spatial clustering of rural poverty and food insecurity in Sri Lanka	Sri Lanka	**Principal component analysis** and synthetic small area estimation technique; clustering (Moran's I); regression analysis to assess drivers of poverty	poverty, with reference to a nutrition-based poverty line The poverty estimate, the proportion of households below the food poverty line, represents households that are both poor and food insecure. A household is poor if it spends more than 50% of its expenditure on food and its per adult equivalent food expenditure is below the food poverty line. Thus, the poverty estimate here is essentially an indicator of poverty and food insecurity in Sri Lanka.	2002 Household income and expenditure survey, *census not indicated in the paper*	Amarasinghe, Samad, and Anputhas (2005)
A Poverty Map for Sri Lanka—Findings and	Sri Lanka	**Small Area Estimation** (26 different models to capture	Household consumption; reference to the national poverty line	Household Income and Expenditure Survey (HIES) 2002	WorldBank and

Lessons		urban – rural and regional consumption differences) Correlation of poverty incidence with accessibility and droughts		Census of Population and Housing 2001	Department of Census and Statistics, Sri Lanka (2005)
Spatially Disaggregated Estimates of Poverty and Inequality in Thailand	Thailand	**Small area estimation** with village dummies	household income	2000 Socio-Economic Survey (SES), 2000 Census	Healy, Hitsuchon, and Vajaragupta (2003)
Measuring Welfare for Small but Vulnerable Groups: Poverty and Disability in Uganda	Uganda	**Small area estimation** (for small target populations)	per capita consumption for each household (with and without disabled household head respectively) in urban areas	1992 Integrated Household Survey, 1991 Population and Housing Census	Hoogeveen (2005)
Environmental Approaches to Poverty Mapping: an example from Uganda	Uganda	Regression analysis for poverty. Satellite data about natural habitats was temporally Fourier-processed to produce 10 separate data layers (the mean, the phases and amplitudes of the annual, bi-annual and tri-annual cycles of change, the maximum, minimum and the variance) with the aim of capturing seasonal processes	household level expenditure	2002/2003 second Uganda National Household Survey Satellite data on direct measures of key climatic variables (such as temperature), descriptor variables of key ingredients of poverty-generating processes (such as agricultural production systems) or proxies for constraints on the health and well-being of the human populations (such as disease-causing pathogens). Spatial data on digital elevation, human population density, access to markets, cattle, sheep, goat and pig densities, and the probability of presence of major tsetse species	Robinson, Emwanu, and Rogers (2007)
Spatial patterns of poverty in Vietnam and their implications for policy	Vietnam	**Small area estimation** (regressions for rural and urban areas separately)	real per capita consumption expenditure	1998 Vietnam Living Standards Surveys and the 1999 Population and Housing Census	Nicholas Minot and Baulch (2005)