Poverty, land, and climate in Africa south of the Sahara: an empirical analysis

Draft, March 15

Carlo Azzarri, Sara Signorelli, Melanie Bacou*

International Food Policy Research Institute (IFPRI)

Abstract

The spatial dimension of poverty is becoming increasingly important to support global development efforts. In particular, there is a growing need to identify the major areas of indigence and to understand their determinants, in order to properly address the roots causes of extremely poor welfare conditions. Existing studies looking and international poverty trends are limited to country level comparisons and, therefore, ignore sub-regional heterogeneity, crucial for understanding the spatial dimension of welfare. In fact, given the recent shifts in the nature of the poverty issue, from a matter of international differences in growth rates to a matter of intra-national welfare distributions, going beyond national boundaries is key.

This study seeks to expand the existing knowledge on the determinants of poverty by opening the black-box of country-level statistics to look at the subnational distribution of welfare, both at the household- and the district-level. Specifically, it examines how landholdings and climatic and environmental conditions can affect welfare distribution after controlling for household level characteristics, aiming to shed some lights on the likely role of climate change in affecting poverty and resilience in Sub-Saharan Africa.

* Corresponding author: c.azzarri@cgiar.org. Authors would like to thank Zhe Guo, Liangzhi You and Jawoo Koo for precious advice, suggestions and comments. Any errors remain our own responsibility.

Our study takes advantage of a unique and innovative household level dataset containing information from representative household surveys of 26 Sub-Saharan African countries representing more than a third of the entire African population and half of Sub-Saharan Africa. To our knowledge, it is the first time that a micro-level dataset with such coverage has been assembled and analyzed. In addition, geospatial biophysical variables capturing the agro-climatic conditions have been matched to the household-level surveys to provide a well-rounded dataset of multi-topic information on poverty correlates linked to environmental characteristics where household operates.

Sub-Saharan Africa subnational-level poverty maps are produced and compared with sub-regional maps of household's asset holdings in terms of human and physical capital, showing a lack of apparent common pattern among these characteristics. Our econometric analysis shows how long term climatic conditions and year-specific shocks play a significant role in explaining overall household and district level welfare. Particularly, vegetation cover seems to be an important indicator of sub-regional welfare, especially in the most populous countries such as Nigeria, Ethiopia, Kenya and Tanzania. Similarly, landholdings size is positively correlated with expenditure per capita, especially in rural areas. Finally, meaningful differences in the relations appear when only food expenditure is considered and when the regressions are weighted by population size, thus providing important insights for designing poverty alleviation policies in the region.

Key words: Mapping, Poverty, Resilience, Climate Change, Sub-Saharan Africa

1. Introduction

Whenever a specific poverty reduction intervention is under study, the first two questions that policy makers need to answer are how many people will be lifted out of poverty and where are these people located. Targeting analysis can answer the first question, while only with spatial targeting and mapping the second question can be adequately and satisfactorily addressed.

The existing literature discussing the spatial dimension of poverty in an international setting mainly focuses on national level poverty measures (Ferreira & Ravallion, 2008) and, in order to obtain national estimates related to comparable years, it combines National Account data with survey level information on distributions, with the associated problematic assumptions (Ferreira *et al.,* 2015; Edward & Sumner, 2014; Chen & Ravallion, 2010; Deaton 2005; Ravallion 2003). In addition, Sumner (2012) discusses how the recent shifts in global poverty – with a greater number of poor living in middle income countries - reveal a change in the nature of the poverty issue, from a matter of international differences in growth rates to a matter of intra-national welfare distributions. In this optic, it becomes even more crucial to go beyond the national level of analysis to see how welfare is spatially distributed across regions and districts within States boundaries. Sub-regional poverty analyses remain limited and mostly focus on only one country (Bellon *et al*., 2005; Benson *et al*, 2005; Kam *et al*., 2005; Amarasinghe, 1999) or at best they perform separate analyses for different countries and then compare the results (Hyman *et al*., 2005) - approach that is often dictated by the lack of comparability across household surveys. In addition, only few of them try to relate sub-regional welfare distributions with landscape level data from the satellite to capture the interdependence of poverty with the natural environment (Kam *et al*., 2005, McGuire *et al.* 2000; Rogers, 2000).

Household welfare within countries is very unequally distributed across space, and the poor tend to be concentrated in sub-regional clusters of indigence (Ayadi *et al*., 2009; Okwi *et al.*, 2007; Bellon *et al*., 2005; Minot & Baulch, 2002; Hentschel *et al*., 2000). Because of these big spatial heterogeneities, the analysis of poverty rates at the national or regional levels is often inadequate to account for the determinants of poverty, which strongly depend on local characteristics such as agro-climatic conditions and access to markets and often cut across administrative boundaries (Benson *et al*., 2005; Davis, 2003).

The majority of people living below the poverty line, especially in the case of Sub-Saharan Africa, are concentrated in remote rural areas and depend on subsistence farming for their survival (Davis *et al*., 2010; Narain *et al*., 2008), which makes them highly interdependent with the evolution of the natural resource base and of the climatic conditions (Bremner *et al.*, 2010; Gyawali *et al.*, 2004; Berry *et al.*, 2003; Dasgupta *et al.*, 2003). At the same time, the size of the landholdings and the tenure status are also known to play an important role in welfare determination (Nkonya *et al*., 2008; Hagos & Holden, 2006; Ali & Pernia, 2003; Besley & Burgess, 2000). These strong interlinkages between the rural farmers and the surrounding natural environment can result in a poverty-environment vicious cycle, in which landscape degradation negatively impacts rural livelihoods and the lack of investment capacity of the farmers contribute to accelerate the natural base deterioration (Bremner *et al*., 2010; Bhattacharya et al., 2006; MEA, 2005; Wood *et al.*, 2004; IPCC, 2000; Duraiappah, 1996; Perrings, 1989).

In addition, due to climate change expected in the upcoming decades, the vulnerability of poor in rural areas is likely to worsen (Benson et al., 2005). Not only they are caught in a poverty trap that prevent them from investing in productivity-enhancing technologies (Dzanku et al. 2015), but their condition is also at risk of further deterioration if the frequency and magnitude of climatic shocks had to increase (McGuigan *et al*.,2002). Dercon & Krishnan (2000) affirm that if negative weather-related shocks would become more frequent, rural poverty rates could increase dramatically. The claim is supported by the observation of high poverty mobility in rural areas: most of the households in these locations find themselves permanently close to the poverty line and thus swing above or below depending on the “good” or “bad” years, which are determined by a combination of individual specific occurrences and district level events. If the district level conditions had to permanently degrade, numerous households could permanently fall below the poverty threshold.

The expected climatic changes will both cause an increase in global inequalities between developing and developed countries (Rosenzweig & Perry, 1994), with Africa being the continent that will be the most negatively impacted (McGuigan *et al*.,2002), and in national inequalities between the rural and the urban inhabitants. Therefore, improving the understanding on the cross-countries determinants of rural poverty becomes even more crucial to tackle the challenges raised by climate change and to design policies able to increase resilience.

In order to analyze the complex mechanisms that determine welfare and to effectively design policies to improve the livelihoods of the least well-off while increasing their resilience, poverty mapping has been increasingly used in the last 10-15 years (Bellon *et al*., 2005; Kam *et al*., 2005; Kristjanson *et al*., 2005) and has attracted a lot of attention from the policy makers, which ascertained their usefulness (Bigman & Srinivasan, 2002; Bigman & Fofack, 2000). Maps allow to put in relationship landscape level characteristics such as agro-climatic zones, altitude, temperature and road density, with household level characteristics such as welfare, nutrition and food security, thus improving the understanding of how these dimensions are related to each other. Furthermore, the construction of a dataset combining information from household surveys with satellite data on agro-climatic conditions allows to explore the spatial linkages through multivariate regression analysis.

With the present study we aim to expand the existing evidence by answering two fundamental questions: 1) How is regional and sub-regional poverty distributed across Sub-Saharan Africa? 2) How are agro-climatic conditions and land ownership interrelated with household poverty? And how important are they in comparison to other household- and local-level characteristics?

We propose an innovative analysis based on internationally comparable sub-national poverty measures for a large set of Sub-Saharan African countries is proposed. We rely only on information from household surveys, therefore avoiding the issues of micro-macro data comparability described by Ravallion (2003). In addition, thanks to the application of national PPP conversion factors, our estimates are comparable cross-country. The constructed measures of welfare are first mapped across the sub-regions of the 26 Sub-Saharan African countries for which data are available, and compared with sub-regional maps of agro-climatic conditions. In a second step, these measures are used as outcome variables in a regression analysis that explores the spatial linkages more in depth.

In order to perform an econometric analysis of the co-determinants of poverty, we construct a unique household level dataset containing harmonized information from 21 countries[1] and representing the population of slightly more than one third of all Sub-Saharan Africa (about 400 hundreds millions people). To our knowledge, no study has already been done pulling together household level data for this large amount of countries. This extremely large coverage allows us to go beyond country specificity to draw some conclusions that are applicable to more than a third of the Africa population and half of the Sub-Saharan African region.

We show how long term climatic conditions and year-specific shocks play a significant role in explaining overall household and district level welfare. Particularly, vegetation cover seems to be an important indicator of sub-regional welfare, especially in the most populous countries such as Nigeria, Ethiopia, Kenya and Tanzania. Similarly, landholdings size is positively correlated with

[1] Five countries appearing in the maps had to be excluded from the econometric analysis because of lack of data for constructing the controls.

expenditure per capita, especially in rural areas. Finally, through some simple simulations we show that the expected climatic changes of the upcoming decades can have a detrimental impact on the poverty rates of the most populous countries of Sub-Saharan African countries. These results bear important policy implications and call for more supportive interventions to increase resilience.

The rest of the paper is structured as follows. Section 2 describes the data used and presents summary statistics for the main variables of interest. Section 3 discusses the methodology used to construct sub-regional poverty measures and the econometric strategy to analyze poverty correlates. Section 4 shows the main results, including the obtained poverty maps and the regression results. Finally, section 5 concludes.

2. Data

Our sub-regional poverty maps include 26 countries within Sub-Saharan Africa, and are based on harmonized data from representative household surveys. We selected the most recent available surveys that are nationally representative and contain reliable information about household consumption. We propose a systematic cross-country approach that yields comparable and consistent sub-national poverty rates based on poverty lines expressed in international equivalent at constant Purchasing Power Parity (PPP) dollars. This approach has the important advantage to allow for statistically reliable sub-national poverty comparisons across most of Sub-Saharan Africa, at the expense of the irregularity of data and absence of time series. A further discussion on the methodology used to construct these estimates is included in the next section. In addition, to perform the econometric analysis of the co-determinants of poverty, we construct a unique dataset combining a subset of 21 countries Sub-Regional poverty estimates with a set of control variables capturing the different capital endowments of the households (human and physical capital) and district level satellite information on year specific weather conditions (e.g. rainfall, temperature, PDSI), agrological environment (NDVI, agro-ecological zones) and market access (e.g. distance to main cities, night lights). Five countries - Angola, RDC, The Gambia, Swaziland and South Africa - are excluded from the regression analysis because of lack of sufficient data on household demographic characteristics and asset ownership to construct the necessary control variables.

Table 1 presents the details of the datasets used, the available number of units of sub-regional disaggregation and basic country statistics on welfare and inequality. Large disparities appear among the countries in the sample, with poverty rates ranging from 8% in Ghana to 87% in Gambia (using the \$1.90/day line in 2011 PPP[2]) and Gini index going from 33 in Niger and Burundi to 69 in Uganda. However, these figures mask large within countries heterogeneity that will become evident looking at the regional and sub-regional poverty maps.

Table 1. Basic information on the study surveys

Country	Dataset code and year	Admin. Level 1 Units	Admin. Level 2 Units	Total household observations	Poverty Headcount Ratio (\$1.90 PPP)	Poverty Headcount Ratio (\$3.10 PPP)	GINI Index
Angola	IBEP-2008	18	-	9002	29%	54%	43
Burundi	CWIQ-2006	17	142	7132	82%	94%	33
Burkina Faso	EBCVM-2003	13	-	8500	77%	90%	46
Cote d'Ivoire	ENV-2002	11	-	10800	30%	57%	48
Cameroon	ECAM3-2007	12	58	11391	34%	58%	43
DRC Congo	123-2012	26	-	21239	76%	90%	42
Ethiopia	ERSS-2011	10	69	3968	65%	84%	47
Ghana	GLSS6-2012	10	170	16772	8%	23%	42
Gambia	PS-1998	7	-	2019	87%	95%	49
Kenya	IHBS-2005	69	69	13212	39%	64%	48
Lesotho	HBS-2002	10	-	5992	62%	79%	52
Madagascar	EPM-2010	22	-	11781	83%	93%	41
Mali	HIS-2006	9	49	4494	59%	81%	39
Mozambique	IOF-2008	11	145	10832	69%	89%	41
Mauritania	EPCV-2000	13	49	5965	32%	59%	39
Malawi	HIS-2011	31	-	12277	69%	87%	44
Niger	ECVMA-2011	8	35	3859	63%	88%	33
Nigeria	GHS-2012	6	37	4536	55%	76%	43
Rwanda	EICV2-2005	12	30	6900	72%	86%	52
Senegal	ESPS-2011	14	45	5953	38%	66%	40
South Sudan	NBHS-2009	10	-	4969	45%	66%	46
Swaziland	HIES-1996	4	-	6308	80%	91%	49
Tanzania	NPS-2012	8	26	4883	42%	67%	42
Uganda	NPS-2012	6	105	2819	72%	88%	69
South Africa	IEF-2011	9	-	25328	14%	32%	65
Zambia	LCMS6-2010	9	72	19389	61%	77%	56

To perform the regression analysis, we further select the 21 datasets containing harmonized and consistent information on household characteristics, asset ownership and access to markets in order to construct the control variables. Angola, DRC, The Gambia, Swaziland and South Africa are excluded because of insufficient information in key dimensions. Since the surveys used come from different sources (mostly LSMS and national budget or consumption expenditure surveys), not all the variables of interest are available for all countries/surveys. Therefore, in order to take full advantage

[2] For international comparison purposes, extreme poverty is defined as living on a daily per capita expenditure of less than \$1.90 per day. The \$1.90 poverty line is the level of total household per capita consumption expenditure (a synthetic indicator of household welfare) expressed in terms of 2011 average purchasing power parity (PPP) exchange rates. The PPP relies on construction of an adjusted exchange rate for each country that equalizes the nominal exchange rate in terms of the local cost of a common basket of goods and services. In this exercise, monetary values in all countries in different years have been converted to international dollars at the 2011 PPP conversion rate.

of the data coverage, we will base our main estimation on the subset of variables common to all the datasets. Tables 2a and 2b report the averages of the main variables of interest for each country in the sample, and show which information is available for each survey.

Table 2a Summary statistics (average at the household-level)

Variable	BDI	BFA	CIV	CMR	ETH	GHA	KEN	LSO	MDG	MLI
Demographic Characteristics										
Household is rural	94%	82%	70%	65%	99%	50%	80%	76%	78%	68%
Head is single	18%	7%	16%	22%	12%	22%	19%	36%	17%	7%
Age of head	43.9	47.3	46.8	44.4	44.9	46.8	46	50.8	43.4	52.1
Education of head (years)	3.54	1.33	3.46	6.12	1.85	10.51	6.36	1.83	4.67	1.91
Head can read and write	43%	20%	43%	65%	45%	54%	67%	77%	75%	25%
Mean household education (years)	3.7	1.4	3	6.1	2.2	9.1	6.6	2.2	4.6	1.8
Household size	6.2	9	8.1	6.5	6.1	5.8	6.2	6.1	6	12.4
Number of males	2.6	4.3	4	3.1	3.1	2.8	3.2	3	3	6.1
Number of females	2.7	4.6	4.1	3.4	3	3	3.4	3.1	3	6.3
Number of children	1.2	1.8	1.4	-	0.2	1	1.2	0.8	1.2	2.6
Agricultural assets and input use										
Size of land owned (sqm)	91475	280133	53862	12118	16969	35926	4916	13147	13066	46825
Number of big livestock owned	0.3	3.8	0.4	1.2	4.3	0.5	7.8	2.6	3.9	5.4
Number of small livestock owned	2.4	7.8	4.3	5.3	1.4	9.9	14.3	8.6	15	6.2
Tractor ownership	-	-	-	-	-	-	-	4%	-	-
Use of improved sees	-	-	-	17%	21%	-	81%	-	-	-
Use of organic fertilizer	-	-	-	-	22%	-	44%	1%	-	-
Use of inorganic fertilizer	-	-	19%	28%	82%	-	57%	2%	-	-
Housing characteristics										
House ownership	95%	91%	69%	69%	96%	65%	78%	-	81%	78%
Availability of electricity	4%	9%	38%	47%	7%	34%	14%	8%	12%	1%
Availability of running water	-	5%	23%	37%	9%	28%	29%	59%	25%	33%
Availability of good quality toilet	-	2%	52%	7%	3%	43%	48%	53%	5%	8%
Floor is made of concrete	-	-	73%	45%	2%	82%	34%	-	-	21%
Fridge ownership	1%	4%	11%	9%	1%	35%	4%	13%	4%	-
Television ownership	3%	10%	27%	33%	3%	56%	19%	16%	11%	90%
Bicycle ownership	12%	86%	37%	15%	2%	27%	31%	3%	-	-
Car ownership	1%	3%	4%	3%	1%	6%	2%	-	1%	-
Telephone ownership	5%	5%	-	54%	28%	89%	0%	14%	4%	-
Distance to main services										
Distance to water source (min)	22.2	1.3	-	18.6	-	13.5	12.6	12.5	-	6.5
Distance to food market (min)	63.2	2.6	-	21.3	-	-	-	-	-	39.8
Distance to public transports (min)	76.7	3.1	-	28	-	-	-	26.6	-	33.3
Distance to hospital (min)	115.8	3.3	-	34.4	-	42.5	-	50.5	-	43.4
Distance to primary school (min)	29.9	2.4	-	14.5	-	-	-	33.3	-	16.1

Table 2b Summary statistics (average at the household-level)

Variables	MOZ	MRT	MWI	NER	NGA	RWA	SEN	SSN	TZA	UGA	ZMB
Demographic Characteristics											
Household is rural	70%	60%	85%	83%	63%	83%	57%	84%	74%	82%	61%
Head is single	18%	0%	19%	7%	11%	27%	14%	7%	22%	21%	21%
Age of head	42.6	49.9	42.5	46.7	51.3	45.1	54.2	43.6	47	43.9	43.4
Education of head (years)	3.47	1.49	5.55	10.98	-	3.46	2.42	4.45	5.51	5.33	7.76
Head can read and write	56%	38%	67%	93%	68%	92%	49%	27%	76%	70%	-
Mean household education (years)	3.3	2.4	5.4	10.2	-	3.7	3.3	2.7	5.6	5.6	6.3
Household size	6	8.8	5.6	8.5	7.6	6.1	12.6	8	6.6	6.7	6.6
Number of males	2.8	4.3	2.8	4.2	3.8	2.9	6	3.9	3.2	3.2	3.2
Number of females	3.1	4.5	2.9	4.3	3.8	3.2	6.7	4	3.4	3.4	3.3
Number of children	1.4	1.5	1.1	2.2	1.2	1.2	2.6	1.7	1.3	1.4	0.3
Agricultural assets and input use											
Size of land owned (sqm)	18285	700127	5535	43554	7765	252166	54097	3953750	15258	12446	97402
Number of big livestock owned	0.8	15.4	0.3	0.9	2.1	0.9	3	-	2.8	2	1.2
Number of small livestock owned	9.1	27.1	3.7	7.7	13.4	4.3	10.2	16.2	9.5	9.4	11.5
Tractor ownership	-	-	0%	0%	1%	-	3%	-	4%	0%	0%
Use of improved sees	-	-	-	3%	-	-	-	-	42%	26%	-
Use of organic fertilizer	-	-	33%	76%	1%	8%	-	-	4%	15%	6%
Use of inorganic fertilizer	-	-	50%	18%	28%	13%	-	-	4%	5%	23%
Housing characteristics											
House ownership	95%	80%	84%	91%	73%	94%	85%	93%	81%	83%	74%
Availability of electricity	15%	18%	7%	10%	57%	5%	52%	3%	16%	191%	23%
Availability of running water	14%	13%	19%	2%	13%	3%	69%	4%	25%	4%	31%
Availability of good quality toilet	11%	39%	7%	1%	45%	1%	57%	1%	25%	5%	34%
Floor is made of concrete	23%	-	25%	12%	68%	15%	50%	-	36%	31%	46%
Fridge ownership	9%	20%	4%	4%	22%	2%	55%	1%	8%	-	18%
Television ownership	15%	49%	10%	9%	47%	3%	12%	5%	17%	12%	33%
Bicycle ownership	42%	-	44%	7%	21%	15%	4%	27%	46%	44%	41%
Car ownership	2%	11%	2%	2%	11%	1%	0%	2%	3%	3%	4%
Telephone ownership	27%	2%	1%	0%	72%	8%	16%	19%	72%	67%	53%
Distance to main services											
Distance to water source (min)	10.2		12.3	99.9	14.6	19.3	3.9	24.8	-	22.7	-
Distance to food market (min)	22.8		-	77.5	38.6	58.6	23	-	-	33.7	29.1
Distance to public transports (min)	23.4		-	84.6	48.1	72.2	14.6	-	-	-	19.8
Distance to hospital (min)	34.8		-	88.4	46.2	195.4	13.9	49.2	-	40.3	33.8
Distance to primary school (min)	21		-	40.1	27.9	24.8	10.1	-	-	21.9	17.4

Finally, biophysical spatial data (mostly at the administrative level 2) are matched to the households in all surveys considered to look at the effect of climate on poverty for a panel of households in 21 Sub-Saharan African countries. These variables capture agro-climatic conditions such as elevation, temperature, rainfall, length of growing period (LGP) and greenness of the ground (NDVI), as well as information on distance to markets (defined as hubs of 50K people or more) and overall level of infrastructure development (captures by night lights intensity). Table 3 includes the summary statistics of these variables, which present once again large cross-country variation.

Table 3: Summary statistics of spatial variables

	Elevation (m)	LGP (days)	Mean Temp. (°C)	Temp. Seasonality	Mean Rain (mm)	Rainfall Seasonality	NDVI (index)	Dist 50k Market (h)	Night light radiation
Burundi	1260	267	19.8	49.2	1185.1	62.2	0.6	1	3.1
Burkina Faso	1402	139	28	218.4	777.7	114.2	0.33	2.4	1.2
Cote d'Ivoire	1222	279	26.3	109.1	1380.9	64	0.62	2.9	0.8
Cameroon	740	261	24	111.8	1932.6	77.1	0.59	2.5	5.3
Ethiopia	1516	183	20.7	125.5	1005.9	82.9	0.46	4.7	0.3
Ghana	175	251	26.7	124.2	1229.6	68.3	0.54	1.7	9.2
Kenya	1201	233	20.5	90.3	1103.8	64.3	0.54	2.8	3.2
Lesotho	1141	179	12	419.3	768.4	59.9	0.39	4.8	0.7
Madagascar	267	278	22.2	217.2	1480	92.6	0.53	5.2	0.1
Mali	322	111	27.6	278.7	695.9	126.8	0.31	4	4.6
Mozambique	250	197	23.7	233.5	1005.7	84.9	0.56	3.3	9.1
Mauritania	392	33	27.6	348.7	172.4	136.9	0.17	7.8	0.2
Malawi	490	186	21.5	235.2	1087.1	103.1	0.52	2.5	2.8
Niger	331	72	28.3	328.4	361.9	146	0.19	3.8	8.2
Nigeria	278	206	26.5	164.2	1434.6	90	0.49	2.1	3.4
Rwanda	1736	302	18.9	29.7	1165.7	50.5	0.58	1.2	2.2
Senegal	39	112	27	200.2	666.4	142	0.34	1.4	5
South Sudan	1331	195	26.8	130.3	963.8	84.7	0.51	5.2	0
Tanzania	795	220	23.6	126.1	1082.1	82.3	0.53	4.1	3.1
Uganda	1144	301	22	69.2	1229.6	43.2	0.64	2	4.2
Zambia	1614	171	21	256.3	1028.6	111	0.53	4.5	5.1

Note: Elevation is measured in meters above sea level, Length of growing period is measured in average days per year, temperature and rainfall are computed as a long term yearly averages and the seasonality accounts for the yearly standard deviation. NDVI is a measure of greenness of the ground and night light measure the light radiation during the night.

3. Methodology

a. Estimating sub-national poverty levels

Our poverty calculations are based on the comparison between the household per-capita consumption expenditure (a synthetic indicator expressing the money-metric welfare utility level) and the $1.90 and $3.10/day poverty lines expressed in international equivalent purchasing power parity (PPP) dollars in 2011. It is crucial to stress that poverty distribution will not be referred to 2011, but they will be referred to the survey year, although they would represent poverty headcount measured at an international comparative level, i.e. expressed in value of the same reference year, 2011. In this regard, cross-country poverty comparison will be viewed as comparisons for a given constant purchasing power of the local currency respect to the international benchmark, rather than for a given point in time. The PPP factor has a significant impact on the poverty measures obtained, and the recent release of the 2011 PPP numbers by the World Bank ICP program[3] significantly changed the relative poverty among countries with respect to the estimates based on the 2005 PPP, although the overall trend of global poverty is confirmed. (see Ferreira et al., 2015 and Jolliffe & Prydz, 2015 for a discussion on the importance of the PPP factor). Despite the PPP recent revisions and the general improvement in data availability for African countries, "tracking poverty in Africa is difficult because the data are deficient on these three domains: availability, comparability, and quality" (Beegle et al., 2015).

Our poverty estimations are based uniquely on household survey information and thus avoid the issues arising with methods that combine income per capita and growth from national accounts and distributions from micro-data (Chen & Ravallion, 2010; Deaton 2005; Ravallion 2003). In addition, this technique allows us to compute consistent values of subnational poverty using the survey expansion factors, which guarantee the validity of the estimates also at the sub-national level, and to make them comparable across countries using the national PPP adjustments. We do this by finding the underlying expenditure distribution used to construct poverty measures and by directly applying the international poverty lines to it, in order to obtain the regional and sub-regional estimations. The obvious trade-off that we face is that we have to limit our analysis to the survey years in which the household level data is available, therefore losing the possibility to look at poverty evolutions across time. The results obtained are further validated by comparing the national statistics with the World Bank PovcalNet data[4].

b. Econometric strategy

Our empirical analysis aims at modeling household total, food and non-food per-capita consumption expenditure, as well as the probability of falling into poverty. The objective is to estimate the relationship and effect of biophysical variables on household welfare, controlling for other confounding factors, both at the household and at the spatial level. The dimensions of welfare considered are five: human capital, physical capital, natural capital, social capital, and financial capital (Kristjanson *et al.,* 2005). For all the 5 domains, relevant representative variables have been included either from the household survey or from the satellite information, in order to mitigate omitted variable bias typical of the pooled cross-country regressions. The regressions will be

[3] http://siteresources.worldbank.org/ICPEXT/Resources/ICP_2011.html
[4] http://iresearch.worldbank.org/PovcalNet/index.htm

performed both at the household and at the district level to be able to compare household versus sub-national poverty correlates.

The basic GLS model estimated to analyze welfare is the following:

$$(1) \quad Y_i = \beta_i + \beta_1 \boldsymbol{H}_i + \beta_2 \boldsymbol{A}_i + \beta_4 \boldsymbol{W}_i + \beta_5 \boldsymbol{B}_i + \boldsymbol{\delta}_i + \boldsymbol{\gamma}_i + \boldsymbol{\rho}_i + \varepsilon_i$$

where $\boldsymbol{Y}$ is the logarithm of per-capita total and food consumption expenditure, $\boldsymbol{H}$ is a vector of household characteristics, including the education and age of the household head, whether the head is female and the number of males, females and children in the household. The inclusion of composition variables should help control for household preferences. $\boldsymbol{A}$ is a vector of agricultural assets, which in our main regressions is composed by the size of land owned. $\boldsymbol{W}$ measures non-agricultural assets and dwelling conditions, including availability of electricity and ownership of durable assets including television, and radio. Finally, $\boldsymbol{B}$ is a vector of biophysical and other spatial variables including slope and elevation, temperature and drought index[5] relative to the year of the survey to capture the effect of weather shocks[6], and long terms averages of temperature, rainfall and vegetation index (NDVI) to capture the effect of long-term climatic conditions, nightlight radiation to capture the level of development and urbanization of the district and total livestock units (TLU) and hectares of irrigated land at the district level to capture overall agricultural characteristics. Finally, we also include the percentage of the surface covered by trees and characterized by low soil nutrient content in order to account for the effect of land quality. $\boldsymbol{\delta_i}$, $\boldsymbol{\gamma_i}$, and $\boldsymbol{\rho_i}$ are vectors of fixed effects for country, year and month of the survey for household *i*, β_2 and β_5 are our main parameters of interest and and ε_i is the error term assumed idiosyncratic. The same model is also estimated using quantile regressions in order to investigate the differential effects in different ranges of the welfare distribution.

In a similar fashion, a model of the likelihood of poverty is estimated through the following probit model:

$$(2) \quad P(Y_i < Pline) = \beta_i + \beta_1 \boldsymbol{H}_i + \beta_2 \boldsymbol{A}_i + \beta_4 \boldsymbol{W}_i + \beta_5 \boldsymbol{B}_i + \boldsymbol{\delta}_i + \boldsymbol{\gamma}_i + \boldsymbol{\rho}_i + \varepsilon_i$$

where the same regressors included in equation 1 are used to predict the probability of the household to fall below the poverty line. The results are used to compute predicted poverty rates of the model

[5] The Palmer Drought Index is based on a supply-and-demand model of soil moisture approximated using an algorithm with temperature and rainfall as inputs. The index has proven most effective in determining long-term drought (several months) rather than short lived events, thus it is especially useful to compare the dryness level across years. The original index measures the level of moisture in the soil, thus we take its inverse to construct a drought index increasing in the level of dryness.

[6] We include quadratic terms for both year-specific temperature and drought index in order to account for non-linearity in the effect.

as well as to perform partial equilibrium simulations of the effect of changes in long term climatic conditions.

Finally, we estimate Equation 1 using district level averages. In the estimates at the district level, the dependent variables are the logarithm of average per-capita total and food expenditure in the district, modeled using GLS.

A careful weighing strategy is crucial in our pooled regressions because unweighted parameter estimates are mostly driven by the survey with relatively higher sample size, therefore shifting the relative importance of each country population. The comparison between weighted and unweighted parameters can provide a useful indication as to the effect of the inclusion of countries with high population in shaping the relationship between dependent and independent variables. If weighting scheme is not taken into account, the relationship is strongly dependent on the relative size of the various surveys, while when weighting is applied the interest is in the relationship to be representative of the households in the countries under analysis (hence, household characteristics in countries with higher population –Nigeria, Ethiopia, Tanzania-have a higher effect on the parameter estimates).

4. Results

a. Poverty Mapping

The maps in figure 1.a and 1.b shows the percentage of population for which household per-capita consumption expenditure (a synthetic indicator expressing the money-metric welfare utility level) is lower than the $1.90 and $3.10 per day poverty line expressed in international equivalent purchasing power parity (PPP) dollars in 2011. From the map it is possible to realize how prevalence differs greatly across and within countries in Sub-Saharan Africa, with some hotspots in Burkina Faso, Southern Mali and Nigeria, in the West; most regions in the DRC Rwanda and Uganda in the Center, some areas of Zambia and Tanzania in the East and virtually the whole island of Madagascar. As such, high poverty prevalence is not concentrated in particular regions, but scattered across the continent.

The spatial comparison of poverty with asset holdings, education, age of the head (Figure 2.a, Figure 2.b), land and livestock (Figure 3.a, Figure 3.b) derived from household surveys could shed light on the possible correlates of poverty, providing some hypotheses empirically testable in a multivariable regression framework. It is apparent that household heads in West Africa tend to be older and on average less educated that the average in the rest of the continent, with the exception of South Africa, where heads seem to be on average older, and Ethiopia, with very low level of education.

If we compare the maps of assets with those of poverty we see that the relation between education and poverty is not that straightforward, at least at the regional level. East and Southern Africa have very high levels of poverty rates despite their higher human capital (proxied by the number of years of education). Observing clear patterns between the distribution of poverty and the distribution of livestock and land holdings is even more difficult. As expected, livestock is highly concentrated in Ethiopia and Northern Kenya while land holdings are bigger in West Africa, with the addition of Zambia.

Figure 1.a : Poverty Rates (1.90$/day)

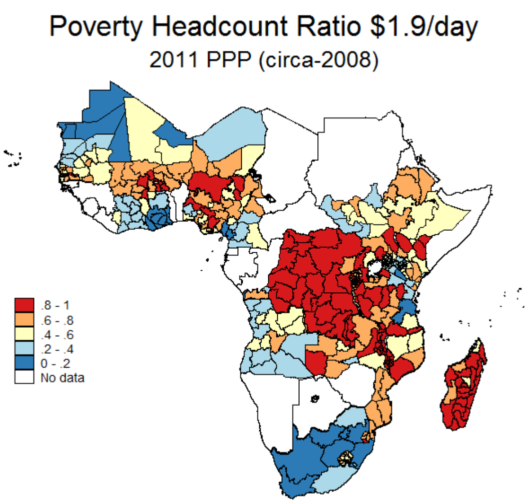


Figure 1.b : Poverty Rates (3.10$/day)

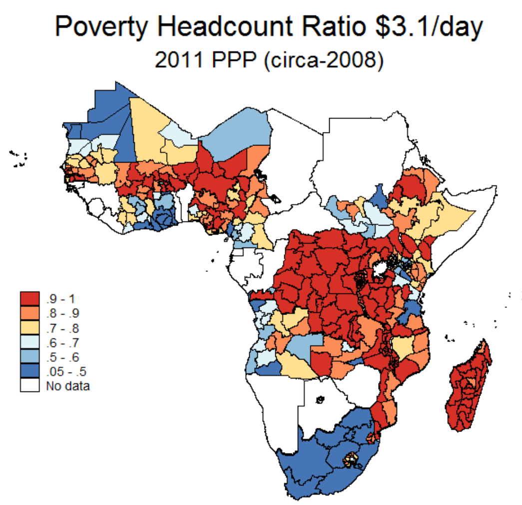
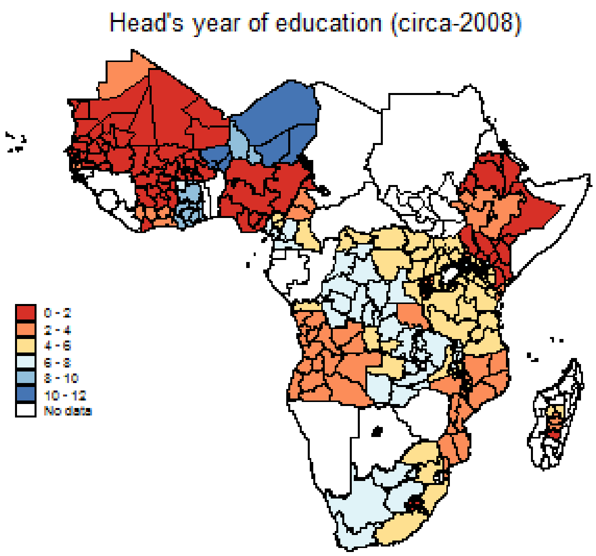


Figure 2.a Household Assets: Education

Figure 2.b : Household Assets: Age



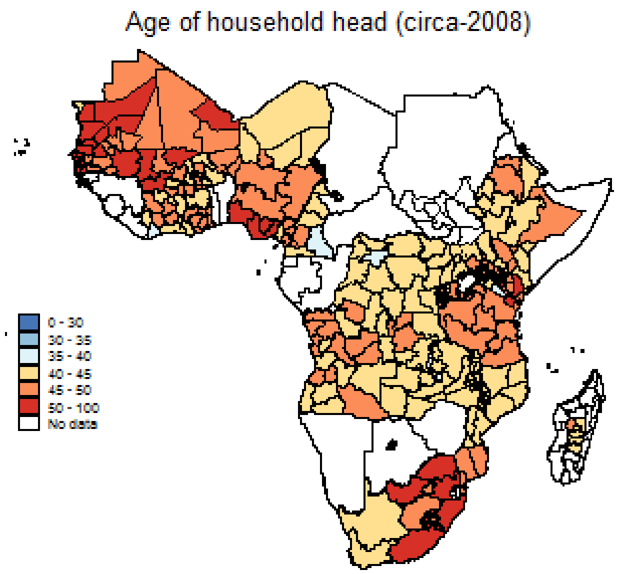
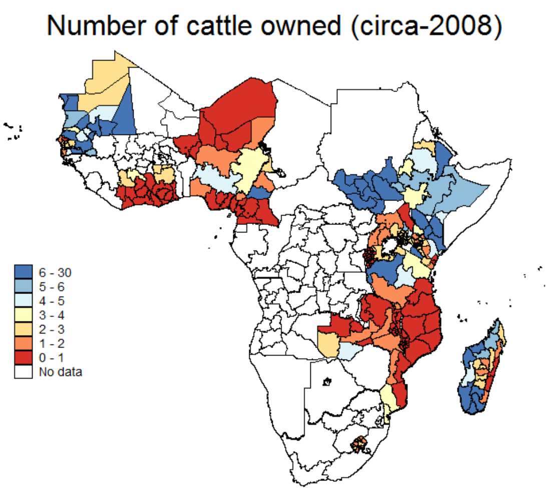
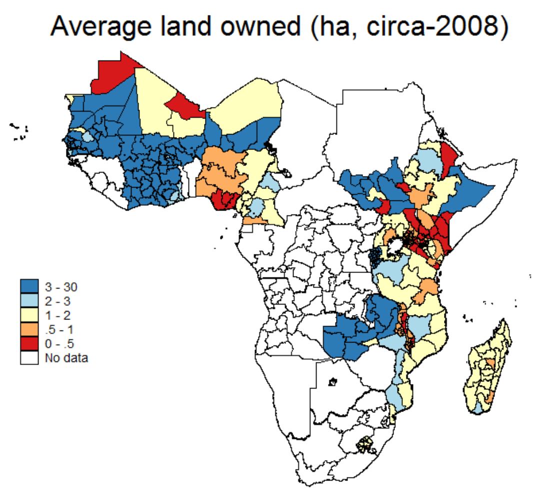


Figure 3.a Household Assets: Livestock

Figure 3.b : Household Assets: Land

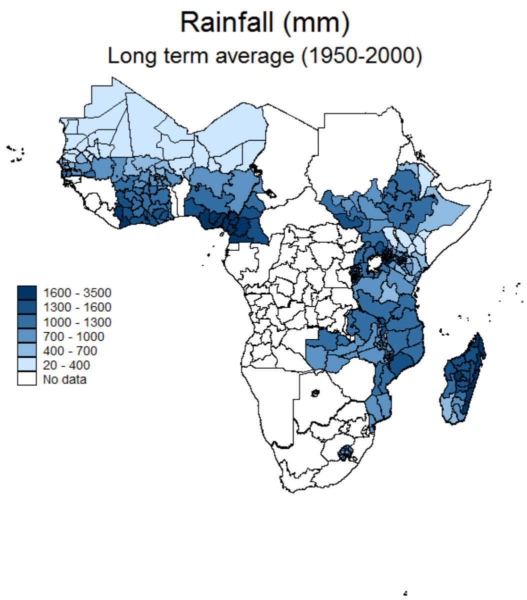


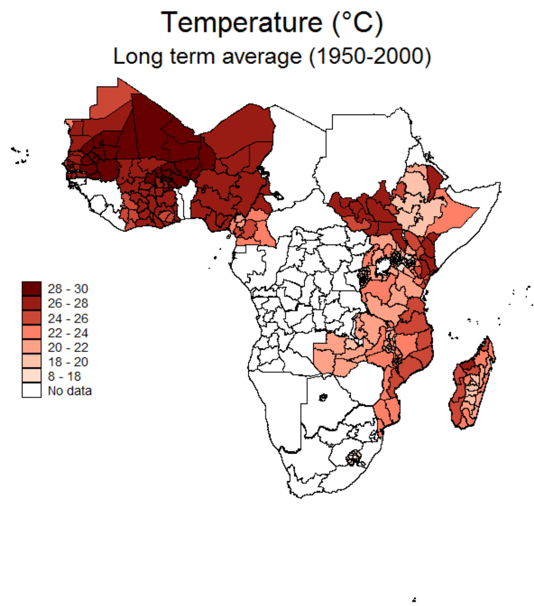


Finally Figure 4.a and Figure 4.b show the long term averages of rainfall and temperature across Sub-Saharan Africa. The desert areas in the North of Mauritania, Mali and Niger and South Sudan display the highest temperatures and lowest rainfall levels. The regression analysis will provide conditional parameter estimates to help understand how these factors relate to poverty.

Figure 4.a Climate: rainfall

Figure 4.b : Climate: temperature





b. Econometric results

Table 4 reports the parameter estimates of the total expenditure OLS regressions for all households and for rural households alone. All the demographic variables have the expected signs. For example, female household headship is negatively related to welfare, regardless of the sample taken (total and only rural sample). Living in rural areas is also negatively correlated with expenditure, as is the number of males and females in the household (greater household size is usually correlated with higher poverty). Contrarily, number of years of education, single marital status, ownership of asset, and good dwelling conditions are all positive related to welfare, controlling for biophysical variables proxies of location and income potential (through more profitable agricultural activities). These general findings at the household level are confirmed at the district level in Table 5, even though at the district level household-specific characteristics play a more limited role and turn sometimes not statistically significant. The size of land owned by the household is highly positively correlated in all the regressions at the household level (Table 4), while at the district level the effect is present when only rural areas are considered (Table 5). District level proxies of agricultural potential, such as total livestock units and total surface of irrigated cropland, are also important in determining household welfare but less than farmers-specific land size (Table 4). Finally, percentage of low soil nutrient and tree coverage are negatively related to welfare only in the weighted regressions, indicating that this relation is especially important in the most populous countries in the sample (Table 4 and Table 5).

Since poverty correlates could be different among the poorest as opposed to the better-off households, we are also interested in the relationship along the whole distribution of expenditures using quantiles regressions at the household level (Table 6). Because of the econometric issues associated with the use sampling weights in quantile regressions, we only present unweighted estimates here[7]. In line with the fact that poor households are more dependent on agriculture for their livelihoods, results show that household land size owned is more strongly related to welfare in the lowest part of the distribution, especially in the case of rural areas (in urban areas the magnitude of the relation is larger but not significant in poorer households, which may be due to higher variation of their livelihood strategies in urban areas). Finally, long term climatic conditions seem to affect the richest households more while year-specific shocks are particularly detrimental for poorer households, who have a limited capacity to absorb them. In particular, the Normalized Difference Vegetation Index index (NDVI) is highly and positively correlated with each measure of expenditure considered, witnessing the great importance that vegetation and natural resource base play in supporting livelihoods. The negative coefficients associated with areas subject to more rainfall can be explained by the higher incidence of malaria and other tropical transmissible diseases in humid environments. These findings are important as our weighted sample represents more than 400 million people in SSA countries, about half of its population. Also, the comparison between the parameters estimates of unweighted as opposed to weighted regressions could provide an indication of the importance of countries with higher population in the sample (Nigeria, Ethiopia, and Tanzania) as opposed to less populous countries.

We perform similar regressions using a probit estimator on the probability of being poor, defined as the poverty line of 3.10$ daily per-capita in 2011 PPP. Results obtained confirm what observed for the entire distribution of consumption.[8] We use the predicted regional poverty rates derived from these regressions to perform different climate change simulations. The predicted poverty rates based on the actual regression models are mapped in Figure 5.a (unweighted) and Figure 5.d (weighted). The effect of moderate climate deterioration, defined by a 15% decrease in NDVI and one degree increase in long term temperatures, can be seen in Figure 5.b and 5.e for the unweighted and weighted models respectively. Finally, the impact of a severe climate deterioration with 30% fall in NDVI and two degrees increase in temperature is visible in Figure 5.c and 5.f. Interestingly, poverty rates are not very much influenced by our climate simulations when each country in our sample is weighted equally, but they become strongly and negatively affected when population sizes are

[7] We plan to present weighted quantile results using bootstrapped standard errors in the next version of the paper.
[8] Results available on request.

considered. In particular, we can see in figures 5.e and 5.f that the countries that are expected to suffer the most from climate change are the most populous ones in our sample (Nigeria, Ethiopia, Kenya and Tanzania). These results speak loudly for the importance of mitigation (and adaptation) to the desertification process, the raise in global temperature and erratic rainfall in order to prevent a massive rise in Sub-Saharan poverty. Once more, these results point to resilience to climate change as a topical theme at the center of the international political agenda.

Table 4 : Results of Expenditure Regressions at the Household Level

	log household total expenditure per capita							
	All households				Rural households			
	unweighted		weighted		unweighted		weighted	
	coef	se	coef	se	coef	se	coef	se
Household head is female	-0.136***	0.007	-0.099***	0.018	-0.114***	0.009	-0.073***	0.020
Area is rural	-0.166***	0.010	-0.207***	0.026				
Highest years of education attained in the household	0.040***	0.001	0.046***	0.002	0.035***	0.001	0.045***	0.002
Household head is single	0.150***	0.007	0.038**	0.018	0.125***	0.009	0.016	0.020
Age of household head	-0.001***	0.000	-0.001*	0.000	-0.000*	0.000	-0.001	0.000
Number of males in the household	-0.091***	0.002	-0.043***	0.004	-0.079***	0.002	-0.039***	0.005
Number of females in the household	-0.083***	0.002	-0.033***	0.003	-0.071***	0.002	-0.030***	0.004
Number of children (<6) in the household	-0.027***	0.003	-0.045***	0.006	-0.033***	0.003	-0.046***	0.007
Land owned (ha)	0.204**	0.097	0.317**	0.126	0.358***	0.119	0.415***	0.153
Tropical Livestock Units ('000s, 2005)	0.000***	0.000	0.000***	0.000	0.000***	0.000	0.000***	0.000
Irrigated cropland area ('000s Ha, 2005)	0.001**	0.000	0.002*	0.001	0.002***	0.001	0.002	0.001
The household has access to electricity in the dwelling	0.307***	0.010	0.143***	0.032	0.173***	0.017	0.120***	0.042
The household owns a television	0.379***	0.008	0.367***	0.024	0.377***	0.012	0.348***	0.031
The household owns a radio	0.173***	0.005	0.168***	0.015	0.212***	0.006	0.188***	0.016
Elevation (mts*100)	0.003**	0.001	0.007**	0.003	0.002	0.001	0.006*	0.003
Year specific drought index	-0.014***	0.004	-0.006	0.010	-0.019***	0.005	-0.002	0.011
sqPDSI	0.002***	0.001	0.002	0.001	0.003***	0.001	0.001	0.001
Year specific temperature	-0.051**	0.021	-0.145***	0.054	0.002	0.027	-0.128**	0.061
sqTemperature	0.001***	0.000	0.004***	0.001	0.000	0.001	0.004***	0.001
Nighlight radiation	0.010***	0.001	0.013***	0.001	0.019***	0.004	0.011**	0.006
Annual Mean Temperature (C*10)	-0.017***	0.004	-0.054***	0.015	-0.027***	0.005	-0.060***	0.017
Annual Precipitation (cm)	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Normalized Difference Vegetation Index, MODIS	0.154*	0.081	1.690***	0.196	0.304***	0.105	1.655***	0.242
Tree %	0.000	0.000	-0.003***	0.001	0.000	0.001	-0.003***	0.001
Low soil nutrient (%)	-0.000	0.000	-0.002***	0.000	-0.000	0.000	-0.003***	0.001
Constant	5.669***	0.234	6.129***	0.602	4.991***	0.301	4.793***	0.580
Number of observations	125,181		125,181		80,612		80,612	
N_pop		125,181.000		372,990,668.069		80,612.000		313,344,576.387
N_strata		21.000		21.000		21.000		21.000
N_psu		10,999.000		10,999.000		7,160.000		7,160.000
R2	0.486		0.358		0.347		0.249	
p		0.000		0.000		0.000		0.000

note: .01 - ***; .05 - **; .1 - *;

Fixed effects by country-year-month included. Standard errors corrected for intra-region correlation.

Table 5 : Results of Expenditure Regressions at the District Level

	mean log household total expenditure per capita by district							
	All households				**Rural households**			
	unweighted		**weighted**		**unweighted**		**weighted**	
	coef	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
Household head is female	-0.157	0.147	-0.575***	0.184	-0.040	0.140	-0.425**	0.186
Area is rural	-0.155**	0.055	-0.090**	0.034				
Highest years of education attained in the household	0.052***	0.007	0.058***	0.011	0.053***	0.011	0.060***	0.015
Household head is single	0.013	0.119	0.572***	0.195	-0.147	0.137	0.517*	0.256
Age of household head	-0.007***	0.003	-0.014**	0.005	-0.001	0.003	-0.014**	0.005
Number of males in the household	-0.064**	0.029	0.018	0.058	-0.059	0.053	0.016	0.120
Number of females in the household	-0.029	0.019	-0.035	0.058	-0.059*	0.033	-0.036	0.082
Number of children (<6) in the household	-0.025	0.051	-0.094	0.070	-0.004	0.054	-0.043	0.059
Land owned (ha)	-0.338**	0.128	0.547	0.339	1.088**	0.478	1.096**	0.406
Tropical Livestock Units ('000s, 2005)	0.000	0.000	0.000**	0.000	0.000	0.000	0.000*	0.000
Irrigated cropland area ('000s Ha, 2005)	0.001	0.001	0.002*	0.001	0.002*	0.001	0.004**	0.001
The household has access to electricity in the dwelling	0.037	0.062	0.030	0.085	-0.047	0.079	0.066	0.078
The household owns a television	0.604***	0.094	0.827***	0.075	0.590***	0.090	0.896***	0.084
The household owns a radio	0.341***	0.077	0.312	0.187	0.429***	0.082	0.320	0.295
Elevation (mts*100)	-0.005	0.003	0.003	0.006	-0.004	0.004	0.001	0.007
Year specific drought index	-0.006	0.011	0.029	0.029	-0.007	0.013	0.043	0.034
sqPDSI	-0.001	0.003	-0.008	0.007	0.000	0.003	-0.012	0.008
Year specific temperature	0.025	0.041	-0.083	0.066	0.005	0.049	-0.091	0.081
sqTemperature	-0.000	0.001	0.003	0.002	0.000	0.001	0.004	0.003
Nighlight radiation	0.008***	0.002	0.010***	0.003	0.013***	0.003	0.007**	0.003
Annual Mean Temperature (C*10)	-0.019	0.016	-0.061*	0.035	-0.011	0.020	-0.069*	0.035
Annual Precipitation (cm)	-0.000	0.000	-0.000**	0.000	-0.000	0.000	-0.000**	0.000
NDVI	0.289	0.365	1.936*	0.964	-0.107	0.395	1.831*	1.001
Tree %	0.001	0.002	-0.005	0.003	0.002	0.002	-0.004	0.003
Low soil nutrient (%)	0.000	0.001	-0.003*	0.001	-0.000	0.001	-0.002	0.002
Constant	4.690***	0.473	5.346***	0.620	4.672***	0.505	5.741***	1.201
Number of observations	1,815		1,815		1,096		1,096	
N_pop		1,815.000		522,034,134.831		1,096.000		395,651,193.965
N_strata		1.000		1.000		1.000		1.000
N_psu		21.000		21.000		21.000		21.000
R2	0.731		0.665		0.660		0.485	

note: .01 - ***; .05 - **; .1 - *;

Fixed effects by country-year-month included. Standard errors corrected for intra-region correlation.

Table 6: Results of Quantile Regressions at the Household Level

	log household food expenditure per capita											
	All households (unweighted)						Rural households (unweighted)					
	p25		p50		p75		p25		p50		p75	
	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se
Household head is female	-0.148***	0.012	-0.169***	0.010	-0.171***	0.011	-0.119***	0.016	-0.133***	0.012	-0.135***	0.012
Area is rural	-0.084***	0.013	-0.069***	0.012	-0.078***	0.012						
Highest years of education attained in the household	0.028***	0.001	0.026***	0.001	0.024***	0.001	0.023***	0.001	0.021***	0.001	0.020***	0.001
Household head is single	0.089***	0.011	0.151***	0.010	0.212***	0.011	0.052***	0.015	0.113***	0.013	0.170***	0.013
Age of household head	-0.001***	0.000	-0.001***	0.000	-0.001***	0.000	-0.001**	0.000	-0.000	0.000	-0.000	0.000
Number of males in the household	-0.084***	0.002	-0.085***	0.002	-0.084***	0.002	-0.073***	0.003	-0.075***	0.002	-0.077***	0.002
Number of females in the household	-0.083***	0.002	-0.082***	0.002	-0.079***	0.002	-0.067***	0.003	-0.068***	0.002	-0.067***	0.002
Number of children (<6) in the household	-0.028***	0.004	-0.025***	0.003	-0.020***	0.004	-0.037***	0.004	-0.033***	0.004	-0.028***	0.004
Land owned (ha)	0.261	0.230	0.251***	0.043	0.111***	0.026	0.463***	0.033	0.320	0.422	0.285**	0.122
Tropical Livestock Units ('000s, 2005)	0.000	0.000	0.000***	0.000	0.000***	0.000	0.000	0.000	0.000**	0.000	0.000***	0.000
Irrigated cropland area ('000s Ha, 2005)	0.002***	0.000	0.001*	0.000	0.000	0.000	0.002***	0.001	0.001**	0.000	0.001	0.001
The household has access to electricity in the dwelling	0.208***	0.013	0.216***	0.014	0.228***	0.014	0.125***	0.027	0.135***	0.027	0.159***	0.026
The household owns a television	0.256***	0.012	0.264***	0.011	0.246***	0.011	0.249***	0.017	0.256***	0.016	0.252***	0.016
The household owns a radio	0.178***	0.007	0.160***	0.006	0.142***	0.007	0.183***	0.008	0.180***	0.007	0.161***	0.008
Elevation (mts*100)	0.008***	0.001	0.006***	0.001	0.004***	0.001	0.006***	0.001	0.005***	0.001	0.004***	0.001
Year specific drought index	-0.026***	0.005	-0.024***	0.005	-0.020***	0.005	-0.025***	0.007	-0.024***	0.005	-0.015***	0.006
sqPDSI	0.004***	0.001	0.004***	0.001	0.003***	0.001	0.003**	0.001	0.003***	0.001	0.002**	0.001
Year specific temperature	-0.052**	0.026	-0.031	0.024	-0.028	0.023	0.009	0.034	-0.007	0.030	0.006	0.029
sqTemperature	0.001**	0.001	0.001*	0.001	0.001*	0.001	-0.000	0.001	0.000	0.001	0.000	0.001
Nighlight radiation	0.006***	0.001	0.006***	0.001	0.007***	0.001	0.015***	0.005	0.014***	0.003	0.011**	0.004
Annual Mean Temperature (C*10)	-0.010*	0.005	-0.013**	0.006	-0.018***	0.006	-0.018***	0.007	-0.024***	0.006	-0.029***	0.007
Annual Precipitation (cm)	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Normalized Difference Vegetation Index, MODIS	0.239**	0.116	0.219**	0.100	0.377***	0.108	0.194	0.137	0.296***	0.112	0.536***	0.113
Tree %	0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.000	0.001	-0.000	0.001
Low soil nutrient (%)	0.001***	0.000	0.001**	0.000	0.000*	0.000	0.000	0.000	-0.000	0.000	-0.000	0.000
Constant	3.682***	0.281	4.042***	0.271	4.540***	0.261	3.414***	0.360	4.304***	0.345	4.760***	0.300
Number of observations	97,031		97,031		97,031		65,035		65,035		65,035	
R2	0.506		0.508		0.503		0.495		0.497		0.491	

note: .01 - ***; .05 - **; .1 - *;

Fixed effects by country-year included. Standard errors corrected for intra-region correlation.

Figure 5.a Predicted Poverty (unw.)

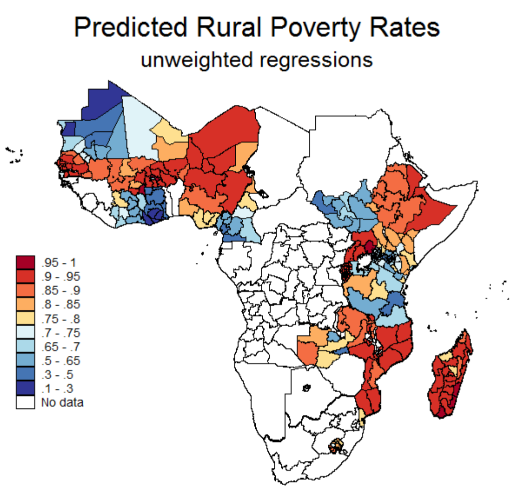


Figure 5.b : Predicted Poverty, moderate sim. (unw.)

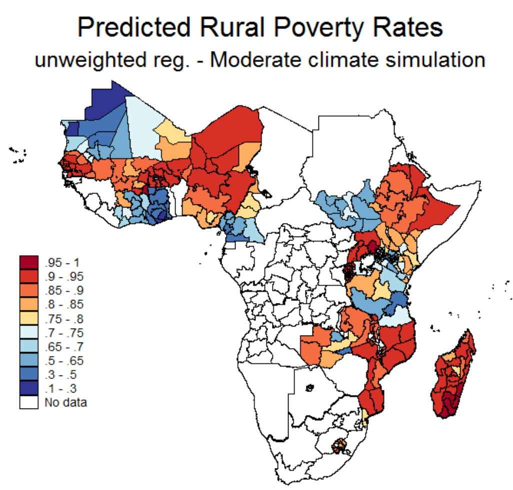
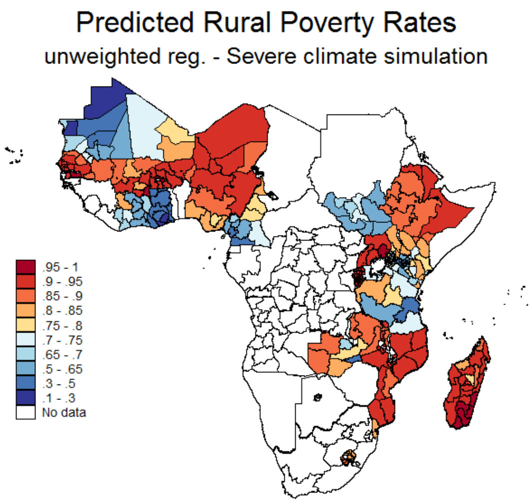


Figure 5.c : Predicted Poverty, severe sim. (unw.)

Figure 5.d : Predicted Poverty (weig.)



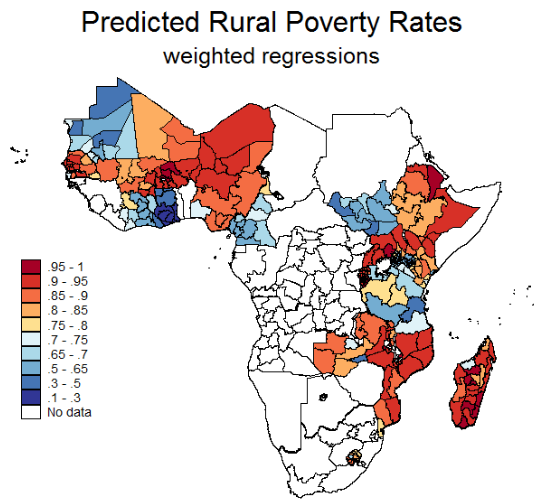
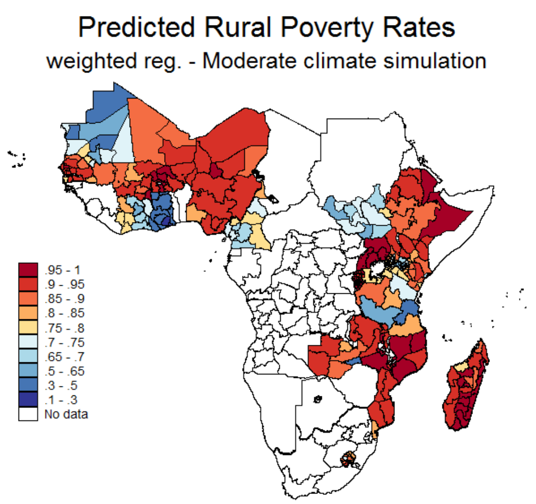
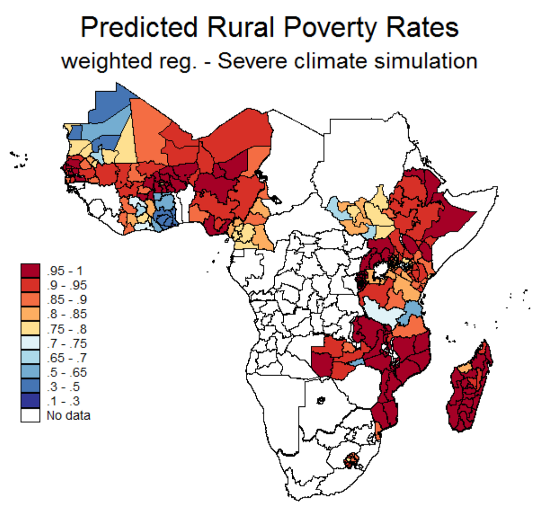


Figure 5.e : Predicted Poverty, moderate sim. (weig.)

Figure 5.f : Predicted Poverty, severe sim. (weig.)





5. Conclusions

The Sub-Saharan Africa sub-regional poverty maps show that the spatial dimension of poverty often crosses national boundaries, and that the link to climatic conditions is not immediately apparent, since it is mediated by idiosyncratic household-level characteristics. Indeed, our analysis of welfare highlights that the complexity of the link requires more rigorous and comprehensive research in order to unveil the dominant determinants of welfare distribution.

Our regression results reveal how household human and physical capital endowments play a very important role in explaining overall welfare distribution, but that the same is true for long term climatic conditions, especially in terms of vegetation and for richer households, and for year-specific weather shocks, especially for poorer households. The size of land holdings is highly positively correlated with household welfare, while at the district level the effect is only visible in rural areas. This result confirms the well documented high dependence from agriculture of rural households. Through simulation we show that the expected climatic evolution of the next few decades has the potential to raise Sub-Saharan poverty rates significantly, and particularly so in the most populous countries in our sample: Nigeria, Ethiopia, Kenya and Tanzania. Our results are even stronger for rural households, underlining the importance for policy makers to enact and implement programs specifically targeted to the extreme poor living in remote areas, since they will also likely be the most affected by climate change in the upcoming decades.

References

Ali, I., & Pernia, E. M. 2003. Infrastructure and Poverty Reduction-What is the Connection?

Amarasinghe, U., Samad, M., & Anputhas, M. 2005. Spatial clustering of rural poverty and food insecurity in Sri Lanka. *Food Policy*, *30*(5), 493-509. Ashley, C., & Carney, D. 1999. *Sustainable livelihoods: Lessons from early experience* (Vol. 7, No. 1). London: Department for International Development.

Ayadi, M. and Amara, M. 2008. Spatial Patterns and Geographic Determinants of Welfare and Poverty in Tunisia. Equity and Economic Development, ERF 15th Annual Conference.

Bebbington, A. 1999. Capitals and capabilities: a framework for analyzing peasant viability, rural livelihoods and poverty. *World development*, *27*(12), 2021-2044.

Beegle, K., Christiaensen, L., Dabalen, A., & Gaddis, I. 2016. *Poverty in a Rising Africa: Africa Poverty Report*. Washington, DC: World Bank. © World Bank. https://openknowledge.worldbank.org/handle/10986/22575 License: CC BY 3.0 IGO."

Bellon, M. R., Hodson, D., Bergvinson, D., Beck, D., Martinez-Romero, E., & Montoya, Y. 2005. Targeting agricultural research to benefit poor farmers: Relating poverty mapping to maize environments in Mexico. *Food Policy*, *30*(5), 476-492.

Benson, T., Chamberlin, J., & Rhinehart, I. 2005. Why the poor in rural Malawi are where they are: An analysis of the spatial determinants of the local prevalence of poverty.

Besley, T., & Burgess, R. 2000. Land reform, poverty reduction, and growth: Evidence from India. *Quarterly journal of Economics*, 389-430.

Berry, L., Olson, J., and Campbell, D. 2003. Assessing the Extent, Cost and Impact of Land Degradation at the National Level: Findings and Lessons Learned from Seven Pilot Case Studies, Global Mechanism and World Bank, Rome, 1-203.

Bhattacharya, H., & Innes, R. 2006. Is there a nexus between poverty and environment in rural India?. In *selected paper presented at the American Agricultural Economics Association Annual Meeting*, 23-26.

Bigman, D., & Fofack, H. (Eds.). 2000. *Geographical targeting for poverty alleviation: Methodology and applications*. World Bank Publications.

Bigman, D., & Srinivasan, P. V. 2002. Geographical targeting of poverty alleviation programs: methodology and applications in rural India. *Journal of Policy Modeling*, *24*(3), 237-255.

Bremner, J., López-Carr, D., Suter, L., and Davis, J. 2010. Population, Poverty, Environment, and Climate Dynamics in the Developing World, *Interdisciplinary Environmental Review*, 11(2/3), 112-126.

Chen, S., & Ravallion, M. 2010. The developing world is poorer than we thought, but no less successful in the fight against poverty. *The Quarterly Journal of Economics*, *125*(4), 1577-1625.

Dasgupta, S., Deichmann, U., Meisner, C. M., & Wheeler, D. 2003. The poverty/environment nexus in Cambodia and Lao People's Democratic Republic. *World Bank Policy Research Working Paper*, (2960).

Davis, B. (2003). *Choosing a method for poverty mapping*. Food & Agriculture Org.

Davis, B., Winters, P., Carletto, G., Covarrubias, K., Quiñones, E. J., Zezza, A., ... & DiGiuseppe, S. 2010. A cross-country comparison of rural income generating activities. *World development*, *38*(1), 48-63.

Deaton, A. 2005. Measuring poverty in a growing world (or measuring growth in a poor world). *Review of Economics and Statistics*, *87*(1), 1-19.

Dercon, S., & Krishnan, P. 2000. Vulnerability, seasonality and poverty in Ethiopia. *The Journal of Development Studies*, *36*(6), 25-53.

Duraiappah, A. 1996. Poverty and Environmental Degradation: a Literature Review and Analysis, CREED Working Paper Series No 8. Available here.

Dzanku, F. M., Jirström, M., & Marstorp, H. 2015. Yield gap-based poverty gaps in rural sub-Saharan Africa. *World Development*, *67*, 336-362.

Edward, P., & Sumner, A. 2014. Estimating the Scale and Geography of Global Poverty Now and in the Future: How Much Difference Do Method and Assumptions Make?. *World Development, 58*, 67-82.

Ferreira, F. H., Chen, S., Dikhanov, Y., Hamadeh, N., Jolliffe, D., Narayan, A., ... & Yoshida, N. 2015. A Global Count of the Extreme Poor in 2012: Data Issues, Methodology and Initial Results. *World Bank Policy Research Working Paper*, (7432).

Ferreira, F. H., & Ravallion, M. 2008. Global poverty and inequality: a review of the evidence. *World Bank Policy Research Working Paper Series, Vol*.

Gyawali, B. R., Fraser, R., Wang, Y., & Bukenya, J. O. 2004. Land Cover and Socio-economic Characteristics in the Eight Counties of Alabama: A Spatial Analysis. In *2004 Annual meeting, August 1-4, Denver, CO* (No. 20173). American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association).

Hagos, F., & Holden, S. 2006. Tenure security, resource poverty, public programs, and household plot-level conservation investments in the highlands of northern Ethiopia. *Agricultural Economics*, *34*(2), 183-196.

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.

Hyman, G., Larrea, C., & Farrow, A. 2005. Methods, results and policy implications of poverty and food security mapping assessments. *Food Policy, 30*(5), 453-460.

International Panel on Climate Change (IPCC). 2000. Land Use, Land-Use Change, and Forestry. IPCC Special Report, Summary for Policy Makers, Cambridge University Press, Cambridge, UK.

Jolliffe, D., & Prydz, E. B. 2015. *Global poverty goals and prices: how purchasing power parity matters* (No. 7256). The World Bank.

Kam, S. P., Hossain, M., Bose, M. L., & Villano, L. S. 2005. Spatial patterns of rural poverty and their relationship with welfare-influencing factors in Bangladesh. *Food Policy*, *30*(5), 551-567.

Kristjanson, P., Radeny, M., Baltenweck, I., Ogutu, J., & Notenbaert, A. 2005. Livelihood mapping and poverty correlates at a meso-level in Kenya. *Food Policy, 30*(5), 568-583.

McGuigan, C., Reynolds, R., & Wiedmer, D. 2002. Poverty and climate change: Assessing impacts in developing countries and the initiatives of the international community. *London School of Economics Consultancy Project for the Overseas Development Institute*, 1-40.

McGuire, M., Bigman, D., & Fofack, H. 2000. Evaluation of food security in the Sahel: an analysis using the Demographic and Health Survey (DHS) data with a geographical information system. *Targeting for Poverty Alleviation*, 209.

MEA. 2005. Ecosystems and Human Well-being: Synthesis, Millennium Ecosystem Assessment Synthesis Reports, Island Press, Washington DC.

Minot, N., & Baulch, B. (2002). *The spatial distribution of poverty in Vietnam and the potential for targeting* (Vol. 2829). World Bank Publications.

Narain, U., Gupta, S., & van't Veld, K. 2008. Poverty and the environment: exploring the relationship between household incomes, private assets, and natural assets. *Land Economics*, *84*(1), 148-167.

Nkonya, E., Pender, J., Kaizzi, K. C., Kato, E., Mugarura, S., Ssali, H., & Muwonge, J. 2008. *Linkages between land management, land degradation, and poverty in Sub-Saharan Africa: The case of Uganda* (Vol. 159). Intl Food Policy Res Inst.

Okwi, P., Ndengec, G., Kristjansona, P., Arungaa, M., Notenbaerta, A., Omoloa, A., Henningerd, N., Bensone, T., Kariukia, P., and Owuora, J. 2007. Spatial Determinants of Poverty in Rural Kenya, *PNAS*, 104(43), 16769–16774.

Perrings, C.1989. An Optimal Path to Extinction? Poverty and Resource Degradation in the Open Agrarian Economy. *Journal of Development Economies*, 30, 1-24.

Ravallion, M. (2003). Measuring aggregate welfare in developing countries: How well do national accounts and surveys agree?. *Review of Economics and Statistics*, *85*(3), 645-652.

Rogers, G. 2000. Applications of a GIS in program impact evaluation: lessons from USAID experience. *Geographic targeting for poverty alleviation. Methodology and application, World Bank Regional and Sectoral Studies, Washington, DC*.

Rosenzweig, C., & Parry, M. L. 1994. Potential impact of climate change on world food supply. *Nature, 367*(6459), 133-138.

Sumner, A. 2012. Where do the poor live?. *World Development*, *40*(5), 865-877.

Wood, E., Tappan, G., and Hadj, A. 2004. Understanding the Drivers of Agricultural Land Use Change in South-central Senegal, *Journal of Arid Environments,* 59(3), 1-18.

World Bank. 2015. Povcal Net. <http://www.worldbank.org>

World Bank. 2011. International Comparison Program (ICP). http://www.worldbank.org