# Welfare Impacts of Climate Shocks: Evidence from Uganda

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*Abstract*

*This paper evaluates the effects of weather/climate shocks on household welfare using a nationally representative panel data from Uganda together with a set of novel climate variation indicators. Where the effect of climate/weather variability has a significantly negative effect on household welfare, we further test the hypotheses that policy-relevant mechanisms can be effective means of mitigating the negative welfare effects. In general we obtain very few significant results with respect to climate/weather shock variables which might point towards a consumption and income smoothing behavior by the households, whose welfare level is not affected by the weather shocks. With regards to the different shocks definition, the reference period used to define the shock does not matter since the coefficients and the signs do not change with the reference period. Different policy action variables have also heterogeneous impact across different outcome variables in terms of mitigating the negative impact of climate/weather shocks.*

Keywords; Climate shock, welfare, Uganda, Africa

JEL codes: Q01, Q12, Q16, Q18

# 1. Introduction

Reducing food insecurity continues to be a major public policy challenge in developing countries. Nearly about 843 million people worldwide are undernourished, and the absolute numbers tend to increase further (FAO, 2013). Unlike almost all other regions of the world, food insecurity in Sub-Saharan Africa (SSA) has been rising over the last decade. The share of people living on less than $1.25 a day in this region started to decrease only from 2008, though it still remains the highest in the world (48.2% in 2010 according to World Bank (2010)). In recent years, poverty alleviation and achieving food security in SSA has been in the forefront of the national and international agenda. As the economies of many African countries and the livelihood of the majority of the poor within them depend on agriculture, the pathway to food security in these countries depends on the growth and development of that sector made through research and technological improvements. However, a significant proportion of the population in these countries that relies on agriculture is highly vulnerable to variability in weather and climate as well as to pests, pathogens and market related factors like price volatility. 1

Recent evidence suggests that global climate change is likely to increase the incidence of environmental disasters, increase the variability of rainfall and temperature, and involve other climatic parameters such as seasonal pattern change and the increase of extreme weather events (IPCC, 2013). Studies have shown that climate and weather variability have negative impacts on the welfare of households relying on agriculture in many regions through potential increases in yield variability and crop failures and reduction in average yields in the longer term (e.g., IPCC (2014); Challinor et al. (2010)). Climate change affects food production directly through changes in agro-ecological conditions and indirectly by affecting the growth and the distribution of incomes, and thus the demand for agricultural products Martin L. Parry and Hanson (2007). According to the IPCC report all aspects of food security are potentially affected by climate change, including food access, utilization, and price stability (IPCC, 2014). Reducing the vulnerability of agricultural systems to climate change is thus an important priority for agricultural development in order to protect and improve the livelihoods of the poor and to ensure food security (Bradshaw et al. (2004); Wang et al. (2009)).

There is an emerging economic literature concerning climate-economy relationships which has largely been sparked by a desire to inform the global community of the potential consequences of global climate change.2 Most of this literature is concerned with establishing linkages between these outcomes of interest and weather using data at aggregated levels (e.g. country, district, and

municipality) including through cross-country studies. In general, the evidence shows a strong and negative relationship between temperature and economic outcome indicators (e.g., Dell et al. (2009); Nordhaus (2006); Dell et al. (2013)). In developing countries, Schlenker and Lobell (2010) find negative impacts from bad weather shocks (higher temperature) on yields for Sub-Saharan Africa. Similarly, Guiteras (2009) for India and Feng et al. (2010) for Mexico estimate that higher temperatures reduce agricultural output. Not completely in line with the previous studies, Welch et al. (2010) estimate for Asian countries that higher minimum temperature reduces yields, whereas higher maximum temperature increases yields. As regards precipitations, Levine and Yang (2014) find using a panel of Indonesian districts a positive relationship between rainfall and rice production. Other studies obtain the same relationship for developing countries when testing other hypotheses (Paxson (1992); Jayachandran (2006); Choi and Yang (2007); Hidalgo et al. (2010)). In summary, past studies generally predict economically and statistically significant negative impacts of hotter temperatures on agricultural output, and these impacts are more pronounced in African countries where the level of irrigation is extremely low.

Uganda, like many other sub Saharan countries, relies heavily on the agricultural sector and consequently the economic impact of weather and climate change is crucial for small-scale farmers' food security and welfare (Mendelsohn et al. (2006); Mendelsohn and Dinar (2009)). Usually, agricultural production is completely dependent on rainfall (approximately 85% of the Ugandan population is vulnerable to climate change (Uganda Bureau of Statistics, 2012)) and is widely based on the adoption of traditional technologies. In response to a change in climate, farmers may alter their use of inputs including fertilizers, change their mix of crops, or even decide to use their farmland for another activity (e.g., a housing complex). Since many smallholder farmers in SSA in general and Uganda in particular view climate/weather variability as a primary source of risk (Barrett et al., 2007), understanding the welfare implication of climate variability is important for policymakers if policies aiming to reduce the associated risk and thus mitigate adverse consequences are to be effective and welfare enhancing. In countries where the agricultural sector is largely based on smallholders and dominates the economy, the main linkages between weather/climate and welfare go directly through agriculture, and when the latter is based on rain-fed subsistence agriculture, this link has substantial implications for food security and welfare. Not only are the average incomes of smallholders low, but also they tend to be highly volatile due to income shocks resulting from climate/weather fluctuations.

In this paper, we evaluate the effects of weather/climate shocks on household welfare in rural Uganda. Besides the important policy implications that can be derived from the investigation of

these issues, we focus on climate/weather-related risk for two additional reasons. First, the growing availability of high quality geo-referenced data on weather makes this important and exogenous component of the environment riskiness measurable, along with the related household's response. Second, although it is not the only exogenous factor affecting income and consumption of rural households, it is spatially covariant. As pointed out by Rosenzweig and Binswanger (1993), this feature makes it an important determinant of income variability that is most likely to influence welfare, especially in developing economies. The goal of this study is, therefore, to provide a comprehensive analysis of the impact of weather risk on rural households' welfare and, to this aim, we use a nationally representative panel data on Ugandan households together with a set of novel weather variation indicators based on interpolated gridded and re-analysis weather data that capture the peculiar features of short term (weather) and long term (climate) variations in rainfall and temperature. In particular, we estimate the effects of weather/climate shocks on a rich set of welfare indicators (i.e. total consumption expenditure, total food expenditure, share of food expenditure, total income and daily calorie intake) and investigate the extent to which they vary according to a different definition of the shock. Where the effect of climate/weather variability has a significantly negative effect on household welfare, we further test the hypotheses that policy-relevant mechanisms can be effective means of mitigating the negative welfare effects of local climate variability both directly and indirectly. We consider four factors that can be altered by policy action, which include access to extension services, access to credit, sustainable land management practices (SLM), and the size of the farm. Finally, since fluctuations in weather patterns may have a heterogeneous impact on different household profiles, we investigate this heterogeneity along the quintiles of the considered outcome indicators. It should be noted that different definitions of what a climatic or weather shock can be used. The latter can be defined as departures from long or short run averages or as peaks in the maximum or minimum values of rain or temperature. Furthermore the departures can be computed overt time or over space. In this paper we try to asses not only if the shock as and impact on the household welfare but also if the impact, if any, changes with different definitions of shock. In particular, we consider four different definitions of shock, according to the reference period with respect to which the climatic variables have been computed, namely the past 25, 10, 5 and 3 years with respect to the year t for which survey data is available (t = 2010,2011). Our results show that in the case of the Ugandan household it seems that the different definition of the shocks has no impact on the outcome variables. The low significance of the shock variables point toward consumption smoothing behavior by the household, whose welfare level is not affected by the weather shocks.

The rest of the paper is organized as follows. Data sources, variable construction and descriptive results are presented in section two. The third section presents the conceptual framework and analytical methods with emphasis on empirical models and hypothesized relationships. Econometric results are presented and discussed in section four. Section five concludes by presenting the key findings and the policy implications.

## 2. Data and variables description

We use two main sources of data in our analysis: socio-economic data from Uganda National Panel Survey (UNPS) and historical re-analysis data on rainfall and temperature from the the National Oceanic and Atmospheric Administration (NOAA) and the European Centre for Medium-Range Weather Forecasts (ECMWF), respectively.

The UNPS, implemented by the UBoS, is part of the Living Standards Measurement Study-Integrated Surveys on Agriculture, a series of nationally representative household panel surveys that assembles information on a wide range of topics, with a strong focus on agriculture and rural development. The survey collects information on socio-economic characteristics, production activities in agricultural, livestock and fisheries sectors, non-farm income generating activities and consumption expenditures. The sample for the 2009/10 UNPS was designed to revisit some of the very households that participated in the 2005/06 Uganda National Household Survey (UNHS). Households were tracked and re-interviewed using identification particulars available in the 2005/06 UNHS. Out of the 7,400 households interviewed during the UNHS 2005/06, about 3,200 households were selected for the 2009/10 UNPS. During data collection, households that had migrated to known places were followed-up and re-interviewed based on the contact information provided by knowledgeable persons: out of the 3123 original households, 2,607 were tracked and interviewed. Similarly, the 2010/11 UNPS was designed starting from the UNHS 2005/06. Out of the 3123 households that were originally sampled for Wave I of the UNPS, a total of 2607 households were successfully interviewed. In the second wave a detailed fisheries module was added. Both samples were designed to be representative at the national, urban/rural and main regional levels (North, East, West and Central regions). Both waves make use of three main questionnaires to collect data: a Household Questionnaire (HQ) collecting information on household composition, educational attainment, health, labor market participation, non-farm and social activities1; an Agriculture Questionnaire (AQ), administered to any household that has engaged in any farming or livestock activities, in which data are collected at both the plot and crop levels on inputs, production and sales; and a Community Questionnaire (CQ) administered to a

group of local leaders determined by the field supervisors and designed to collect information about the community where the selected households are located.

One of the main reasons to use the two consecutive waves and not the the 2005/2006 one was mainly driven by the fact that starting from the UNPS 2009/10 a comprehensive agriculture module is also included, which will be administered annually to all households in the main sample identified during the main interview as being involved in crop and/or livestock or fishery production. The Agriculture Questionnaire will allow, among other things, for the estimation of land area, both owned and cultivated, and detailed production cost for selected crops. The 2009/10 UNPS was undertaken from September 2009 to August 2010, while the second wave of the UNPS and was conducted from November 2010 to October 2011. The analyzed sample in the first wave consists of 2,492 households (1,943 households in rural areas and 549 urban areas). The second consists of 2,216 households (1,859 households in rural areas and 346 urban areas).

## 2.1. Weather fluctuations and climate shocks

Our data on rainfall and temperatures come from the daily ARC2 (Africa Rainfall Climatology version2) database. Rainfall (measured in millimeters of rain) and temperature (measured in Celsius degrees) data are summed at decadal (10-days) values and corrected for possible missing daily values at county level. The ARC2 rainfall (max*temperature) database contains data at a spatial ground resolution of 1/10 of degree for African countries for the period 1983-2012 (1989-2010). As reported by Novella and Thiaw (2013) the benefits of ARC2 include a high-resolution long-term data set, with minimal, continuous inputs that minimize bias and error, with availability in near real-time.

Uganda is characterized by a hotter northern region, where the average max temperature is approximately 5 degrees more in the south (see Figure 36) while total rainfall is more abundant in the central areas (see Figure 37) although the coefficient of variation is higher in the norther region. Preliminary analysis of Uganda's climatic characteristics showed that the characteristics of an area do not change if we change the reference period used to define the shock (i.e if an area has a high rain volatility with the 25 years reference period the same is generally true for the 3 years reference period). The north is characterized by both higher temperatures and higher variations of temperatures but the difference between the first and the last quintile of the maximum temperature distribution is only 8 degrees, leading to a small variability of the maximum temperature Coefficient of Variation.

We construct a series of intra- and inter-seasonal indicators to measure both the level and variability of rainfall and maximum temperature for the specific planting and harvesting calendar for the main crops in Uganda from January to June. This enables us to highlight relevant differences between weather fluctuations and climate shocks as they represent essentially different phenomena and are expected to have different welfare implications (see for example Deschenes and Greenstone (2007) and Fisher et al. (2012)).2 Indeed, while intra-seasonal indicators measure weather fluctuations, or the short-term variation within the same cropping season, inter-seasonal indicators allow the measurement the climate in a specific area, or the variation of weather in that area for a specified reference period. As discussed in section 4, permanent climate shocks may cause farmers to alter the activities they conduct on their land. For example, they might switch crops because their income would be higher with an improved high-yield crop, or they might adopt specific land practices to mitigate the adverse impact of the permanent change. In order to investigate how different definitions of the reference period may affect the results, we construct both the intra- and inter-seasonal indicators with respect to different reference periods, namely the past 25, 10, 5 and 3 years.

Of special note is that we consider an intra-seasonal measure of rainfall seasonality that allows to the characterization of a specific county according to the rainfall seasonality pattern. In particular, we consider a discrete version of the Seasonality Index (SI) following the qualitative classification of degrees of seasonality suggested by Walsh and Lawler (1981). The resulting discrete indicator is equal to 1 if the continuous index is less than 0.4, indicating those enumeration areas in which precipitations are equally distributed over the cropping season; it is equal to 2 when the continuous index is greater or equal to 0.4 and less than 1, indicating those enumeration areas in which precipitations can be defined as seasonal; and it is equal to 3 when the continuous index is greater than 1, indicating those enumeration areas in which almost all rain falls in 1-3 months.

In what follows, we denote with RP the reference period, SS the survey cropping season, and with t = 2009,2010 the year for which survey data on outcome measures and controls is available.

As for precipitation, we consider the following indicators:

**Inter-seasonal measures**

1. the between-years average of SS precipitation totals computed for the RP ($R_1$); For example, the average total rainfall in the cropping season computed over the 25,10,5,3 years span before the survey period
2. the between-years standard deviation of SS precipitation totals computed for the RP ($R_2$);

For example, the standard deviation of the average total rainfall in the cropping season computed over the 25,10,5,3 years span before the survey period

3. ratio of the between-years Coefficient of Variation (COV). For example, The between-years COV is computed as the ratio between $R_2$ and $R_1$ for a given reference period. COV is computed for the past 10, 5 and 3 years (past with respect to the year t for which survey data is available) over the 1983-2012 between-years COV ($R_3$).

**Intra-seasonal measures**

1. we computed the Walsh and Lawler (1981) Seasonality Index (SI) for the year t and then constructed a dummy variable equal to 1 if the the SI changed class with respect to the reference period class; 3

2. the SS precipitation shortfall in year t computed with respect to the between-years average of SS precipitation totals for the RP ($R_5$). For example, how much less rain fell in the year t cropping season compared to average of the 25,10,5,3 previous ones.

As for temperature, we consider the following indicators

**Inter-seasonal measures**

1. the between-years average of the SS average maximum temperature computed for the RP ($T_1$); For example, the average maximum temperature in the cropping season computed over the 25,10,5,3 years span before the survey period

2. the between-years standard deviation of the SS average maximum temperature computed for the RP ($T_2$); For example, the standard deviation of the average maximum temperature in the cropping season computed over the 25,10,5,3 year span before the survey period

**Intra-seasonal measures**

1. the number of dekades (10 days) in which the maximum temperature have exceeded the SS average maximum temperature computed for the RP ($T_3$).

*2.2. Outcome measures and other controls*

As for households' welfare indicators, we consider *i*) per capita daily calories intake, *ii*) per capita food expenditures, *iii*) food expenditure's share (over total expenditures), *iv*) per capita gross total income, *v*) per capita total expenditures and *vi*) value of own produced crops. Our measure of

income includes agricultural and non-agricultural wages, self-employment wages, revenues from own-produced crops, revenues from livestock and revenues from private and public transfers.

As for controls, we consider a set of socio-demographics including age, gender, marital status of the household head, as well as household size, average years of education and dependency ratio. In order to control for income and consumption smoothing strategies, we consider access to the credit market and the adoption of Sustainable Land Management (SLM) practices (e.g. maize-legume intercropping, soil and water conservation practices, and the use of organic fertilizer) defining as adopters the households that have treated at least one plot with these practices, irrespective of the area covered.4 Dummies for extension advice and smallholders are also included.

As for wealth indicators, we include a wealth index based on durable goods ownership and housing conditions and dummies for the ownership of radio and mobile phone. We also include land related characteristics collapsed at the household level, such as the hectares of cultivated land and if the land is irrigated. In order to control for external shocks, we include dummies for the death and illness of at least a household's member. To control for transaction costs, we consider the distance from home to markets and hospitals as well as if the household is a small landholder or not.

*2.3. Descriptive analysis*

Tables 1 and 2 report the summary statistics for the both the outcome variables and the sociodemographic controls for the two waves considered in the study. As for control variables, we observe small differences between the households across the two (consecutive) waves. For both samples about a third of the households are female-headed or are headed by a single person. Household size slightly decreased between wave 1 and wave 2 from 5.4 to 4.8, as did the average age of household head from 47.1 to 46.7. The within-household dependency ratio remained stable at 1.5 across the two waves while we observe a drop in the wealth index, from .47 in 2009/10 to -.25 in 2010/11. Agricultural production in Uganda is characterized by a large majority of smallholders, more than 70% of the sample, in mainly rain-fed areas. Only 1% of the households have irrigated land in both waves, and few households use sustainable land management practices (around 10% in 2009/10 and 2010/11). About a third of the households received extension services, i.e the application of scientific research and new knowledge to agricultural practices through farmer education, in 2009/10 while only 20% of the households had been reached in 2010/11. With regards to access to credit, around 60% of the sample had no access to any kind of credit, with a high risk of being financially constrained.

## 3. Conceptual framework and methodology

As in Dercon et al. (2005) we define shocks as "adverse events that lead to a loss of household income, a reduction in consumption and/or a loss of productive assets." In this study, we focus on climatic shocks due to their role in determining household welfare (see, among the others, Dercon, 2004; Kazianga and Udry, 2006; Tol, 2009). In particular we investigate wether long or short-term climate shocks, i.e calculated with respect to different reference periods, have a different impact on welfare variables. In order to analyze the impact of climatic shocks on welfare, we follow the conceptual framework proposed in Skoufias et al. (2011).

In this framework, the environment affects consumption mainly through its impacts on current agricultural production or income. This implies that weather shocks have a short-term direct impact on the agricultural production (and consequently on the agricultural income), since higher temperatures and highly variable rainfall patterns are likely to change the hydrological cycle, ultimately affecting crop yields and total factor productivity. For example, weather changes have short-term effects on crop yields through changes in temperatures when they exceed the optimal thresholds at which crops develop (see for instance Lansigan et al. (2000) or Prasad et al. (2008) on rice and sorghum respectively). Similarly, mismatches between the amount of water received and required along the growing and harvesting seasons, and the timing of the water stresses faced by the crops, affect agricultural productivity (see for example Wopereis et al. (1996)on rice or Otegui et al. (1995) on maize. On the other side, when water comes or does not come in extreme quantities, its potential impact can be very high due to the losses of lives and infrastructure, as in the case of floods (IPCC, 2001). A decrease in agricultural income will then, affect food consumption (as share of production or income), depending on the subsistence nature of the agricultural activity or on the price of the purchased products. When the agricultural activity is of subsistence, the effect on consumption is through the quantities produced while in the case of market-oriented activity, the effect can be both through quantities and prices.

According to the Agricultural Household Model and in the case of market-oriented agriculture there could be a positive net effect on households income and subsequently on consumption (Singh et al., 1985). A decrease in income will affect different types of consumption in different ways. Generally, food consumption is likely to decrease less than non-food consumption Skoufias and Quisumbing (2005), in some cases depending on household characteristics (for example the sex of the income earner as in (Duflo and Udry, 2004). Moreover, even when the yield is more or less the same, erratic weather can stress the crops and lower the quality of the harvest, pushing the household to purchase out of home produced food.

The indirect impacts of weather shocks are mainly on agricultural productivity and come primarily from two channels. First, there is a direct effect on the development of vector/water/food-borne diseases, altering the parasites life cycles because weather variations can provide particular conditions that allow pathogens already existing in the environment to develop and spread, or make their life longer than their usual historic range (Anderson et al., 2004). For example, Piao et al. (2010) have shown in a recent study on China that changed local ecology of water borne and food borne infective diseases can cause an increase in the incidence of infectious diseases and crop pests. This applies to parasites affecting human beings as well, leading to the second indirect effect of weather variability on agricultural productivity. The research has highlighted that individuals are affected in different ways by changes in illness and death rates as well as injuries and psychological disorders due to higher temperatures or complex extreme events such as floods and storms (McMichael and Haines, 1997). For instance, vector-borne diseases sensitive to weather changes such as the mosquitoes responsible of malaria and yellow fever, and diarrhea and other infectious diseases are likely to increase due to the prolonged range and activity of pathogens (Haines et al., 2006). Then the productivity of the labor force, especially in the agricultural sector, is potentially highly affected. Finally, the malnutrition effects on human capital are one of the most explored phenomena following lower food productivity through the food consumption effects of weather variability (de la Fuente and Dercon, 2008). Malnutrition affects adults and children in different ways. Adverse consequences in the short-term can be brought about through the impact on productivity of adults on the workplace. Summarizing, it is worth emphasizing that the climatic adverse effects will take place depending on whether households are able to put in place effective *ex-ante* and/or *ex-post* coping measures. The latter are essentially represented by income and consumption smoothing (Morduch, 1995).

Income smoothing consist of decisions concerning production, employment and the diversification of the economic activities. On the production side, rural households can chose different types of crops to be cultivated and change input intensities (Morduch, 1995). However, despite ensuring a certain amount of income, these strategies can have also adverse effect on households final welfare. For example, Dercon (1996) found that the absence of developed markets for credit, combined with the lack of accessibility to off-farm labor, gave the incentive to cultivate low-risk, low- return crops (sweet potatoes) to rural households in the Shinyaga District of Tanzania. A poverty trap of low-income and asset ownership, induced low-risk, low-return crop choices and hence low-income and asset accumulation seemed to capture the households in the area (Dercon, 1996). Analogously, intercropping (that combines mixed cropping with field fragmentation) or adoption of new production technologies (like high- yielding varieties-HYV and fertilizers) can lower the risk of the

agricultural activity. Behavioral norms and households specific characteristics can play a further important role in the decision process (Foster and Rosenzweig, 1995).

On the other side, consumption smoothing comprises decisions regarding borrowing and saving, selling or buying non financial assets, modifying the labor supply and making use of formal/informal insurance mechanisms (Bardhan and Udry, 1999). For example, Paxson (1992) found that household in Thailand were able to use savings to compensate for losses of income due to rainfall shocks, hence leaving consumption unaffected. Dercon (2004) showed, instead, that households in 342 rural communities in Ethiopia were able to offset the risk of food consumption losses from shocks at the household level (idiosyncratic shocks) thanks to the allocation of the risk within the village, leaving the aggregate rainfall shocks uninsured. These two strategies differ in the time horizon over which they deal with shocks. Income smoothing is generally aimed to prevent or mitigate the effects of shocks before they occur, while consumption smoothing is concerned with the reduction of these effects after they have taken place. It is worth noting that, potentially, no effects of climatic shocks could be found in the case where households effectively engaged into one (or more) of these strategies. However, if coping strategies are not effective or are not enough to provide an insurance against the aforementioned adverse effects, we expect to find a significant evidence of the aforementioned adverse impacts on food consumption.

### 3.1. Econometric strategy

The goal of our econometric analysis is to assess whether and how weather fluctuations and climate shocks affect households income and expenditure decisions. Furthermore, we want to verify if these effects, if present, are sensible to different shock definitions. In particular, we want to test if shocks defined over different time periods (25, 10, 5 and 3 years) have a different impact on the outcome variables.

To this aim, we estimate the following model

$$y_{it} = \alpha_i + R_{it}\delta + T_{it}\gamma + X_{it}\beta + \varepsilon_{it} \tag{4.1}$$

where

$$R_{it}\delta = \frac{1}{R_{1,it}}\delta_1 + R_{2,it}\delta_2 + \left(\frac{1}{R_{1,it}}\right)^2 \delta_3 + R_{2,it}^2\delta_4 + \frac{R_{2,it}}{R_{1,it}}\delta_5 + 1\{R_3 > 1\}\delta_6$$
$$+ 1\{R_4 < 1\}\delta_7 + 1\{R_4 > 1\}\delta_8 + 1\{0 < R_5 \le p_{33}\}\delta_9 + 1\{p_{33} < R_5 < p_{66}\}\delta_{10}$$
$$+ 1\{R_5 > p_{66}\}\delta_{11}$$

and

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$$T_{it}\gamma = \frac{1}{T_{1,it}}\gamma_1 + T_{2,it}\gamma_2 + \left(\frac{1}{T_{1,it}}\right)^2\gamma_3 + T_{2,it}^2\gamma_4 + \frac{T_{2,it}}{T_{1,it}}\gamma_5 + 1\{p_{25} < T_3 \leq P_{50}\}\gamma_6 +$$
$$1\{p_{50} < T_3 \leq p_{75}\}\gamma_7 + 1\{T_3 > p_{75}\}\gamma_8$$

where the outcome variable $y_{it}$ is represented by a bundle of welfare indicators described in section 3.1 and 3.2, $R_{it}$ and $T_{it}$ represent precipitation and maximum temperature related variables, and $X_{it}$ represents control variables which may affect the level of the considered outcome variables and includes information on household structure, household assets and idiosyncratic shocks for a detailed description).

For the specification of the precipitation and temperature variables in model (4.1), we allow for non-linear effects in different ways. First, intra-annual measures are included in the model as a series of percentiles dummies (variables $R_5$ and $T_3$).1 As for the discretized SI we include a dummy, equal to 1 if the county in which the household is located has experienced a bottom-up shock in the rainfall pattern, i.e. from the case in which precipitations are equally distributed to the one in which almost all rain falls in 1-3 month. Second, for inter-annual measures we recognize that, since the COV is just an interaction between the inverse of the mean and standard deviation, it has to be included in the model along with its components, which are indeed the variable of interest in our analysis, i.e. the inter-annual level and variability of precipitations and temperature. As the model would require inclusion of the variables that comprise it as first-order terms, including the COV alone is likely to mix the effect of first and second moments of the precipitation and temperature distributions (the mean and the standard deviation) that may have independent effects on the considered outcome measures. Moreover, the scale-invariance property of the COV is too restrictive in our context. As in Kronmal (1993), we argue that the true impact of weather variability could be confounded by that of the precipitations level in a model in which only the COV is used as explanatory variable. Hence, we consider a quadratic polynomial which also includes the interaction of the first and the second moment of the between-years rainfall and maximum temperature distribution, i.e. $\frac{R_{2,it}}{R_{1,it}}$ and $\frac{T_{2,it}}{T_{1,it}}$. Finally, in order to allow for its meaningful interpretation, the ratio of the RP average rainfall COV over its long run average ($R_3$) has been included as a dummy variable equal to 1 when the ratio is greater than 1.

Model (4.1) allows one to test the hypothesis that households are unable to completely mitigate the negative effects of weather and/or climate shocks. As mentioned before, we consider four different

specifications of model (4.1) according to the reference period with respect to which the climatic variables have been computed, namely the past 25, 10, 5 and 3 years with respect to the year t for which survey data is available (t = 2009,2010).2 Moreover, we investigate the impact of relevant policy variables in order to test if they are effective in reducing the negative welfare effects of weather and climate shocks. To this aim, we interact the weather and climatic variables with a dummy equal to 1 in the presence of adoption of SLM practices, extension advices and access to credit.

Further, in order to investigate the effect of the weather and climatic variables on different household profiles, especially the poorest ones, we conduct a Quantile Regression (QR) analysis based on pooled data. It is worth noting that median regression is more robust to outliers than classical mean regression, and it can be viewed as semi-parametric as it avoids assumptions about the parametric distribution of the error process. Thus, OLS can be inefficient if the errors are highly non-normal, as QR is more robust to non-normal errors and outliers. QR also provides a richer characterization of the data, allowing us to consider the impact of a covariate on the entire distribution of the outcome variables, not merely its conditional mean.3.

As for the appropriate functional form for the weather variables, a common approach measures these variables in levels (e.g. degrees Celsius for temperature or millimeters for precipitation). In a panel set-up, the identification thus comes from deviations in levels from the mean. Another common approach, aimed at revealing non-linear effects, considers the weather realizations falling into different bins. The key advantage lies in avoiding functional form specifications since this method is relatively non-parametric and it is well suited in presence of high-resolution data.

## 4. Empirical results

In this section, we present the evidence obtained by the estimation of model (4.1) by the Generalized Least Squares random effects approach for each of the outcomes discussed in section 3.31. Our empirical results are presented in the form of elasticities computed at covariates means taking into account the fact that our model specification includes second-order terms for some of the covariates. This implies that the coefficients for continuous variables report the percentage change in the outcome variable for a 1% change in the explanatory variable, while coefficients for the dummy variable report the percentage change in the outcome variable if the dummy changes from zero to one. Results are reported in Table from 3 to 8 for the regressions without the interactions with the policy variables and from Table 15 to 26 for the interacted policy variables.

In general we obtain very few significant results which on one side may be explained by the imprecision associated with the very small length of our panel, while on the other side it might point towards a consumption and income smoothing behavior by the households, whose welfare level is not affected by the weather shocks. Given the significant effect of the socio-demographic control variables reported in Tables from 9 to 14 the second explanation seems plausible. As for income the results we obtain are in line with our expectation and with the international consensus: we observe a stable negative and significant relationship of household size and a positive and significant relationship with the average years of education. Household income is positively affected by the size of the land operated and by irrigation, increasing the outcome variable as in many empirical studies in developing countries. From a policy perspective access to credit and to extension services play a very important role, with a estimated elasticity of 11% and 14% (respectively) while SLM practices have no significant effect on income.

Consumption-related variables such ad the number of people in the household negatively affects all the outcome variables while education positively affect per capita food expenditures and per-capita total expenditures. No significant relationship is observed for these controls with own-produced crop value, food expenditure share and daily calories intake. This might imply that while more "general" consumption variables do depend on the level of education, when we consider outcomes that are more related to subsistence the role of education disappears. This result is consistent with the expectations presented in section 3.3. The dummy for irrigation and the size of the land operated exhibit the expected positive and significant effect, with the access to irrigation displaying the higher elasticity (22% for total food expenditure and 43% for own produced crop value). Like in the income regression we observe a strong and positive effect from access to credit and extension services.

Turning to the analysis of the weather shocks Figure 1 plots the marginal effect of the rainfall average on per capita gross total income for different reference periods. We observe a positive effect for the 25 and 5 years reference period while a negative relationship is observed for the 3 year reference period. With regards to the different shocks definition, reported in Table 3, the reference period used to define the shock does not matter since the coefficients and the signs do not change with the reference period. Extreme values of rain variability have a negative effect on households total income for the 3 years reference period, as shown in Figure 13. Higher average temperatures, if computed over 25 or 10 years, have a negative impact on the outcome variable (Figure 21) while long term temperature variability is bell shaped, with a positive effect for small deviations form the trend and a negative effect for bigger deviations (Figure 25). Defining the temperature shocks over

different time periods changes the magnitude of the effect but not its sign (Table 3), with a positive significant effect for the long term temperature variability that affects all the quartiles of the income distribution, as shown in Figure 29. Figure 30 and 31 show that the positive effect of higher temperature is positive, significant and increases with the income quartile, when the reference period is 10 or 5 years. correlated with the The results reported in Table 15 highlight the fact that the adoption of sustainable land management practice significantly ensures the households against negative rain shocks while household that do not engage in SLM practices are more affected by higher temperature shocks, when measured by the first moment of the distribution.

Food related outcome variables (per capita food expenditures, both total and own produced crop value, and the share of expenditures dedicated to food) exhibit very weak relationships with the shock variables, across all reference periods. As shown in Figure 3 there is a positive relationship between the average level of rainfall and per capita food expenditures but the effect is not statistically significant, and nor are the effects of the different shock variables reported in Table 4. As shown Figure 15 rain variability negatively affects per capita food expenditures for all reference periods except the 3 year period, while rising average temperature seems to positively affect the outcome variable but the coefficients are never significant, nor are those related to temperature variability (Figure 27 and 23). Pooled quantile regressions show a negative and significant impact of the temperature variability computed over the longer reference periods on lower quantiles of the outcome variable distribution (Figure 32, 33) while the effect is no longer significant for shorter reference periods. Access to credit services and SLM practices enables the households to contain the negative effects of higher short term rain and temperature variability on per capita food expenditures computed using only the value of own produced crops, but we observe no significant relationship between the average level of rain and this outcome variable for all reference periods as shown in Figure 5. The same is true for the variability of rain as seen in Figure 17. Again, different shock definitions, for both rain and temperature, do not change the impact on the value of own produced crops as shown in Table 5 with the coefficient remaining either non significant (e.g rain) or maintaining the same sign (e.g. temperature). Figures from 34 and 35 show the results of the pooled quantile regressions for share of expenditures dedicated to food. The effect of the shock variables, no matter the definition, on the outcome is almost never significant but it is worth noting that the relationship does not change across different quantiles, remaining flat around zero. This implies that irrespective of the shock definition and of the position of the household in the food expenditures distribution both rain and temperature shocks have no effect. Furthermore, moving to panel analysis, the share of expenditures dedicated to food seems not to be affected by the long term average level of rain, (Figure 9), while short term average rainfall has a positive, but not significant,

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impact on the food share. Again, using different shocks definition does not change the impact on the outcome variable (Table 7 for both rain and temperature.

Another welfare related outcome variable we analyze is per-capita daily calories intake. We observe a negative and significant relationship between the amount of daily calories consumed by the household members and the average level of rain, except for the 25 years average level (Figure 11). Except for the latter reference period the sign and the magnitude of the effect do not depend on various shock definitions. Rain variability does not have a significant effect on the outcome variable. Higher average temperatures have a slight positive impact on the daily calories intake while temperature variability has a non significant impact as shown in Table 8. Per capita total expenditures are positively affected by the average level of rainfall, except when the latter is computed over 3 years, but the effect is never significant (Figure 7). Table 6 shows that the outcome is not influenced by different shock definitions. Rain variability (Figure 19) seems to have a positive effect on the outcome variable. Long term average temperature has no effect on total expenditures while short term average temperature has a positive but not significant effect.

Thus the evidence points towards the presence of both income and consumption smoothing. The latter results are in line with previous studies on the effects of weather shocks on Ugandian agricultural households (e.g. Bosco Assiimwe and Mpuga (2007)) whose authors found that "households are engaged in consumption smoothing to mitigate the impact of shocks on welfar". The aforementioned study did find some evidence of a significant effect on weather shocks on income but "the coefficients and level of significance are smaller" in the case of the rural-only subsample, which in per case constitute the analyzed sample.

**5. Conclusions**

In this paper, we evaluate the effects of weather/climate shocks on household welfare (i.e. total consumption expenditure, total food expenditure, share of food expenditure, total income and daily calorie intake) using a nationally representative panel data on Uganda households together with a set of novel weather variation indicators based on interpolated gridded and re-analysis weather data that capture the peculiar features of short term (weather) and long term (climate) variations in rainfall and temperature. Our paper also attempts to further investigate to which extent the effects vary according to a different definition of the shock i.e., calculated with respect to different reference periods. Where the effect of climate/weather variability has a significantly negative effect on household welfare, we further test the hypotheses that policy-relevant mechanisms can be effective means of mitigating the negative welfare effects of local climate variability both directly

and indirectly. We consider four factors that can be altered by policy action which includes access to extension services, access to credit, sustainable land management practices (SLM), and the size of the farm. Finally, since fluctuations in weather patterns may have a heterogeneous impact on different household profiles, we investigate this heterogeneity along the quintiles of the considered outcome indicators.

In general we obtain very few significant results with respect to climate/weather shock variables which on one side may be explained by the imprecision associated with the very small length of our panel, while on the other it might point towards a consumption and income smoothing behavior by the households, whose welfare level is not affected by the weather shocks. Given the significant effect of the socio-demographic and wealth control variables the second explanation seems plausible. With regards to the different shocks definition, the reference period used to define the shock does not matter since the coefficients and the signs do not change with the reference period. Different policy action variables have also heterogeneous impact across different outcome variables in terms of the mitigating the negative impact of climate/weather shocks. For instance access to credit services and use of sustainable land management practices enables the households to contain the negative effects of higher short term rain and temperature variability on per capita food consumption from own produced crops but not the case for some of the outcome variables

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**Tables -** full list of tables can be available from authors

Table 1: Summary statistics of selected variables (rural households' subsample, Wave 1)

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Total gross income per capita (1000s Ugandian Sh) | 1869 | 624.54 | 714.71 | 42.67 | 5973.21 |
| Value of own produced crops per capita | 1874 | 132.66 | 115.63 | 0 | 641.33 |
| Food expenditure per capita (1000s Ugandian Sh) | 1862 | 307.63 | 203.26 | 43.91 | 1669.2 |
| Yearly total expenditure per capita (1000s Ugandian Sh) | 1855 | 935.88 | 1555.79 | 90.58 | 20396.96 |
| Share of food expenditure | 1846 | .52 | .24 | .02 | .95 |
| Daily Calories Intake | 1854 | 2574.42 | 2048.64 | 163.67 | 13809.41 |
| Female hh's head | 1936 | .28 | .45 | 0 | 1 |
| Single hh's head | 1943 | .31 | .46 | 0 | 1 |
| hh's size | 1936 | 5.43 | 2.88 | 1 | 23 |
| hh's age | 1808 | 47.13 | 15.13 | 13 | 95 |
| hh's avg yrs of education | 1943 | 5.47 | 2.21 | 1 | 17 |
| hh's Dependency Ratio | 1936 | 1.55 | 1.2 | 0 | 9 |
| Land operated | 1804 | 2.55 | 2.35 | 0 | 23.83 |
| Irrigation (1=yes) | 1943 | .01 | .1 | 0 | 1 |
| Home-mkt distance (Km) | 1943 | 5.48 | 4.04 | 0 | 27.2 |
| Home-Hospital distance (Km) | 1943 | 22.98 | 11.68 | 1 | 86 |
| Wealth Index | 1914 | .47 | 1.87 | -2.37 | 17.97 |
| Radio tenure (1=owned) | 1914 | .62 | .48 | 0 | 1 |
| Cell. tenure (1=owned) | 1914 | .42 | .49 | 0 | 1 |
| Death of HH Member (1=occurred) | 1943 | .04 | .2 | 0 | 1 |
| Illness of HH Member (1=occurred) | 1943 | .13 | .33 | 0 | 1 |
| SLM practices (1=Yes) | 1943 | .1 | .29 | 0 | 1 |
| Access to extension services | 1943 | .27 | .44 | 0 | 1 |
| Access to credit | 1943 | .43 | .49 | 0 | 1 |
| Smallholders (1=yes) | 1943 | .73 | .45 | 0 | 1 |
| AEZ==Busoga Farming System | 1943 | .13 | .33 | 0 | 1 |
| AEZ==Eastern Highlands | 1943 | .06 | .25 | 0 | 1 |
| AEZ==Eastern Savannah | 1943 | .1 | .3 | 0 | 1 |
| AEZ==Karamoja | 1943 | .04 | .2 | 0 | 1 |
| AEZ==Lake Albert Crescent | 1943 | .13 | .33 | 0 | 1 |
| AEZ==Northern Farming System | 1943 | .11 | .31 | 0 | 1 |
| AEZ==South Western Highlands | 1943 | .05 | .21 | 0 | 1 |
| AEZ==West Nile Farming System | 1943 | .1 | .31 | 0 | 1 |
| AEZ==Western Range Lands | 1943 | .12 | .33 | 0 | 1 |
| Wave2 (1=yes) | 1943 | 0 | 0 | 0 | 0 |

Table 2: Summary statistics of selected variables (rural households' subsample, Wave 2)

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Total groos income per capita (1000s Ugandian Sh) | 1752 | 705.86 | 877.05 | 39.1 | 6772.18 |
| Value of own produced crops per capita | 1747 | 125.75 | 124.29 | 0 | 652.6 |
| Food expenditure per capita (1000s Ugandian Sh) | 1734 | 355.53 | 259.5 | 43.33 | 1651 |
| Yearly total expenditure per capita (1000s Ugandian Sh) | 1745 | 1147.59 | 1767.63 | 84.03 | 19518.97 |
| Share of food expenditure | 1750 | .51 | .23 | .02 | .95 |
| Daily Calories Intake | 1756 | 2440.34 | 2094.05 | 166.23 | 13660.74 |
| Female hh's head | 1855 | .29 | .45 | 0 | 1 |
| Single hh's head | 1859 | .33 | .47 | 0 | 1 |
| hh's size | 1855 | 4.77 | 2.6 | 1 | 17 |
| hh's age | 1700 | 46.7 | 15.57 | 13 | 96 |
| hh's avg yrs of education | 1859 | 5.61 | 2.27 | 1 | 17 |
| hh's Dependency Ratio | 1855 | 1.51 | 1.22 | 0 | 9 |
| Land operated | 1667 | 2.62 | 2.42 | 0 | 23.9 |
| Irrigation (1=yes) | 1859 | .01 | .11 | 0 | 1 |
| Home-mkt distance (Km) | 1859 | 6.29 | 6.94 | 0 | 53 |
| Home-Hospital distance (Km) | 1859 | 26.57 | 18.88 | .5 | 150 |
| Wealth Index | 1815 | -.25 | 1.3 | -2 | 21.23 |
| Radio tenure (1=owned) | 1815 | .64 | .48 | 0 | 1 |
| Cell. tenure (1=owned) | 1815 | .5 | .5 | 0 | 1 |
| Death of HH Member (1=occurred) | 1859 | .03 | .17 | 0 | 1 |
| Illness of HH Member (1=occurred) | 1859 | .11 | .31 | 0 | 1 |
| SLM practices (1=Yes) | 1859 | .09 | .29 | 0 | 1 |
| Access to extension services | 1859 | .2 | .4 | 0 | 1 |
| Access to credit | 1859 | .4 | .49 | 0 | 1 |
| Smallholders (1=yes) | 1859 | .71 | .45 | 0 | 1 |
| AEZ==Busoga Farming System | 1859 | .11 | .32 | 0 | 1 |
| AEZ==Eastern Highlands | 1859 | .07 | .26 | 0 | 1 |
| AEZ==Eastern Savannah | 1859 | .11 | .31 | 0 | 1 |
| AEZ==Karamoja | 1859 | .04 | .2 | 0 | 1 |
| AEZ==Lake Albert Crescent | 1859 | .11 | .31 | 0 | 1 |
| AEZ==Northern Farming System | 1859 | .13 | .34 | 0 | 1 |
| AEZ==South Western Highlands | 1859 | .04 | .2 | 0 | 1 |
| AEZ==West Nile Farming System | 1859 | .12 | .32 | 0 | 1 |
| AEZ==Western Range Lands | 1859 | .1 | .31 | 0 | 1 |
| Wave2 (1=yes) | 1859 | 1 | 0 | 1 | 1 |

Table 3: Per-capita total gross income. Elasticities (at means). Reference Period (RP), Between-years (B), Average (AVG), Standard Deviation (SD), Survey growing season (SS).

**Rainfall**

| | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | -0.119 | -0.102 | -0.044 | 0.335 |
| RP-B-SD | 0.021 | -0.063 | -0.005 | 0.059 |
| SI shock: equable → extreme | -0.028 | -0.024 | -0.004 | -0.056 |
| SS Shortfall - 2$^{nd}$ quartile | 0.051 | 0.005 | 0.026 | -0.020 |
| SS shortfall - 3$^{rd}$ quartile | 0.112* | 0.095 | 0.131** | 0.111* |
| SS shortfall - 4$^{th}$ quartile | 0.126* | 0.118 | 0.111 | 0.129* |
| RP-B-COV / 1983-2012 B-COV | | -0.105 | -0.004 | 0.100 |

**Maximum temperature**

| | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | 2.929*** | 1.926 | 1.262 | 0.032 |
| RP-B-SD | 0.708*** | 0.357 | 0.358* | -0.066 |
| SS # Dekads > RP-AVG - 2$^{nd}$ quartile | 0.061 | 0.038 | 0.170** | 0.004 |
| SS # Dekads > RP-AVG - 3$^{rd}$ quartile | 0.068 | 0.154** | 0.312*** | 0.168* |
| SS # Dekads > RP-AVG - 4$^{th}$ quartile | 0.255*** | 0.248*** | 0.319*** | 0.207** |
| $R^2$ | 0.262 | 0.263 | 0.262 | 0.264 |

Table 4: Per-capita food expenditure.

**Rainfall**

|  | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | -0.286 | -0.059 | -0.007 | 0.073 |
| RP-B-SD | -0.113 | -0.018 | -0.002 | 0.014 |
| SI shock: equable → extreme | -0.013 | 0.007 | -0.003 | 0.001 |
| SS Shortfall - 2$^{nd}$ quartile | -0.008 | 0.006 | 0.036 | -0.003 |
| SS shortfall - 3$^{rd}$ quartile | 0.025 | -0.015 | 0.053 | 0.026 |
| SS shortfall - 4$^{th}$ quartile | 0.051 | -0.022 | -0.009 | -0.033 |
| RP-B-COV / 1983-2012 B-COV | | -0.082 | -0.041 | 0.070 |

**Maximum temperature**

|  | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | 0.544 | -0.157 | 0.179 | -0.044 |
| RP-B-SD | 0.202 | -0.008 | 0.105 | -0.037 |
| SS # Dekads > RP-AVG - 2$^{nd}$ quartile | -0.001 | -0.005 | 0.047 | -0.040 |
| SS # Dekads > RP-AVG - 3$^{rd}$ quartile | -0.015 | 0.045 | 0.139** | 0.017 |
| SS # Dekads > RP-AVG - 4$^{th}$ quartile | 0.054 | 0.021 | 0.086 | -0.040 |
| $R^2$ | 0.353 | 0.352 | 0.354 | 0.353 |

Table 5: Value of own produced crops.

**Rainfall**

|  | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | 0.116 | 0.107 | -0.341* | -0.024 |
| RP-B-SD | 0.019 | -0.068 | -0.066 | -0.015 |
| SI shock: equable → extreme | 0.006 | 0.019 | 0.021 | 0.022 |
| SS Shortfall - $2^{nd}$ quartile | -0.020 | 0.004 | 0.065 | 0.018 |
| SS shortfall - $3^{rd}$ quartile | 0.055 | -0.035 | -0.009 | -0.044 |
| SS shortfall - $4^{th}$ quartile | 0.085 | -0.155** | -0.137** | -0.138** |
| RP-B-COV / 1983-2012 B-COV |  | 0.036 | -0.016 | 0.065 |

**Maximum temperature**

|  | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | -0.939 | -1.462 | 1.320** | 0.193 |
| RP-B-SD | -0.430** | -0.562** | 0.185 | -0.185* |
| SS # Dekads > RP-AVG - $2^{nd}$ quartile | 0.005 | -0.032 | -0.018 | -0.060 |
| SS # Dekads > RP-AVG - $3^{rd}$ quartile | -0.068 | -0.041 | -0.057 | -0.183** |
| SS # Dekads > RP-AVG - $4^{th}$ quartile | 0.055 | -0.046 | -0.030 | -0.159* |
| $R^2$ | 0.220 | 0.216 | 0.218 | 0.217 |

Table 6: Per-capita total expenditure.

**Rainfall**

|  | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | -0.647 | -0.329 | -0.074 | 0.215 |
| RP-B-SD | 0.077 | -0.018 | 0.274*** | 0.102** |
| SI shock: equable → extreme | 0.006 | 0.042 | -0.001 | 0.009 |
| SS Shortfall - 2$^{nd}$ quartile | -0.028 | -0.068 | -0.099 | 0.003 |
| SS shortfall - 3$^{rd}$ quartile | 0.040 | -0.002 | 0.074 | -0.049 |
| SS shortfall - 4$^{th}$ quartile | -0.024 | -0.110 | 0.010 | 0.006 |
| RP-B-COV / 1983-2012 B-COV |  | -0.218* | 0.035 | 0.092 |

**Maximum temperature**

|  | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | -0.091 | 1.355 | -1.597 | -1.174 |
| RP-B-SD | 0.470 | 0.533 | 0.206 | -0.089 |
| SS # Dekads > RP-AVG - 2$^{nd}$ quartile | 0.040 | 0.086 | 0.255*** | -0.000 |
| SS # Dekads > RP-AVG - 3$^{rd}$ quartile | -0.072 | 0.111 | 0.274** | 0.123 |
| SS # Dekads > RP-AVG - 4$^{th}$ quartile | 0.091 | 0.129 | 0.225** | -0.007 |
| $R^2$ | 0.233 | 0.234 | 0.236 | 0.234 |

Table 7: Food expenditure's share.

**Rainfall**

|  | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | -0.007 | 0.057 | -0.153 | -0.194** |
| RP-B-SD | 0.054 | 0.065 | -0.046 | -0.031* |
| SI shock: equable → extreme | -0.005 | -0.011 | -0.009 | -0.005 |
| SS Shortfall - 2$^{nd}$ quartile | -0.016 | 0.005 | 0.013 | -0.008 |
| SS shortfall - 3$^{rd}$ quartile | -0.020 | -0.039 | -0.046 | -0.000 |
| SS shortfall - 4$^{th}$ quartile | 0.018 | 0.023 | -0.059* | -0.031 |
| RP-B-COV / 1983-2012 B-COV |  | 0.018 | -0.045* | 0.007 |

**Maximum temperature**

|  | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | 0.305 | -0.416 | 0.682* | 0.396 |
| RP-B-SD | -0.112 | -0.177 | 0.053 | 0.036 |
| SS # Dekads > RP-AVG - 2$^{nd}$ quartile | -0.014 | -0.028 | -0.049 | -0.001 |
| SS # Dekads > RP-AVG - 3$^{rd}$ quartile | 0.008 | -0.020 | -0.085** | -0.041 |
| SS # Dekads > RP-AVG - 4$^{th}$ quartile | 0.027 | 0.031 | -0.029 | 0.024 |
| $R^2$ | 0.252 | 0.252 | 0.254 | 0.251 |

Table 8: Per-capita daily calories intake.

**Rainfall**

| | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | -0.086 | 0.453** | 0.308 | 0.334** |
| RP-B-SD | -0.201 | 0.085 | -0.073 | -0.008 |
| SI shock: equable $\rightarrow$ extreme | -0.000 | 0.030 | 0.017 | -0.003 |
| SS Shortfall - $2^{nd}$ quartile | -0.071* | -0.048 | 0.007 | -0.061 |
| SS shortfall - $3^{rd}$ quartile | -0.071 | -0.112** | -0.034 | 0.002 |
| SS shortfall - $4^{th}$ quartile | -0.183** | -0.108* | -0.019 | -0.059 |
| RP-B-COV / 1983-2012 B-COV | | -0.037 | 0.058 | -0.085 |

**Maximum temperature**

| | 25 years | 10 years | 5 years | 3 years |
|---|---|---|---|---|
| Inverse of RP-B-AVG | -0.196 | -1.679* | -0.856 | -0.944 |
| RP-B-SD | 0.180 | -0.204 | -0.066 | -0.080 |
| SS # Dekads > RP-AVG - $2^{nd}$ quartile | 0.021 | 0.001 | 0.017 | -0.108* |
| SS # Dekads > RP-AVG - $3^{rd}$ quartile | 0.053 | 0.065 | 0.086 | -0.139* |
| SS # Dekads > RP-AVG - $4^{th}$ quartile | 0.072 | -0.093 | -0.009 | -0.248*** |
| $R^2$ | 0.319 | 0.318 | 0.321 | 0.320 |

**Figures** – full list of figures can be available from authors

Figure 1: Marginal effect of rainfall AVG (mm) on per-capita gross total income by reference period.
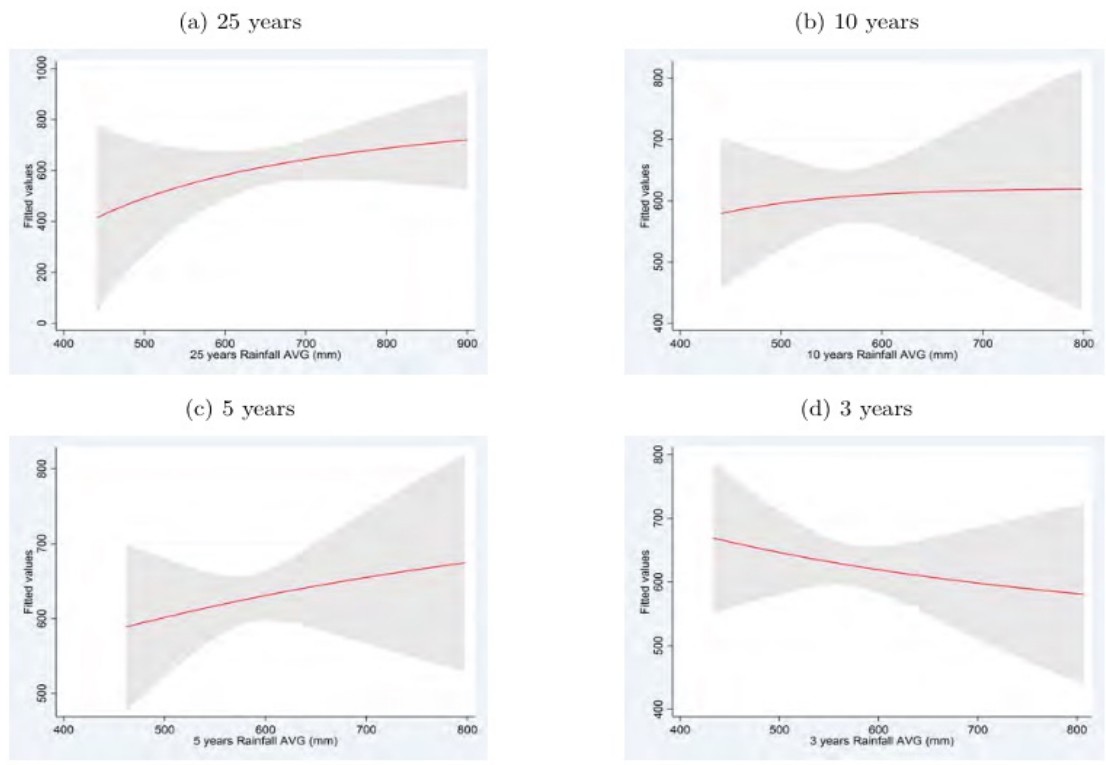


Figure 2: Marginal effect of rainfall AVG (mm) on per-capita food expenditure by reference period.
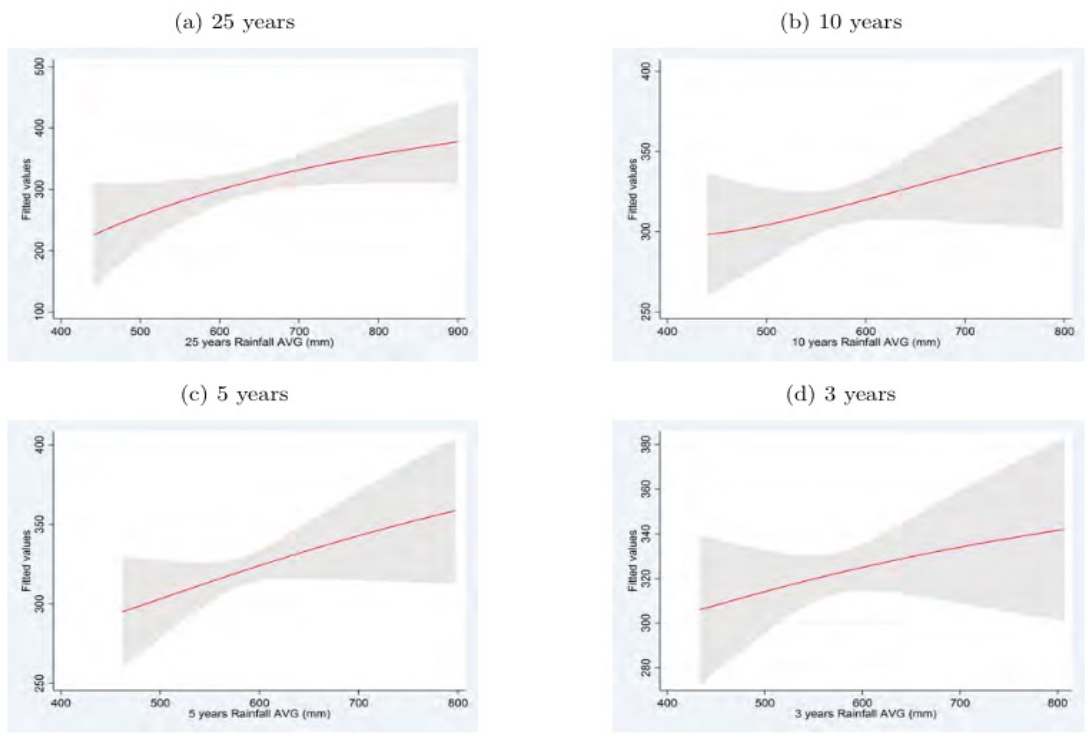
Figure 3: Marginal effect of rainfall AVG (mm) on Value of own produced crops by reference period.
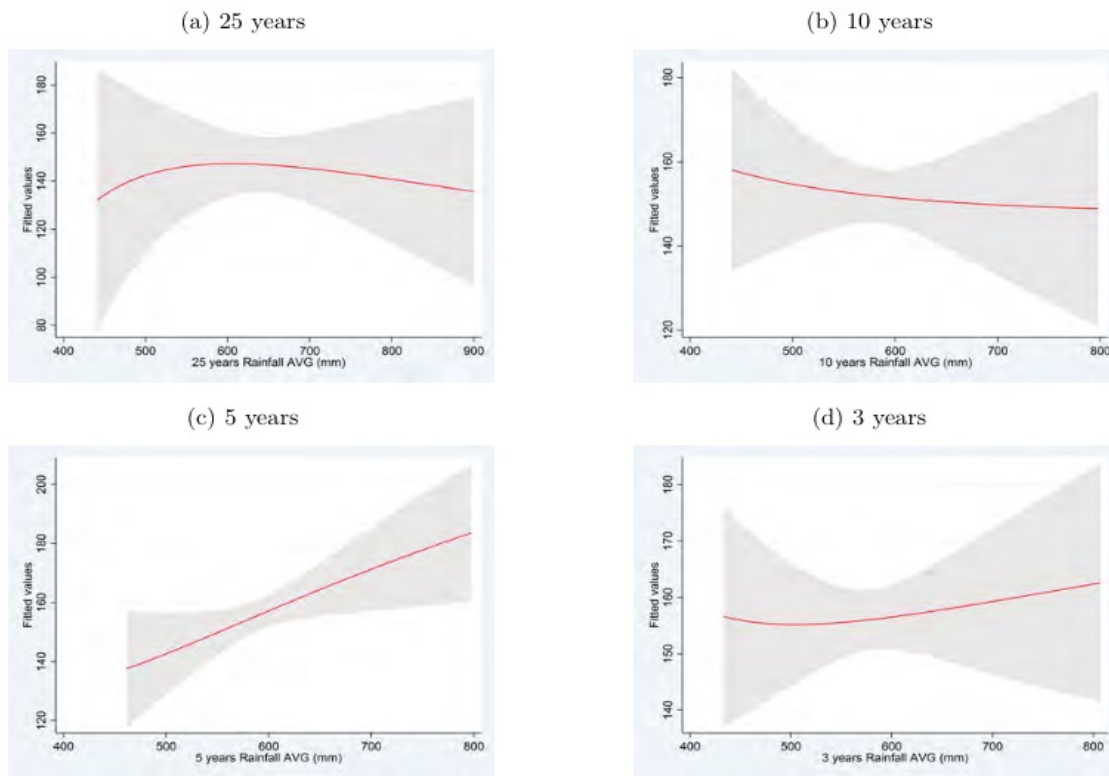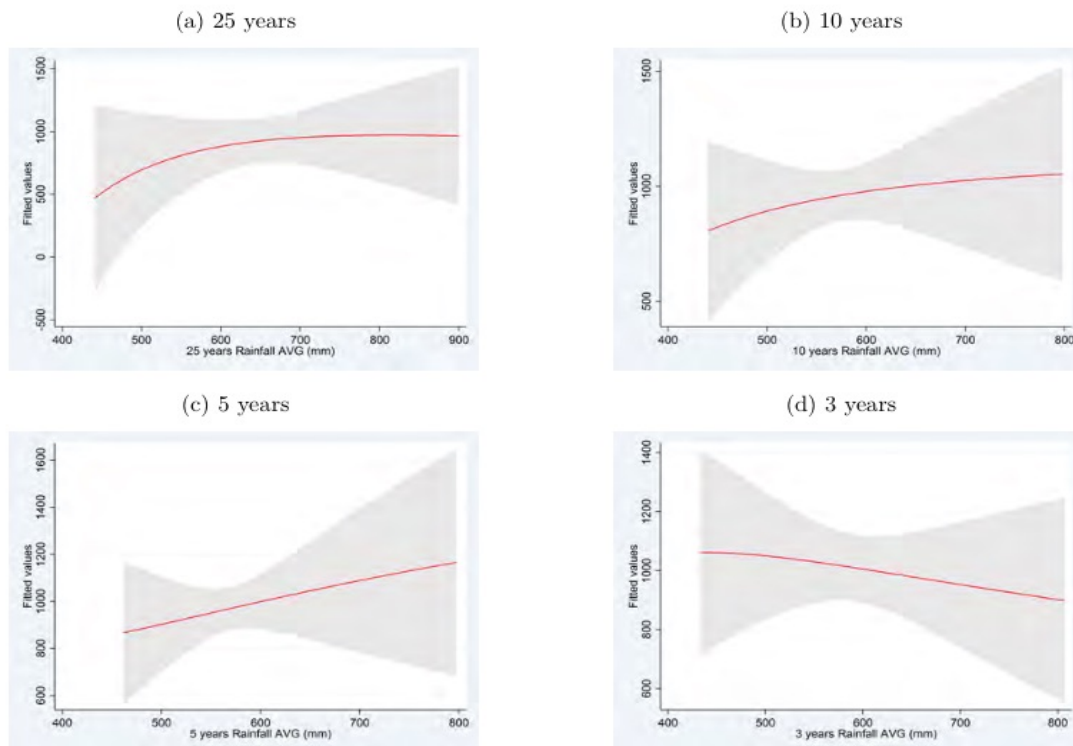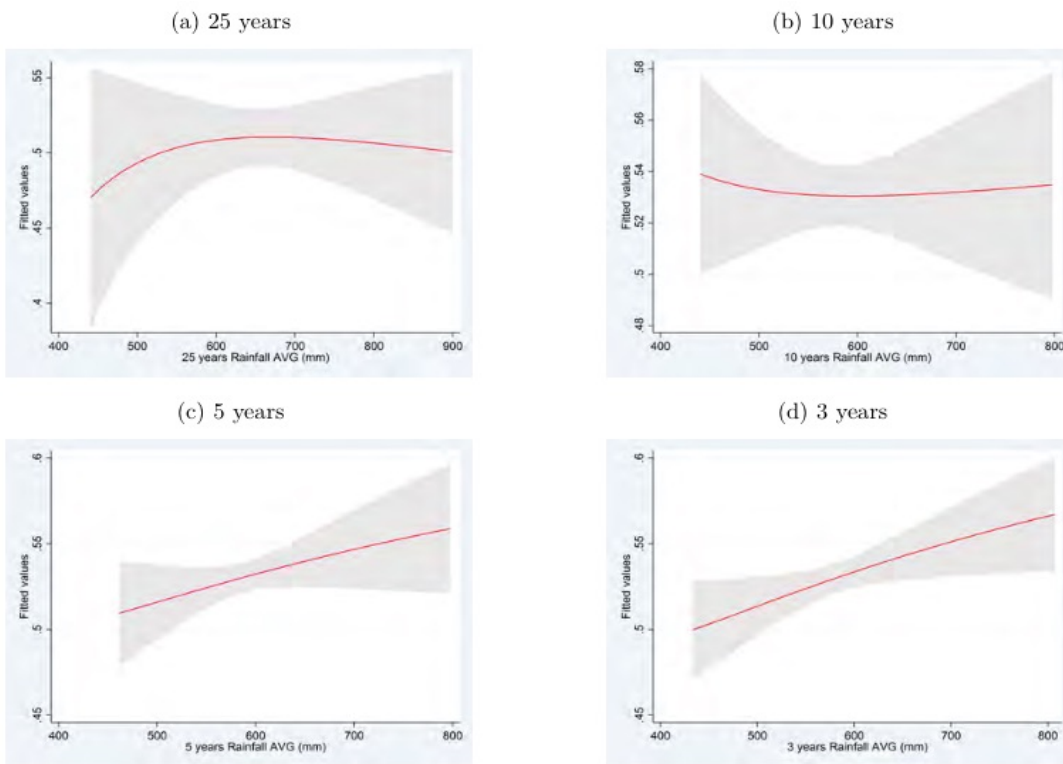


(a) 25 years

(b) 10 years

(c) 5 years

(d) 3 years

Figure 4: Marginal effect of rainfall AVG (mm) on per-capita total expenditure by reference period.



(a) 25 years

(b) 10 years

(c) 5 years

(d) 3 years

Figure 5: Marginal effect of rainfall AVG (mm) on food expenditure's share by reference period.



(a) 25 years

(b) 10 years

(c) 5 years

(d) 3 years

Figure 6: Marginal effect of rainfall AVG (mm) on per-capita daily calories intake by reference period.



(a) 25 years

(b) 10 years

(c) 5 years

(d) 3 years
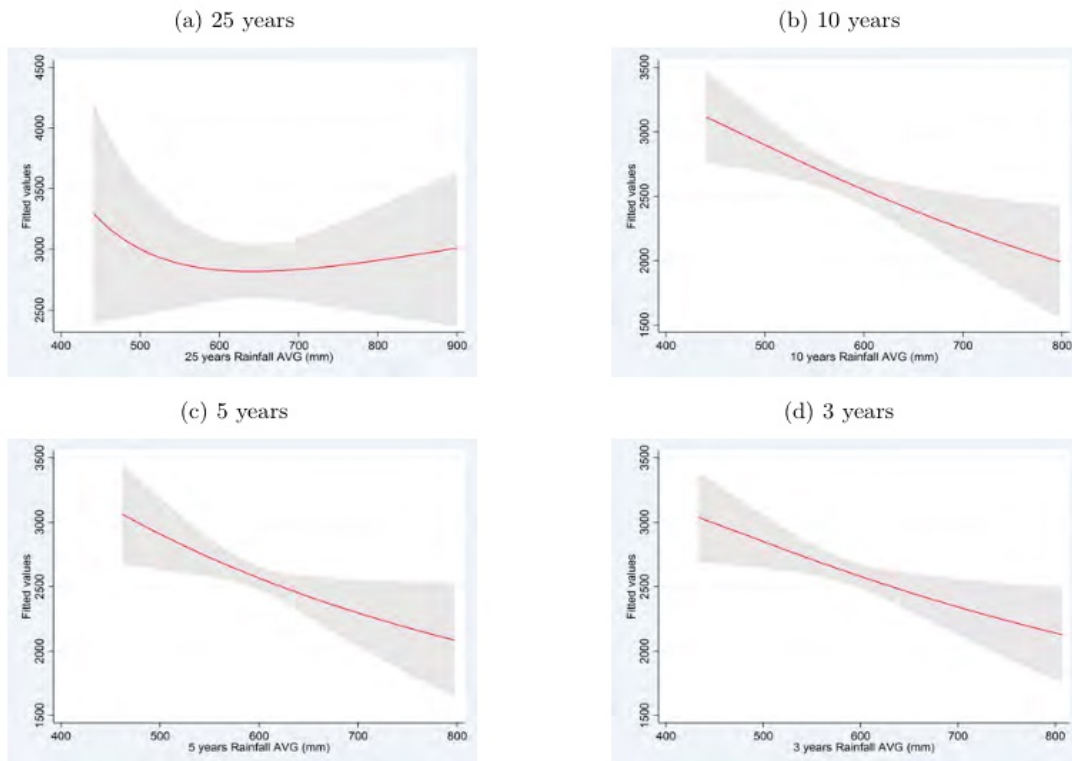
Figure 22: AVG Max Temperature (Average over waves)
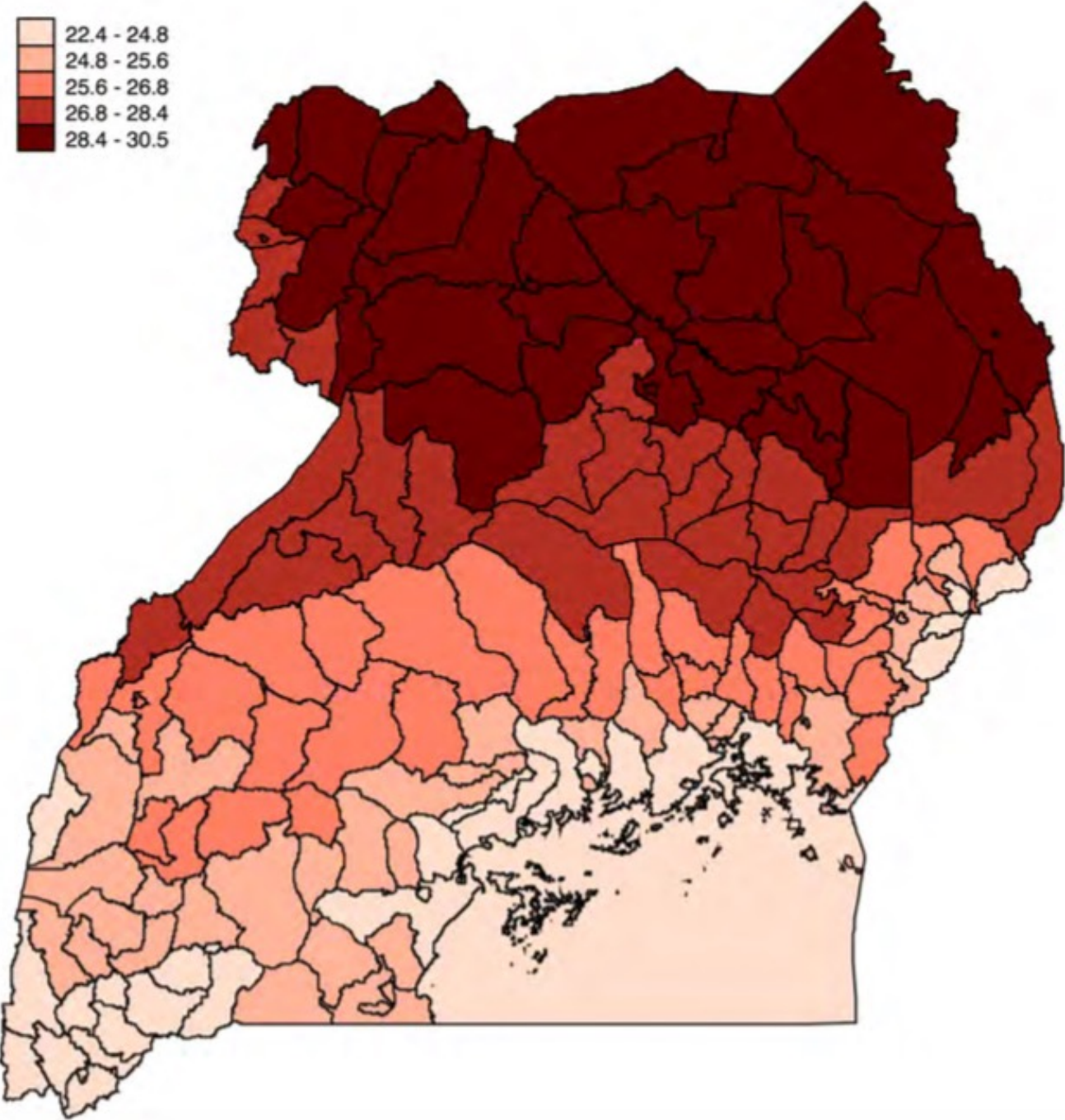


22.4 - 24.8
24.8 - 25.6
25.6 - 26.8
26.8 - 28.4
28.4 - 30.5

Figure 23: Total Rainfall (Average over waves)



Legend:
- 316.1 - 540.2
- 540.2 - 607.8
- 607.8 - 662.2
- 662.2 - 729.8
- 729.8 - 1073.6