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Climate Variability and Household Welfare Outcomes in Uganda

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Abstract

This study examines the impact of climate variability on household welfare outcomes in Uganda by combining long-term climate data (1979-2013) interpolated at household level, and six waves of the Uganda National Panel Survey (2009-2019). Pooled average ordinary least squares and random effects models are used for empirical analysis. The results indicate that climate variability has a significant nonlinear impact on household welfare outcomes. Access to extension services, value of household assets, education level, gender and location of the household head were also found to influence Uganda's household welfare outcomes. These findings, therefore, highlight the need for policy-makers to move swiftly to counter climate variability and its effects by designing and adopting appropriate measures that mitigate climate variability, and enhance household welfare outcomes among the people of Uganda.

Keywords: climate variability, household consumption expenditure, Uganda

JEL Codes: I31, Q12, Q54

1. Introduction

Recent empirical studies indicate that changes in global climate are likely to accelerate occurrences of environmental tragedies, including variability in precipitation and temperature among others (IPCC, 2012; 2018).[1] East African countries, like many countries in the tropics, are experiencing climate variability. For example, over the past two decades Uganda has, and still is, experiencing several climatic shocks ranging from floods, altered rainfall patterns, rising temperatures, landslides and prolonged dry seasons (Mubiru et al., 2018; UBOS, 2019). These shocks are likely to affect natural resources and all their dependants, including agriculture and human beings (Adhikari et al., 2015;Mubiru et al., 2018). Some studies have already projected that variability in climate will have a negative net impact on agricultural productivity in sub-Saharan Africa, and Uganda in particular (Oort & Zwart, 2018; Mwaura & Okoboi, 2014).

These climatic changes are likely to add more challenges to the already vulnerable groups, especially the rural farming households, hence posing a serious challenge to their livelihoods and the overall development aspirations of the country (Arslan et al., 2017; Lazzaroni, 2012). For instance, Uganda, registered a declining trend in poverty headcount ratios from 1999/00 to 2012/13 (Figure 1).

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[1] IPCC reports on Uganda's climate show an increasing trend in temperature and altered rainfall patterns.

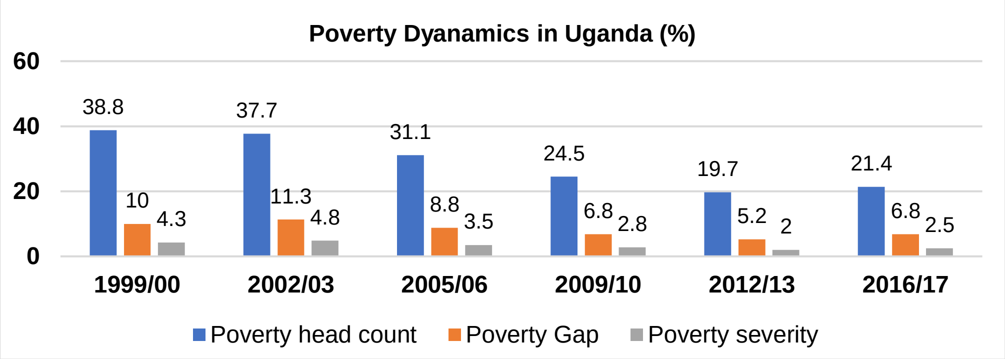

Figure 1: Changes in Poverty Status: Dynamic Perspective
Source: Uganda Bureau of Statistics (2018)

However, this trend changed between 2012/13 and 2016/17, where a rising trend was observed. This was mainly attributed to the unfavourable climatic changes, specifically the prolonged drought that was experienced in 2011 in many areas of Uganda, which negatively affected agricultural yields and thus household income levels (UBoS, 2017, 2018; Bank of Uganda, 2019).

Similarly, according to the Uganda National Panel Survey report for 2018/19, 338,520 (8.4 per cent) out of the projected 40.3m Ugandans slid back into poverty during the financial year 2018/19 alone. At the same time, poverty incidence is high in rural areas where a majority of the people depend on agriculture for survival (31 percent) compared to urban areas (15 percent). In terms of regions, Eastern Uganda has the highest poverty incidence of about 35.7 percent (Wossen et al., 2018; UBOS, 2019). Thus, there is need for a wider and deeper analysis to comprehend the reasons behind this rising poverty trend in Uganda. The findings of such a study will provide the required evidence to formulate appropriate, effective and targeted policy actions, interventions, and programs that are aimed at addressing climate variability and enhancing household welfare.

Currently, although a large body of poverty literature exists, there is a dearth of literature on household welfare implications of climate variability. And yet, the world's poor and the majority of the global rural population largely depend on agriculture for a living, and usually have inadequate reserves to fall back on in the event of a poor harvest (Skoufias et al., 2011; Yonas & Jonathan, 2013; Dzanku, 2015). Therefore, any manifestation that affects their seasonal harvest, automatically affects their welfare (Mwaura & Okoboi, 2014; Beliyou et al., 2018; Mwungu et al., 2019). Hence, climate variability is likely to expose millions of the world's most vulnerable people to hunger and poverty, slowing down the global efforts to achieve sustainable development goals (SDGs) 1 and 2[2] (IPCC, 2018).

[2]The SDGs were adopted in 2015 by the United Nations member countries to be achieved by 2030. SDG 1 is about eliminating poverty, while SDG 2 is about erasing hunger in the world by the year 2030.

This study combines across-sectional household survey data pooled over a period of 10 years and long-term climate data to estimate household welfare implications of climate variability, including its effect on household consumption expenditure in Uganda. This paper serves as a tool of not only supporting policy formulation and appropriate interventions in combating climate variability, but also building resilience among farming households by proposing pro-poor climate variability mitigation and adaptation measures.

The rest of the paper is arranged as follows. The next section presents a review of literature on climate variability and household welfare outcomes. This is followed by a section on the methodology and data used in the study. Section four presents the empirical results. Section five concludes the paper and presents policy recommendations and areas for further research.

2. Literature Review

Theoretically, climate variability impacts household welfare outcomes through direct and indirect channels (Slesnick, 1998; Skoufias et al., 2011). In the direct channel, climate variability affects household welfare outcomes through biophysical changes and market responses (Leichenko & O'Brien, 2008). Biophysical changes include changes in the state of the environment, for example, excessive floods and prolonged drought (high temperatures) that makes it hard for individuals to survive well in those areas, hence affecting their welfare (Lekobane & Seleka, 2017; Jha et al., 2017). Market response mainly results from variations in agricultural yields as a result of changing climatic conditions in a country (Amare et al., 2018). This in turn leads to changes in price, mainly for the food items, and income levels for those who depend on agriculture or nature for income (Hertel et al., 2010; Asfaw et al., 2016). Changes in prices and household income levels have direct implications on household welfare outcomes such as consumption smoothing, food security, and poverty status (Azzarri & Signorelli, 2020; Herrera et al., 2018; Vu & Glewwe, 2011). For example, evidence suggests that the occurrence of extreme climate variability events such as floods may force households to alter their resource distribution and optimal consumption path (Skoufias & Vinha, 2013; Tesfaye & Tirivayi, 2020).

On the other hand, the indirect channel is largely rooted in the vulnerability framework where climate variability makes households vulnerable to changes in their welfare and other livelihood aspects (Yonas & Jonathan, 2013;Dzanku, 2015). Vulnerability results from the presumed negative climate variability impact on households' livelihood sources such as agriculture (Asfaw et al., 2016; Mwungu et al., 2019). The agricultural sector, which employs the majority of the world's rural population, and agro-industries directly depend on nature, and are thus likely to be affected by variability in climate (Skoufias et al., 2011; Mwaura & Okoboi, 2014). For instance, it has been argued in the literature that countries more dependent on rain-fed agriculture are more exposed to negative economic consequences when experiencing climate shocks such as drought and altered rainfall patterns (Dell et al., 2012; Auffhammer & Schlenker, 2014). This is because extreme climate variability occurrences, such as prolonged drought, significantly decrease crop yields, thereby reducing total agricultural production and hence revenues, consequently reducing consumption and other welfare measures; eventually leading to arise in poverty (Yonas & Jonathan, 2013).

In addition, climate variability leads to income uncertainties as households are not certain of their returns, especially from the agricultural sector. This is best explained by the optimal expectations theory (Brunnermeier& Parker, 2005; Yonas & Jonathan, 2013). In the optimal expectations theory, households do not only care about their present wellbeing but also their future welfare (utility), which is largely determined by the beliefs about future circumstances (Wossen et al., 2018). The magnitude of the impact is likely to be worse among rural farming households given that their welfare largely depends on the reliability and availability of rainfall, and have limited or no insurance and adaptive capacity (Skoufias et al., 2011; Mulwa & Visser, 2020).

Considerable empirical works on welfare implications of variabilities in climate exist. For instance, through a survey of the existing literature and empirical analysis, Skoufias et al. (2011) discovered that changes in precipitation and temperatures affect households' agricultural incomes and other income sources in rural Mexico. This in turn affected the various household welfare outcomes including consumption, poverty, health and food security, leading to a general loss in welfare of household members. The study also projected that variabilities in climate will adversely affect global poverty reduction efforts, and might instead increase poverty levels especially in tropical countries. Similarly, still in Mexico, a study by Skoufias & Vinha (2013), using ordinary least squares,found climate variability impact on poverty to be regressive, affecting more the poor (mainly the rural population) than the rich. However, Yonas and Jonathan (2013), Herrera et al. (2018), and Azzarri and Signorelli (2020) found both food and non-food per capita household expenditures to be vulnerable to variabilities in climatic conditions, although this might vary across countries, and thus the need for country-specific empirical studies.

Skoufias and Vinha (2013) further established that experiencing a drought or flood during an agricultural season leads to large losses in both food and non-food consumption among households. The authors, however, noted that this depends on the climatic zone location of a household, and the season when the extreme climatic condition occur. In Kenya, Kabubo-Mariara et al. (2016) investigated the climate variability impacts on nutrition and food security using three waves of panel data (2004, 2007, and 2010). Employing a Ricardian approach, the study established a nonlinear impact of climate variability on household welfare outcomes, whereby small-scale farmers were more affected due to limited adaptation abilities and resources. Based on the study findings, the authors recommended the design of policies that encourage the adoption of advanced farming techniques as one of the appropriate mechanisms to adapt to climate variability. Earlier, Kabubo-Mariara (2009) had established that long-run changes in climate are likely to increase poverty, vulnerability, and loss of livelihoods among Kenyans. However, Kabubo-Mariara's (2009) study ignored households that rely on crop production for livelihood and survival.

In Uganda, using the trade-off examination model, Bagamba et al. (2012) explored the effects of weather variability on peoples' living conditions in three regions (Central, Greater Masaka, and Southwest). The study findings show that about 70-97 percent of households within the area of the study had their day-to-day living conditions negatively affected by variability in weather. Southwestern Uganda was the most affected region because of having many small-scale farmers with limited living alternatives and adaptive capacity as compared to Central Uganda. However, Bagamba et al.'s study (2012) ignored other regions of Uganda, and thus its results may not be generalized across the country. Earlier, Matovu and Buyinza (2010) had applied the computable general equilibrium (CGE) methodology to identify the impacts of climate variation on Uganda's growth and welfare. By combining climate data from the Uganda National Meteorological Authority (UNMA), household level survey data, and Uganda's social accounting matrix (SAM), Matovu and Buyinza (2010) established that unreliable rainfall and varying temperatures have a negative impact on people's income due to declines in agricultural yields. The study further projected that poverty in rural areas of Uganda would increase by 0.6% due to changes in climate. However, this study only uses poverty as a proxy household welfare indicator, and ignores other indicators such as the per adult equivalent household consumption expenditure, which is the widely recommended measure of welfare outcomes (Skoufias et al. 2011; Lekobane & Seleka, 2017).

In a study funded by the Food and Agricultural Organization (FAO) of the United Nations, Asfaw et al. (2016) evaluated the effect of weather shocks on household welfare outcomes using nationally representative data from the Uganda National Panel Survey (UNPS), together with a set of novel climate variation indicators. They estimated the data using the generalized least squares (GLS) random effects and quantile regression models, and established a negative impact of weather shocks on consumption and income smoothing behaviour of the households. Similarly, Beliyou et al. (2018) analysed the impact of climate variability on household monthly per capita expenditure in rural areas of Ghana, Tanzania, and Uganda. The study combined three sets of data: temperature data from 1950 to 2013 recorded on monthly basis, monthly precipitation data from 1981-2013 data, and household survey data from the three countries collected between 1998 and 2014. Their empirical results, using a short panel data, indicates a negative impact of higher mean precipitation levels on Uganda's per capita expenditure, and a positive impact on Tanzania's per capita expenditure. The analysis of pooled data over a period of ten years showed a positive impact of higher mean temperatures on per capita expenditure for Uganda and Ghana, but negative for Tanzania. However, this study ignored other forms of precipitation such as moisture, which plays a big role in influencing output from the agricultural sector.

Using trend equations and the Ricardian approach, Nkegbe and Kuunibe (2014) were able to show that variability in climate negatively affects incomes from agricultural activities and revenues from farms, and thus the general household welfare in Ghana. Their findings corroborates those established in Northern Ghana by Wossen and Berger (2014) using stimulation experiments. They both recommended economic diversification among households to hedge themselves against dangers posed by variability in climate. However, these studies were limited in scope as they ignored other regions of Ghana, hence making it difficult to generalize their findings. In Malawi, Asfaw & Maggio (2017) by combining three data sources (social economic panel survey, plot management, and ownership data from Malawi integrated panel survey (IHPS), and historical rainfall and temperature data), established that temperature shocks reduces consumption and increases poverty, especially among women, as compared to rainfall shocks. However, their study failed to establish any significant and consistent welfare implications of rainfall shocks in Malawi.

In Ethiopia, Yayeh and Leal (2017) show that variability in climate negatively affects income levels of about 80 percent farming households as a result of variations in their agricultural harvests. Their findings demonstrate the significance of individualizing climate variability studies in each country to identify areas and persons who are more exposed to climate variability and its impacts to aid the formulation of target policies and program interventions to alleviate the likely adverse effects of variability in climate on the welfare of the people in a particular country. Still in Ethiopia, Coromaldi (2020) investigated the impact of climate variability on rural farmers' welfare using socio-economic data from the Ethiopia Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) 2011/12, and a historical re-analysis of data on rainfall and temperature from the National Oceanic and Atmospheric Administration (NOAA), and the European Centre for Medium-Range Weather Forecasts (ECMWF), respectively. Using an instrumental variable technique, the study findings indicate that both rainfall and maximum temperature variability have a negative impact on household welfare outcomes (food security, consumption, and poverty). However, this study ignored other components of temperature, such as minimum temperature, which plays a big role in determining the overall surface temperature. Therefore, the findings makes it hard to generalize the impact of temperature variability on household welfare.

Applying a novel economic-climate investigation structure, Ahmed et al. (2009) examined climate volatility impacts on poverty in sixteen developing countries across the globe, and found that volatility in climate increases poverty in all countries under study; with urban areas being less affected as compared to rural areas of the countries under study. On the other hand, using primary survey data obtained from 825 farming households in India's Godavari river basin, Srinivasan et al. (2019) found climate variability to greatly affect household welfare outcomes. The study findings indicate that climate variability leads to an increase in poverty and worsens income inequality vacuum between the farming households and those involved in non-agricultural activities, such as the service and industrial sectors.

However, the main weakness of Srinivasan et al.'s (2019) study is that it only examined one form of climate variability: decline in the water levels of Godavari river, and ignored other forms of climate variability such as variations in temperature and precipitation.

In summary, therefore, given the increasing threats of adverse impact of climate variability on household welfare outcomes, especially consumption patterns and expenditure, there is a need for fresh evidence to aid the understanding of the impact and inform policy formulation. Some of the existing studies in Uganda such as Bagamba et al. (2012) did not use statistical data, but only depended on people's perceptions about climate variability; while Matovu & Buyinza (2010) ignored household consumption expenditure, which is relatively considered as the main indicator of household welfare outcomes. The lack of an up-to-date concrete evidence limits the understanding of the magnitude of the impact on household welfare outcomes, while households remain vulnerable to variability in climate and its effects. Inadequate evidence further reduces the ability of households to adapt to climate variability, and the government's efforts to design and implement effective and appropriate policy measures aimed at preventing or mitigating negative household welfare implications of climate variability. Thus, this paper seeks to investigate the magnitude and direction of the impact of climate variability on household welfare outcomes in Uganda with the objective that the generated evidence will aid targeted policy actions and interventions that smoothen consumption expenditure hence improving welfare; and at the same time combat climate variability and its impacts in the country.

3. Methodology

3.1 Theoretical Framework of the Study

The theoretical analysis of the impact of climate variability on welfare outcomes among households is based on the utility maximization theory, following the works of Deaton (1989) where a representative household maximizes its utility (welfare) subject to its budget constraint and variations in climate (Lekobane& Seleka, 2017; Vu & Glewwe, 2011). According to Deaton (1989), the social household welfare takes the form of a utility function as:

$$U_i = f(q_i, X_i) \quad (1)$$

Where U_i is a household's utility level, q_i is a vector of household consumption goods and services, while X_i is a vector of household welfare indicators, including non-income household characteristics such as the demographic, institutional, and climate factors (precipitation and temperature).

In this case, all households are assumed to have similar utility functions (Skoufias & Vinha, 2013; Lekobane & Seleka, 2017). Maximizing equation (1) subject to a budget constraint yields a utility maximizing consumption bundle at price P_i and total expenditure y_i as:

$$q_i = q(p_i, y_i, X_i) \quad (2)$$

Substituting equation (2) into equation (1) yields the household's indirect utility function:

$$V_i = v(p_i, y_i, X_i) \; (3)$$

Equation (3) gives the household's maximum welfare attained at given prices p_i, income levels y_i, and other household characteristics X_i, including variations in climate (Skoufias et al., 2011).

Inverting equation (3) gives the household expenditure function as:

$$E_i = e(u, p_i, X_i) \; (4)$$

The household expenditure function (equation 4) is the minimum cost of household welfare (u) for a given household i, attained at prices p_i and household welfare indicators (X_i), that also includes climate variability (C_i). However, prices (p_i) and welfare (u) are assumed fixed (Skoufias & Vinha, 2013), and hence household consumption expenditure (E_i) in this case is only influenced by X_i, which includes household and institutional factors (x_i) and climate variability factors (C_i).

Hence, equation (4) becomes:

$$E_i = e(x_i, C_i) \; (5)$$

Equation (5) forms the theoretical model of the study, which implies that household expenditure is influenced by household and institutional factors (x_i), and climate variability factors (C_i).

According to Deaton and Zaidi (1999) and Skoufias et al. (2011), household consumption expenditure is a satisfactory indicator of household welfare in developing countries. This is because it is reliable and better captures the long-run welfare losses than the current income (Deaton & Zaidi, 1999; Meyer et al., 2003). In addition, consumption expenditure is believed to capture other aspects of welfare such as income, food security, freedom, life expectancy, health and education (Skoufias et al., 2011; Skoufias & Quisumbing, 2007).

3.2 Empirical Model

Following the theoretical model in equation (5) and Skoufias et al. (2011), the empirical model of this study is specified as:

$$lnE_{it} = \alpha_0 + \theta_i C_{it} + \beta_i x_{it} + \varepsilon_{it} \; (6)$$

Where E_i is the per adult equivalent consumption expenditure for household i in period$t$, $C_i$is a vector of climate variability factors (precipitation variability $(PrecV)$ and temperature variability $(TempV)$. Temperature variability includes minimum temperature variability $(MinTempV)$, and maximum temperature variability $(MaxTempV)$.

Hence, $C_i = (PrecV, MinTempV, MaxTempV)$. x_i is a vector of other explanatory variables in the model such as age, location of the household, region, household assets, education level, marital status of the household head; and institutional factors such as access to extension services. α_0, θ_i and β_i are the model parameters to be estimated, while ε_{it} is the random disturbance term assumed to be normally distributed and uncorrelated with the model regressors.

To capture for the non-linearity impact of climate variability, this study includes quadratic terms of climate variability factors. The study also interacts precipitation variability with access to extension service to ascertain whether access to extension services by households can alter the precipitation variability impact on household welfare. Putting all these into consideration, equation (6) becomes:

$$lnE_{it} = \alpha_0 + \theta_1 PrecV_{it} + \theta_2 PrecV^2{}_{it} + \theta_3 MinTempV_{it} + \theta_4 MinTempV^2{}_{it} + \theta_5 MaxTempV_{it} + \theta_6 MaxTempV^2{}_{it} + \beta_i x_{it} + \gamma_1 (PrecV * Ext) + \varepsilon_{it} \quad (7)$$

where $PrecV$ is precipitation variability, $MinTempV$ is variability in minimum temperature, $MaxTempV$ is variability in maximum temperature, x_{it} is a vector of household characteristics such as gender, location, region, education , assets, marital status and access to extension services (Ext), which is an institutional variable.

In this case, the marginal effects of climate variability variables on household per adult equivalent consumption expenditure are obtained as follows:

$$\frac{\partial lnE_{it}}{\partial PrecV_{it}} = \theta_1 + 2\theta_2 Prec + \gamma_1 Ext \quad (8)$$

$$\frac{\partial lnE_{it}}{\partial MinTempV_{it}} = \theta_3 + 2\theta_4 MinTempV \quad (9)$$

$$\frac{\partial lnE_{it}}{\partial MaxTempV_{it}} = \theta_5 + 2\theta_6 MaxTempV + \cdots \quad (10)$$

The marginal effects are calculated at the mean values of climate variability variables. The marginal effects give the percentage change in per adult equivalent household consumption expenditure due to a small change in precipitation and temperature variability.

Pooled OLS, random effects, and fixed effects models can be used to estimate equations (6) and (7) depending on whether the panel is balanced or unbalanced, assumptions on the unobserved fixed effects, and the length of the panel (Hill et al., 2012; Nkegbe & Kuunibe, 2014). However, according to Baltagi (2013) and Hill et al. (2012), the fixed effects regression model is not efficient, and thus not recommended for unbalanced and short panels. Hence, this study uses pooled average OLS and random effects model to estimate the two models. In addition, both the pooled average OLS and random effects models accounts for correlation of observations over time for a given household (Green, 2012). To select between the two models, the Breusch-Pagan Lagrange multiplier test is used. The null hypothesis of the test is pooled OLS against the alternative hypothesis of random effects. Rejecting the null hypothesis implies that there are random effects, and hence the random effects model is appropriate (Hill et al., 2012; Baltagi, 2013).

3.2 Definition and Measurement of the Study Variables

Dependent Variable: Household welfare outcomes in this paper are measured by per adult equivallent household consumption expenditure (total household consumption expenditure divided by the number adult equivalents in a household - UBoS, 2018). It is a continous variable.

Independent Variables: Independent variables in this study are divided into three categories: Category one consists of the climate variability factors (precipitation and temperature (minimum and maximum) variability). The second category inculdes household characteristics such as gender, age, marital status, income level, household size, education level of household head, and location of household. The last category consists of the institutional and community variables, including access to extension services, market, and credit services. The definition measurements and expected impacts on per adult equivalent household consumptionexpenditure are presented in Table 1.

Table 1: Definition and Measurement of the Study Variables

Variable	Definition and Measurement	Expected Sign	Literature Source
Per household equivalent expenditure	Total household consumption expenditure divided by the number adult equivalents in a household.	Dependent variable	UBoS (2018)
Climate variability	Coefficient of variation averaged for 30 years for temperature (minimum and maximum) and precipitation	+/-	Wossen et al. (2018)
Sex of the household head	Dummy (=1 Male, 0 otherwise)	+/-	Hisali et al. (2011)
Age of the household head	Complete years	+/-	Guloba (2014)
Education of the HH head	Years of schooling	+	Hertel et al. (2010)
Marital status of HH head	Dummy (1 =Married, 0 otherwise)	+/-	Skoufias et al. (2011)
Household size	Number of people in household	+	Dzanku (2015)
Farm size	Plot size in acres	+	Guloba (2014)
Regional dummies	Central region (1 = Yes, 0 otherwise)[3] Eastern region (1=Yes,0 otherwise) Western region (1 = Yes, 0 otherwise) Northern region (1 = Yes, 0 otherwise)	-/+	Asfaw et al. (2016)
Location	Area of residence (=1 urban, 0, otherwise	+/-	Skoufias et al. (2011)

[3] Central region is the reference category

Land tenure	Land ownership (1= Formal, 0, otherwise	+	Beliyou et al. (2018)
Household assets	Value in Uganda shillings	+	Skoufias & Vinha (2013)
Access to credit	Dummy (1=Yes, 0, otherwise)	+	Dzanku (2015)
Access to market	Dummy (1 =Yes, 0, otherwise)	+/-	Skoufias et al. (2011)
Access to extension services	Dummy (1 =Yes, 0, otherwise)	+	Wossen et al. (2018)

3.4 Data Sources and Types

This paper uses two data types: household level survey data, and climate data. The household level data is part of several waves of the Uganda National Panel Survey (UNPS). The UNPS is a nationally representative data set, which is part of the Living Standards Measurement Study (LSMS) of the World Bank conducted by the Uganda Bureau of Statistics (UBoS). Each wave covers a period of twelve months to account for the seasonality associated with Uganda's agricultural sector, and the composition of consumption expenditure in a year. It is conducted in two visits to better capture agricultural outcomes associated with the two cropping seasons of the country. Each household is interviewed twice in a year with the two visits approximately six months apart. Therefore, the UNPS data provides an opportunity to understand the welfare dynamics at the household level.

The study makes use of six UNPS waves (2009/10, 2010/11, 2011/12, 2013/14, 2015/16, and 2018/19) with each wave covering an average of about 2,500 households with complete requisite data, giving a total study observations of about 12,500 households. These surveys contain information on household socio-economic, agricultural, and community data. The data set is big enough and reliable to guarantee a binding analysis, consistent, and efficient model estimates. On the other hand, the long-term climate data is sourced from the United States' National Oceanic and Atmospheric Administration (NOAA). The NOAA records data on all climate variables for most countries in the world on a daily basis.
However, in this study, the daily climate data are disaggregated into monthly and then annually data, before obtaining the coefficient of variation averaged for 30 years. This is done to align the climate data with the household level data. The climate data are then merged with the household level panel data, using household GPS information contained in the UNPS.

4. Empirical Findings

4.1 Descriptive Statistics

4.1.1 Household Consumption Expenditure and Poverty Trends (2009 – 2019)

Table 2 provides the summary statistics of the two household welfare indicators (household consumption per adult equivalent and poverty status) over the period 2009/10 to 2018/19.

Table 2: Summary Statistics of Household Welfare Outcomes

Welfare Indicator	Mean	Std. Dev.	Min	Max
Household Consumption expenditure per adult equivalent (shillings)	62001.76	98317.4	3380.6	5816762
Poverty status (= 1 if poor (below poverty line))	0.30	0.46	0	1

Source: Author's calculations based on UNPS data sets (2009/10-2018/19)

Table 2 shows that, on average, monthly household consumption expenditure per adult equivalent (welfare) is about UGX62,001.76 (US$17.7) for the period under study. According to the UNHS 2016/17 report, mean annual household expenditure marginally decreased from UGX328,200 (US$94) in 2012/13 to UGX325,800 (US$93) in 2016/17 (UBOS, 2017). A decline in consumption expenditure is associated with a decline in the welfare of the household members. Only 30% of the households in this study were below the poverty line, and thus categorized as poor. In Table 3, we disaggregate household poverty status by region from 2009 to 2019.

Table 3: Average Poverty Statistics by Region (2009 - 2019)

Region	Poverty Status		Total
	Non-poor	***Poor***	
	2,847	497	3,344
Central	85.14%	14.86%	100%
	2,223	1,352	3,575
Eastern	62.18%	37.82%	100%
	2,278	1,564	3,842
Northern	59.29%	40.71%	100%
	2,751	925	3,676
Western	74.84%	25.16%	100%
	10,099	**4,338**	**14,437**
Total	69.95%	30.05%	100%

Source*:* Author's calculations based on UNPS data sets (2009/10-2018/19)

Table 3 shows significant variations in average poverty incidences across the four regions of Uganda, with the Northern region having the highest percentage of households (40.7%) below the poverty line. It is closely followed by the Eastern region, with 37.8% of its households below the poverty line; while Western Uganda is third with 25.2% of the households below the poverty line. The central region, which also includes the Uganda's capital city, Kampala, has the lowest average poverty head count ratio of only 14.9%. This shows that there is an unequal distribution of income across the regions of Uganda. However, from the latest UNHS of 2016/17, Eastern Uganda had significantly the highest overall poverty rate of 35.7, which was higher than the national poverty rate of 21.4 percent. In the same report, 38.2 percent of children in the eastern region of Uganda live below the national poverty line (UBOS, 2019). Before 2016/17, Northern Uganda had the highest poverty rate mainly due to the prolonged civil war of the Lord's Resistance Army (LRA), which made the region lag behind others (Asfaw et al., 2016). The poverty incidence is higher in rural areas when compared to urban areas, with the rural areas (accounting for about 76 percent of the total population) contributing about 89 percent to the national poverty rate. Urban areas accommodate about 24 percent of the Ugandans, but contribute only 11 percent to the national poverty rate (UBOS, 2017; 2018; 2019).

Using the 2016/17 UNHS data, UBOS categorized Ugandans into three groups: poor, non-poor but insecure, and non-poor. The poor are those who live below the poverty line, while the non-poor but insecure are those who have adult equivalent expenditure that is less than double the poverty line. On the other hand, the non-poor are those whose adult equivalent consumption expenditure is greater than double the poverty line. These categories are shown in Table 4 following the 2016/17 UNHS report.

Table 4: 2016/17 Poverty Groups Based on UBOS Calculated Survey Weights

Poverty Status Group	Population	Frequency	Cum. Frequency
Poor	8,032,202	21.42	21.42
Non-poor but insecure	15,347,787	40.93	62.35
Non-poor	14,118,784	37.65	100.00
Total	**37,498,773**	**100.00**	

Source*:* Author's calculations based on UNHS 2016/17

Table 4 shows that only 21.4 percent of Ugandans were poor by the financial year 2016/17; out of the 37.5m Ugandans. However, the table further shows that 40.9 percent of Ugandans in the financial year 2016/17 were non-poor, but insecure. This implies that, although they are currently above the poverty line, they are vulnerable to poverty. In other words, these can easily fall back into poverty in the case of any slight shock in their source of livelihood. Examples of such shocks that may affect their income sources, especially those who depend on agriculture and nature, include floods, hailstorms, landslides, prolonged drought, altered rainfall patterns which are largely due to climate variability (Asfaw et al., 2016; Call et al., 2019;). Hence, cumulatively, 62.3 percent of Ugandans are vulnerable to poverty, and thus the need for evidence-based policy actions to fight against poverty and be able to achieve the second goal of the United Nations sustainable development goals. On a good note, 37.7 percent of Ugandans were non-poor and secure during the 2016/17 financial year, with a low likelihood of falling back into poverty. The regional distribution of head count poverty ratio, following the 2016/17 UNHS is shown in Appendix Figure 3 and it shows that high poverty rates are still found in the eastern and norther parts of country.

The summary statistics support the possibility of variability in precipitation with an average of 0.58, and this is higher than that of minimum and maximum temperature, all of which confirms the presence of climate variability in Uganda. This corroborates with what other scholars established over the presence of climate variability in the country (see, e.g.,Egeru, 2012; Nuwagaba & Namateefu, 2013).

Table 5: Summary Statistics of other Variables in the Analysis

Variable	Mean	Std. Dev.	Min	Max
Precipitation Variability	0.58	0.14	0.04	1.27
Min Temperature Variability	0.05	0.02	0.02	0.19
Max Temperature Variability	0.08	0.01	0.05	0.16
HH head Gender (=1 if Male, 0 otherwise)	0.71	0.45	0	1
HH head Age	48.15	15.28	14	100
HH head Marital status (=1 if married)	0.71	0.45	0	1
Location (=1 if Urban)	0.11	0.32	0	1
Lan tenure system (=1 formal, 0 otherwise	0.52	0.50	0	1
Education (years of schooling)	5.42	3.89	0	17
Household Assets (shillings)	48713.68	239222.70	0	1.67E+07
Land size (hectares)	2.70	16.56	0.01	820.6
Regional dummies				
Central	0.23	0.42	0	1
Eastern	0.25	0.43	0	1
Northern	0.27	0.44	0	1
Western	0.25	0.44	0	1
Market Access	0.85	0.35	0	1
Credit Access	0.75	0.43	0	1
Access to extension services	0.39	0.49	0	1

Source: Author's calculations based on UNPS data sets (2009/10-2018/19)

Table 5 shows that 71 percent of the household heads were male with an average age of 48 years, the youngest household head being 14 years. Only 11% of the households in this study are located in urban areas: a majority (89%) of them are located in rural areas. 52 percent of the households had formal land ownership, a positive step in ensuring improved land productivity and welfare among households (Urgessa, 2015). Northern Uganda had slightly more households (27 percent) as compared to other regions in the country.

On average, household heads had attained at least 5 years of education, which is equivalent to primary seven; and thus knew how to read and write. 85 percent of the households had access to market, while 75 percent had access to credit from various financial institutions in the country. However, only 39 percent of the households had access to agricultural extension services in the country. This is below the average, and thus the government of Uganda and all stakeholders concerned should ensure that at least 50 percent of the farming households in the country have easy access to extension services (Yonas & Jonathan, 2013). This is because extension services act as an engine of stimulating productivity among farmers (Asfaw et al., 2016).

Regression Results

This study estimates both pooled OLS and random effects regression models over the entire sample to assess the vulnerability of household consumption expenditure to variations in climate. The estimates from the two models are presented in Table 6. The robust standard errors are clustered at household level. This clustering corrects for the correlation between the omitted unobserved effects and the disturbance term (unobserved heteroscedasticity) over time for a particular household i. This is important in solving the problem of endogeneity and yields consistent and efficient model estimates.

Table 1: Regression Results
(Dependent Variable: Household Consumption Expenditure per Adult Equivalent)

Variables	**Pooled OLS Model**			**Random Effects Model**		
	1	**2**	**3**	**4**	**5**	**6**
Precipitation variability	1.345***	1.029***	1.200***	1.227***	1.099***	1.239***
	(0.316)	(0.285)	(0.289)	(0.217)	(0.220)	(0.224)
Precipitation variability squared	-0.752***	-0.575***	-0.575***	-0.717***	-0.635***	-0.628***
	(0.245)	(0.221)	(0.221)	(0.167)	(0.170)	(0.172)
Minimum temperature variability	-5.365***	-4.058***	-4.029***	-4.079***	-3.723***	-3.742***
	(1.730)	(1.358)	(1.364)	(0.994)	(1.006)	(1.011)
Minimum temp variability squared	42.242***	28.555**	28.692**	31.083***	28.371***	28.907***
	(15.868)	(12.130)	(12.197)	(8.813)	(8.941)	(8.996)
Maximum temperature variability	5.602	2.131	2.439	6.894***	5.824**	6.178**
	(3.742)	(3.276)	(3.274)	(2.425)	(2.510)	(2.498)
Maximum temp variability squared	-29.466	-8.656	-10.571	-38.701***	-31.922**	-34.094**
	(22.424)	(19.521)	(19.500)	(14.588)	(15.136)	(15.052)
Household head gender (male)		-0.131***	-0.130***		-0.088**	-0.088**
		(0.032)	(0.032)		(0.037)	(0.037)
Household head age		0.003	0.003		0.008*	0.008*
		(0.004)	(0.004)		(0.005)	(0.005)
Household age squared		0.000	0.000		-0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Marital status (married)		-0.060*	-0.059*		-0.041	-0.039
		(0.036)	(0.036)		(0.038)	(0.038)
Value of household assets		0.061***	0.060***		0.018***	0.017***
		(0.007)	(0.007)		(0.005)	(0.005)
HH head Education level (years)		0.062***	0.062***		0.048***	0.048***
		(0.003)	(0.003)		(0.004)	(0.004)
Land size (hectares)		0.012***	0.012***		0.001	0.001
		(0.004)	(0.004)		(0.004)	(0.004)
Land size squared		-0.000***	-0.000***		-0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Regional dummies						
Eastern region		-0.306***	-0.306***		-0.382***	-0.382***
		(0.038)	(0.038)		(0.036)	(0.036)

Northern region		-0.379***	-0.378***		-0.485***	-0.484***
		(0.039)	(0.039)		(0.038)	(0.038)
Western region		-0.185***	-0.184***		-0.178***	-0.178***
		(0.031)	(0.031)		(0.031)	(0.031)
Residential location (urban)		0.280***	0.280***		0.233***	0.233***
		(0.039)	(0.039)		(0.037)	(0.037)
Land tenure system (formal ownership)		0.090***	0.090***		0.034	0.033
		(0.029)	(0.029)		(0.029)	(0.029)
Access to extension services		-0.149***	0.076		-0.118***	0.072**
		(0.013)	(0.048)		(0.010)	(0.036)
Precipitation variability*Extension			-0.401***			-0.341***
			(0.083)			(0.063)
Constant	10.042***	9.465***	9.361***	10.077***	9.742***	9.648***
	(0.174)	(0.199)	(0.200)	(0.116)	(0.175)	(0.175)
Observations	12,601	11,854	11,854	12,601	11,854	11,854
R-squared	0.006	0.240	0.241			
F-statistic	12.55***	56.10**	54.57***			
BPLM Test: Var($v_i = \mu_i + \varepsilon_{it}$)[1]= 0				10668.4***	7003***	7023.5***

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations based on UNPS (2009-2019) and climate data (1979-2013)

[1]The error term has two components (unobserved individual effects μ_i assumed to be randomly distributed and independent of model regressors and the disturbance term ε_{it}). Rejecting the null hypothesis implies that RE is the appropriate model that is consistent with the data set (Hill et al., 2012).

The Breusch-Pagan Lagrange Multiplier test is used to choose between the pooled OLS and the random effects model. The results reject the null hypothesis that there are no random heterogeneity effects in the model at 1 percent level of confidence. This implies that the random effects (RE) model, and not the pooled OLS, is appropriate or consistent with the data set (Baltagi, 2013; Green, 2012). Hence, the essay discusses only the random effects model estimates (models 4, 5, and 6).

Discussion of the Findings

The results show a significant non-linear climate variability impact on per adult equivalent household consumption expenditure in Uganda. This is because the model estimates (coefficients) of both the linear and squared terms of precipitation and temperature variability are statistically significant. The findings indicate that variability in precipitation has a significant concave impact on household welfare per adult equivalent consumption expenditure, other factors remaining constant. This is shown by the statistically significant positive coefficient of the linear, and statistically significant negative coefficient of the squared terms of precipitation variability. This implies that variability in precipitation increases household consumption expenditure up to a certain threshold (precipitation variability = 0.26), and then it starts to decline. In other words, it is only extreme cases of variability in precipitation that may force households to reduce their consumption expenditure. According to Skoufias et al. (2011), Yonas and Jonathan (2013), and Asfaw et al. (2016), this is done as one of the ways of adapting to climate variability. In addition, extreme changes in climate variability directly affects agricultural yields, leading to a decline in both food items and income. This forces the households to cut down their consumption expenditures (Skoufias & Vinha, 2013; Hertel et al., 2010; Alem et al., 2010). However, this finding differs from that of a study by Asfaw and Maggio (2017) in Malawi, which established a non-significant precipitation variability impact on household consumption expenditure; and that of Herrera et al. (2018), which established only a negative impact of precipitation variability on household welfare.

Variability in minimum temperature has a significant convex relationship with household per adult equivalent consumption expenditure, other factors being constant. This finding implies that household consumption expenditure reduces with variability in minimum temperature up to a given point (minimum temperature variability = 3.8^{o}C). This, therefore, implies that it is the slight changes in minimum temperature variability that is associated with a fall in household consumption expenditure, and hence welfare. The finding is line with the projections of the IPCC (2014): that a 2^{0}C increase in temperature will be associated with about 0.2 – 2.0 percent loss in household economic activities, which will drastically affect their welfare. In the literature, the convex relationship between household welfare outcomes and changes in minimum temperature variability has been largely attributed to autonomous adaptation practices by households (Burke et al., 2015; Beliyou et al., 2018).

However, variability in maximum temperature has a hill-shaped relationship with per adult equivalent household expenditure in Uganda. The results show that slight changes in maximum temperature variability is associated with an increase in household per adult equivalent consumption expenditure, while excessive changes in maximum temperature variability is associated with a fall in household consumption expenditure. This corroborates with the findings of a global study by Burke et al., (2015), which showed that temperature and income have an inverted U-shaped pattern. In the literature, it is argued that excessive changes in temperature might be associated with the occurrence of pests and diseases that never used to occur. These pests and diseases affect both crop and livestock yields affecting household income levels, leading to a decline in their welfare outcomes such as consumption (Hertel et al., 2010; Lazzaroni, 2012).

The results further indicate that household consumption expenditure increases with years of education of the household head. Specifically, an extra year spent in school by a given household head increases welfare by 0.048 percentage points, other factors remaining constant. According to Skoufias et al. (2011), education is an indicator of human capital, which makes one more productive and capable of diversifying his/her income sources. It also enables a household head to easily find new opportunities as alternatives to agricultural income, as well as adapt to changing climatic conditions in a country (Beliyou et al., 2018).

Similarly, the findings show that welfare improves with the value of assets owned by a given household. A unit increase in the value of household assets increases per adult equivalent household consumption expenditure by 0.018 percentage points, other factors remaining constant. According to Dzanku (2015), the value of assets indicates the wealth status of a given household. Therefore, a household can use assets as a collateral security to obtain credit from a given financial institution to smoothen its consumption pattern, or start up non-farm income generating activities (Asfaw et al., 2016; Skoufias & Vinha, 2013).

In terms of regions, the findings indicate that the northern region suffered the largest decline in welfare, followed by the eastern region, and lastly the western region, as compared to the central region. However, it is important to note that all the three regions experienced a decline in welfare in comparison to the central region. Mwungu et al. (2019) also found out that northern Uganda was the most hit region by climate variability in the forms of prolonged dry seasons and floods that adversely affected agricultural yields; and thus income of farmers and all who depend on agriculture and nature. Similarly, households located in urban areas were associated with higher per adult equivalent expenditure in comparison to their counterparts in rural areas. Having a residence in an urban area increased welfare by 0.23 percentage points, as compared to being in rural areas. This finding corroborates with that of Skoufias et al. (2011) who attributed this to the fact that urban areas have a wide range of non-agricultural economic activities unlike in rural areas where the main activity is agriculture, which is highly vulnerable to climate variability and its effects.

Access to extension services increases household welfare by 0.07 percentage points. Extension services equip farming households with skills and information required to improve their productivity and income sources (Asfaw et al., 2016). Improved productivity and income sources imply improved welfare (Skoufias & Vinha, 2013). In addition, through extension services, households are able to adapt to changes in climate variability (Ali & Erenstein, 2017). The findings show that when farmers are given information on climate variability, they respond by reducing their consumption expenditure by 0.34 percentage points. This indicates a decline in welfare as result of getting information on climate variability, which is in line with the optimal expectations theory where households reacts to expectations about the future (Yonas & Jonathan, 2013). Households cut down their expenditures including that on consumption as a way of responding to variability in climate (Nelson et al., 2010; Lazzaroni, 2012).

5. Conclusion and Policy Implications

This paper has analysed the implications of climate variability on household welfare in Uganda using per adult equivalent household consumption expenditure as the welfare indicator. The results indicate that variability in precipitation has a hill-shaped relationship with household welfare, which implies that it is extreme changes in precipitation variability that negatively affects welfare. Thus, the results suggest that moderate changes in precipitation are associated with an increase in welfare through increasing per adult equivalent consumption expenditure. The literature shows that moderate variability in precipitation tend to favour agricultural production, unlike extreme cases that may lead to floods, heavy hailstorms, and landslides that greatly destroy crops and livestock; leading to income losses and thus a fall in welfare (Beliyou et al., 2018; Skoufias et al., 2011).

For temperature variability, its two components (minimum and maximum variability) have different impacts on consumption. The findings demonstrate that slight changes in minimum temperature variability leads to a decline in consumption, while marginal changes in maximum temperature variability are associated with an increase in welfare. It is argued that a slight change in minimum temperature leads to a change in the overall surface temperature (Asfaw et al., 2019). Reduction in consumption expenditure has been considered as one way of adapting to climate variability, and the fact that changes in temperature results into reduced agricultural production and income opportunities leading to a fall in welfare, while increased consumption expenditure due to excessive minimum temperature variability has been justified (Nkegbe & Kuunibe, 2014; Skoufias & Vinha, 2013; Dzanku, 2015). It is further argued that extreme climate variability events such as floods, landslides, and prolonged dry seasons threaten socio-economic progress with the capability of undermining economic gains achieved over the years (Mwungu et al., 2019). For example, due to floods and landslides, Uganda's household poverty head count ratio was projected to be 25% in 2020, up from 21.4% reported in 2017 (UBOS, 2019). Other factors that were found to influence household welfare in Uganda included location of a household (urban versus rural), gender of household head, value of household assets, and access to extension services.

Based on the findings, the study recommends that the government of Uganda subsidize all those programs that will encourage the adaptation to climate variability, such as subsidizing irrigation equipment that will ensure constant supply of water to agricultural farms. This will stabilize agricultural yields and incomes, and hence the welfare outcomes of households. Similarly, the government can introduce non-farming employment alternatives in all regions of Uganda, such encouraging equitable distribution of industries and resources across the country. This will reduce the over-dependence—especially of the rural population—on agriculture, which is highly vulnerable to climate variability and its effects. In addition, all policy actions should be gender-sensitive to ensure that both men and female-headed households benefit equally from them. In addition, the government should improve the accessibility of extension services in the country that is timely provision of relevant information such as climate variability, skills and ways of adapting to climate variability. Extension services should also provide households with an avenue to share information and ways of improving their productivity, income, and welfare; including forming saving groups that will help them smoothen consumption patterns in times of shocks, such as floods or prolonged droughts (Coromaldi, 2020).

However, this paper was unable to assess the impact of climate variability on demand for goods and services. An analysis of demand implications of climate variability is important to ascertain the magnitude and direction of the effect of climate variability on demand for goods and services—such as food staffs, durables and non-durable goods—in an economy. It also helps to obtain elasticities of demand with respect to climate variability for major goods in an economy. Thus, future studies can analyze demand implications of climate variability to close the existing gaps in the literature. Moreover, the study did not cover the impact of the adaptation to climate variability on household welfare, and what factors largely influence household's decision to adapt. This is also important to generate evidence to encourage adaptation among households, and the formulation of policies that are pro-adaptation. Given that the study's findings support the presence of climate variability in Uganda, adaptation could be the only appropriate response that could improve welfare. However, this requires scientific evidence that can only be obtained through conducting an empirical research.

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APPENDIX

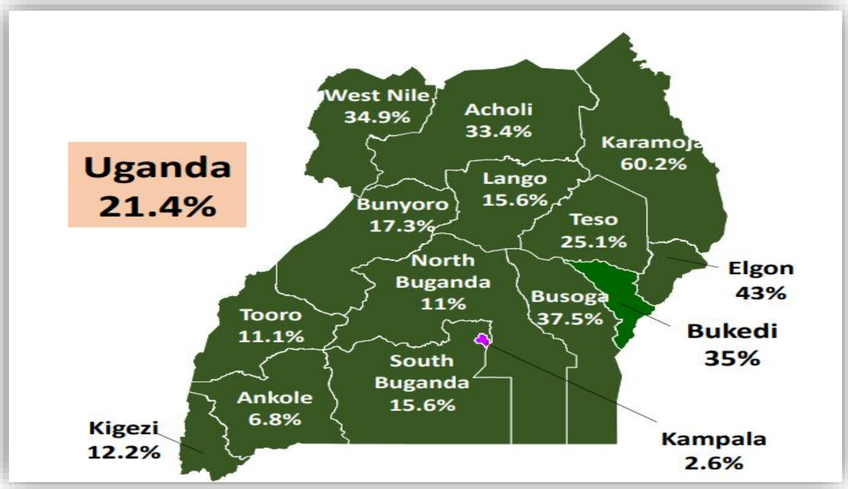

Figure A1: ***Map Showing Household Poverty Distribution in Uganda following 2016/17 Uganda National Household Survey (UNHS)***

Source: *Uganda Bureau of Statistics, 2020*