

Journal of Economic Policy and Management Issues

ISSN: 2958-6313 Volume 2, Issue 1, 2023, pp. 14-27

Climate change and household vulnerability to poverty in Uganda

H. Sebukeyera
National Planning Authority, Kampala, Uganda
Email: henrichsebs@gmail.com

I. Mukisa
Makerere University, School of Economics, Kampala, Uganda

E. Bbaale
Makerere University, School of Economics, Kampala, Uganda

Abstract

Keywords:

- Climate change
- Household vulnerability
- Poverty
- Uganda

Economic growth is expected to reduce poverty. However, Uganda has not leveraged its impressive growth outcomes to sustainably address the high poverty levels. This is particularly due to, among other factors, the high levels of vulnerability of household consumption patterns to climate change effects. Numerous studies indicate that Uganda is affected by variations in climate. However, the country ranks 48th in terms of preparedness and 14th in terms of vulnerability. This study investigates the effect of climate change on the vulnerability of Ugandan households to poverty. Using the Global Positioning System data, the study integrates data on changes in climate with six waves of data on household characteristics and vulnerability to poverty from the Uganda National Panel Survey between 2009 and 2019. The study estimates the binary panel using the pooled binary logit regression model. The results indicate that climate variability significantly affects the probability that a household will be vulnerable to poverty. In addition, household asset value, residence in urban or rural areas, household size, education status (highest level attained) of the household head, employment type, and household access to financial credit also influence the probability that households in Uganda will be vulnerable to poverty. The study, therefore, recommends policies that enable households to diversify employment from agriculture to service sectors, increase access to affordable financial credit, as well as support, increased investment in and popularisation of household risk hedging frameworks to reduce exposure to adverse effects of changes in climate and its bearing on household vulnerability to poverty.

1. Introduction

Economic growth is expected to reduce poverty (Toshihiro et al., 2001; Mansi et al., 2020). However, Uganda has not leveraged its impressive growth outcomes to sustainably address the high poverty levels. This is particularly due to the high household vulnerability to climate change. For example, Uganda's economy has been expanding, and in the financial year 2018/19, the economy grew by 6.5 percent from a growth of 6.2 percent in 2017/18, almost reaching the projected growth of 6.5 percent. However, in 2017/18, there was a reversal in the poverty status of the country. Poverty increased from 19.7% in 2012/13 to 21.4% in 2017/18 (UBOS, 2019) against an expected fall to 14.2% (GoU, 2015a). By 2021, poverty was 20.4%, way above the reduction levels in 2012/13. However, Hill & Mejía-Mantilla (2017) explain that the reduction in poverty and the many gains in agricultural income growth came about because of good weather. This trend is affirmed in a World Bank report which highlights that "Agricultural income growth particularly benefited poor households aided by peace in northern Uganda, improved regional markets, and good weather" World Bank (2016). This further underscores the utmost importance of climate change in reducing household vulnerability to poverty through its reduction.

The huge reversal and stagnation in poverty statistics over a medium-term period imply that most households are susceptible to poverty in Uganda. The country did not leverage these growth benefits in the form of reduced poverty. The long-term growth and poverty dynamics for Uganda are highlighted in Figures 1 and 2.

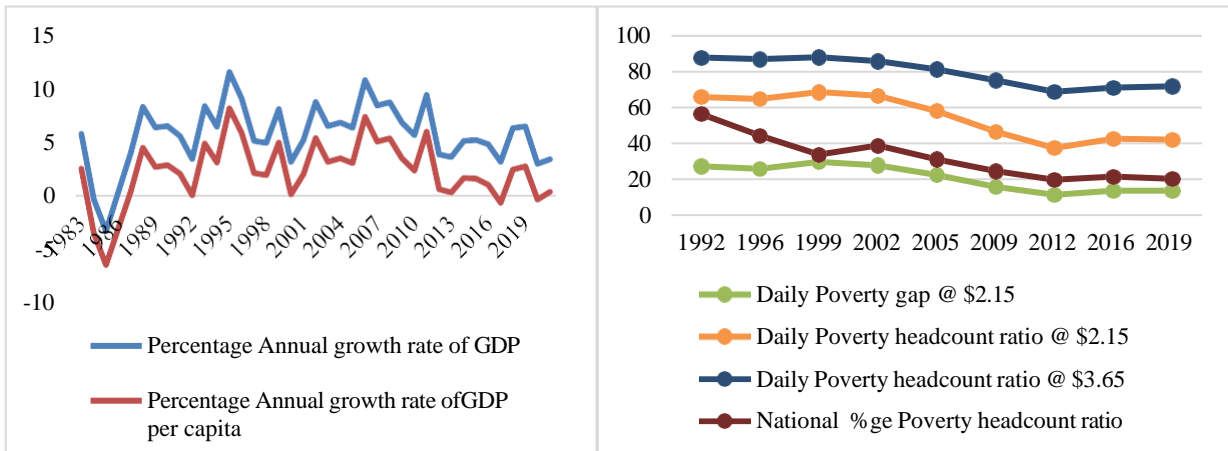


Figure 1: Poverty gap and daily headcount ratios are at 2017 PPP. Data Source: World Bank Development Indicators

According to UBOS (2021), between 2015 and 2020, 10% of Ugandans left poverty, 7.5% fell into poverty, and 6.5% remained chronically poor. The poverty cycle demonstrates the vulnerability of Ugandan households. Figure 1 shows that nearly half of Uganda's population lives on less than \$2.15 daily. The number of poor households is expected to rise due to climate-related consumption shocks. Relatedly, several studies, including Goulden (2008), USAID (2011), MoWE (2015) and Irish Aid (2017) provide compelling evidence for the prevalence of climate variability in Uganda. Despite this, the country ranks 155th out of 181 regarding climate vulnerability. Furthermore, Uganda is the 14th most vulnerable state and the 48th least prepared country for climatic variability regarding poverty, household food consumption, population health, water systems, and infrastructure (Ministry of Foreign Affairs of the Netherlands, 2018).

Various environmental factors influence the household's quality of life and contribute to climate variability. According to Aduralere et al., (2022), harmful emissions that promote climate variability have claimed the lives of seven million people in Western Africa. According to Abiud (2022), climate variability is a major concern for developing countries food security, and the author advocates smart farming techniques.

Indeed, long-term temperature and precipitation variations make Ugandan communities more vulnerable to poverty. Floods, prolonged droughts, and devastating landslides, among other things, are expected to have significant microeconomic consequences, such as an increase in households' susceptibility to total consumption, food security, and eventual poverty because most impoverished households lack adequate access to food. This means that these people are more vulnerable to starvation as a result of negative climate variations such as drought and flooding (Turyahabwe et al., 2013)

Unfortunately, there are few empirical studies on climate variability and household poverty in Uganda. Most previous research focused on the occurrence and causes of poverty. Others have investigated climate-related disasters in specific areas and sub-populations. This study investigates the impact of climate change on household poverty vulnerability in Uganda. The study uses GPS data, combining climate variability (precipitation/ rainfall variations) from the National Aeronautics and Space Administration (NASA)¹ with six waves of data on household characteristics and vulnerability to poverty from the Uganda National Panel Survey (UNPS).

The rest of this study is organised as follows. Section 2 provides the theoretical and empirical literature underpinning the study. Section 3 discusses the methodology and the estimated model. The empirical results and their interpretation are covered in Section 4, while the conclusion and policy implications are in section 5.

2. Review of literature

2.1 Theoretical review

This section presents theoretical literature measuring vulnerability to poverty and climate variability's effects. According to Luers, (2005), "vulnerability" has no universally accepted definition because it is used differently in different applications. According to Nkondze et al., (2013), vulnerability is defined as household stress caused by changes in social or environmental conditions that disrupt livelihoods. On the other hand, Sullivan et al., (2013) define vulnerability as the inability to withstand the negative consequences of exposure to strains or shocks due to environmental and social changes. Adzawla et al., (2020) define vulnerability as exposure, sensitivity, and adaptability to climate risk. Household vulnerability is assessed in a variety of ways. The most common measures of vulnerability are household Vulnerability

¹ NASA's Prediction of Worldwide Energy Resources

Expected Poverty (VEP), Low Expected Utility (VEU), and Uninsured Risk Exposure (VER) (Megersa, 2015). VEP was popularised by Chaudhuri et al., (2002a), Christiaensen and Subbarao, (2005) and Pritchett and Sumarto (2000), who emphasised the probability that future well-being will fall below the benchmark, which is the expected poverty. According to Chaudhuri et al. (2001), vulnerability is the chance that household consumption per capita will drop less than the poverty benchmark and/or line in the subsequent period, given several observable individual characteristics.

The VEP method categorises vulnerable people into high and low mean consumption groups (low vulnerability in consumption). High-consumption groups are particularly vulnerable. Due to a sizeable idiosyncratic shock, this high-consumption group may fall into poverty. This technique categorises the poor as chronically poor (expected consumption consistently lower than the poverty benchmark/line) or transient poor (expected consumption above the poverty benchmark/line). Poor or vulnerable people live in vulnerable households (Fujii, 2016b). The VEP approach is also used by Kamanou and Morduch, (2004) to measure vulnerability as the difference between the anticipated poverty and the present poverty. They apply the Monte-Carlo approach to estimate the likely possible results for individuals based on observed features and observed consumption variations of comparable individuals.

The VEU is the second approach, also referred to as a welfare approach (Fujii, 2016c). The technique emphasises the welfare/utility gap between a specific well-being metric and the expected level of the household. The method derives household happiness from consumption. According to Ligon and Schechter (2003), the VEU vulnerability concept is divided into three parts: cumulative (universal) risk, distinctive (individual) risk, and unexplained risk. Poverty accounted for nearly half of all vulnerabilities in actual investigations using this decomposition method. Poverty is the most common source of household vulnerability. Because different populations have different per capita consumption levels, this approach measures relative vulnerability rather than poverty (Ligon and Schechter, 2003). Elbers and Gunning (2003) employ the VEU technique in the Ramsey income and asset shocks model. Because this method considers future consumption, vulnerability is quantified by the impact of risk on mean and variance consumption.

The VER is the third approach which was famously employed by (Hooegeven, 2005) as an after-exposure assessment of the impact of an adverse shock on welfare loss. This measure is similar to the others in that it computes welfare and welfare losses when specific hazards are better and insured. However, its backward-looking methodology distinguishes it. This is a post-exposure estimate of how much a shock reduced welfare, not a pre-exposure assessment of expected (Hoddinott and Quisumbing, 2003).

According to Megersa (2015) the VEP framework is a widely accepted development economics concept. Furthermore, Chaudhuri et al. (2002a), Jalan and Ravallion (2005), and Tschay and Bauer (2012) have famously employed it. Rodgers and Rodgers (2009) and Rodgers et al., (2018) applied Rodgers' (1993) approach to measure vulnerability to poverty while Personal and Archive (2012) developed a measure of household vulnerability to poverty using the utility approach (VEU).

2.2 Empirical literature

This section summarises previous research on climate change and household poverty vulnerability. Furthermore, the section highlights several global, regional, and national findings to help fill the research gap.

Descheemaeker et al., (2019) investigated household sensitivity and coping strategies in rural Uganda. To assess the effect of rainfall and temperature on household susceptibility, the Eco-crop model and crop suitability maps were used. According to the report, 30% of families will experience a 3°C temperature increase and a 10% decrease in rainfall as crops become less suitable for growing places. Therefore, the study recommended that households protect their water supplies and grow drought-tolerant crops to adapt to rising temperatures, declining rainfall, and/or drought.

Twinomuhangi et al., (2021) investigated the perceptions and vulnerabilities of impoverished households in Kampala, Uganda. Using various techniques, climate change (increased temperatures and decreased rainfall), droughts, and floods were identified as climatic threats. The findings suggest that the head of household education, marital status, the primary source of income, and housing status all influence household climate change sensitivity. According to the study, flooding was the most dangerous in households with low wealth, low education, informal trades, and insecure housing.

Oriangi and Baldassarre (2020) investigated household resilience in Mbale, Uganda. The research examined how demographic and socio-economic factors influence household adaptation to climate-related hazards. Household resilience has been linked to social and familial bonds, non-governmental organisations, and small household sizes. According to an Irish-Aid (2018) study on climate risk in Uganda, the country is already experiencing climatic events that primarily affect agriculture. As a result, households are particularly vulnerable to droughts, floods, and landslides. In addition, the paper emphasises households' inability to tolerate climate variability.

Cooper and Wheeler (2017) investigated Ugandan rural households' vulnerability to climate risk. Their study used a mixed-method approach to assess subsistence farmers' vulnerability to climate variability hazards. Drought was the most concerning for wealthy farmers, while floods were the most concerning for low-income farmers. Households

can cope by storing food, growing drought-resistant crops, caring for animals, and planting drought-resistant cultivars. Similarly, Asfaw et al., (2016) investigated the impact of natural disasters on Ugandan households. The study attempted to investigate the impact of weather risk on the well-being of rural households. The study discovers only a few weather shock variables that are relevant. This is primarily due to the imprecision of the short panel data. Insignificant findings could imply that households unaffected by weather shocks smooth their consumption and income. Nkondze et al., (2013) used the household vulnerability index to investigate vulnerability to climate variability. The study made use of multinomial logistic regression. According to the study, the number of employed family members and family disease increase households' sensitivity to climate change. Furthermore, disease/morbidity exposure and occupation type are critical variables.

Diwakar and Lacroix (2021) investigated key correlates of poverty persistence and the consequences and coping strategies of climate-induced shocks and stressors in Niger, Tanzania, and Uganda. The authors relied on household panel data merged with data on subnational disasters across the three countries and employed multiple measures to capture disaster prevalence of droughts, floods, and epidemics, recorded variably at the household and subnational levels. Their multivariate regression analysis uncovered that environment shocks prolong poverty through direct biophysical impacts and indirectly through various negative consequences and distress coping mechanisms in which vulnerable households engage. These include reduced food consumption and food insecurity and reduced asset values. The authors recommend ensuring a supportive financial environment for poor households, alongside risk-informed policy and programming, would help alleviate key stressors that keep households persistently under the poverty line in contexts of climate-induced shocks and stressors.

To estimate the effects of weather conditions on welfare globally, cross-country comparisons need to rely on international poverty lines and comparable data sources at the micro-level (Azzarri and Signorelli, 2020). The authors sought to expand the existing knowledge on the determinants of poverty by examining how long-term climatic conditions and year-specific weather shocks affect expenditure per capita in 24 sub-Saharan African (SSA) countries. Their analysis relied on a linear and spatial model at the household and district levels, respectively, controlling for socio-economic, demographic, and geographic confounding factors. The authors found that results are consistent across econometric approaches, showing that living in more humid areas is positively associated with welfare and vice-versa. Given the heterogeneous effects of climatic events across SSA macro-regions, local-specific adaptation and mitigation strategies are suggested to help bring households on a sustainable path.

In addition, Hisali and Buyinza (2011) employed data from the 2005/06 Uganda national household survey to identify adaptation strategies and factors governing their choice in Uganda's agricultural production. The authors found that factors that mediate or hinder adaptation across different shocks and strategies include the age of the household head, access to credit and extension facilities and security of land tenure. There are also differences in the choice of adaptation strategies by agro-climatic zone. Therefore, the appropriate policy-level responses should complement the autonomous adaptation strategies by facilitating technology adoption and informing farmers about climate-related forecasts and available weather and pest-resistant varieties.

Cuevas (2018) investigated climate variability, risk, and vulnerability. The term "responsibility" refers to determining whether a person is responsible for their actions. There are four types of climate change: changeability, concentration, incidence, and amount. The vulnerability was identified in the socio-economic, biophysical, technical, and institutional domains. Finally, the study classified the threats into five categories: income, biodiversity, health, mortality, and infrastructure.

On the other hand, Bonnie et al., (2011) investigated the climate vulnerability of Eastern and Central Africa. The findings point to climate change in Eastern and Central Africa, including increased droughts, saturating rains, wildfires, desertification, and coastal erosion. Furthermore, the study emphasises political, social, economic, and demographic issues as important climate change determinants.

Climate unpredictability is mentioned in USAID's 2013 assessment of Uganda's climate vulnerability. The study employed a mixed-method approach that included past climate analyses and estimations, a value chain analysis of eight selected crops, and a review of how climatic variability influences agricultural growth and household life. The study discovered that current and projected climate patterns impact crop value chains and the well-being of dependent households. Climate unpredictability, according to several studies, increases poverty vulnerability, as Stringer (2013), Fujii (2016) and Oakes et al., (2016), and discovered that climate-related events increased the risk of household poverty. These studies demonstrate the role of economic diversification in reducing household climate change risk.

3. Methodology

The methodology highlighted in this section estimates the effect of climate change and/or variability on household poverty vulnerability in Uganda. In addition, this section further delves deeper into the study's theoretical and empirical techniques, model specifications, data, and sources.

3.1 Theoretical framework

The theoretical framework of utility maximisation is applied to evaluate the effect of climate variability on household poverty vulnerability. A household maximises utility in a given period but is subject to some constraints, given income and commodity prices within the consumption basket. Haughton and Khandker (2016) provide a theoretical framework for analysing household susceptibility to poverty. However, this household vulnerability can be determined/ estimated by examining changes in well-being, which begin with changes in per capita consumption. Consequently, poverty vulnerability can only be measured through simplified assumptions.

Measuring household poverty vulnerability requires calculating the probability that the household will slip into poverty under specific conditions. Therefore, it is critical to estimate the poverty line, which we denote as (z), expected household consumption in the next period, which can be denoted by $E(c_{t+1})$, and the variations of the expected and/or future consumption, which is denoted by (σ^2). With this information and the assumption that household consumption per capita follows a normal distribution, the likelihood that a household would be poor, expressed as (V_{ht}), can be estimated. Poverty vulnerability is theoretically due to either low levels of expected/ future consumption or substantial variation in consumption. Therefore according to Haughton and Khandker (2016), the possibility of a household being poor in the next period defines the household's vulnerability. Therefore, the distinction between poverty and poverty vulnerability is that. In contrast, poverty measures whether or not one has previously fallen below the poverty line, and poverty vulnerability measures the possibility of dropping into poverty in the future. As a result, vulnerability is a forward-looking concept that measures "poverty exposure rather than poverty outcome".

Let $c_{h,t}$ be the household h 's individual level of consumption at the time denoted t and z denote the poverty line in a one-period case. Then a household is poor if and only if the condition below is met:

$$c_{h,t} \leq z \quad (1)$$

Define the household h 's vulnerability at a particular period t to be denoted by $V_{h,t}$, which defines the likelihood that that particular household will slip into poverty at the next period $t+1$. This is represented as equation 2:

$$V_{h,t} = Pr (c_{h,t+1} \leq z) \quad (2)$$

However, it is essential to note that, being a futuristic expectation, consumption of the household in the next period denoted by $c_{h,t+1}$ cannot be observed directly. This is because it just symbolises the household's consumption level expectation in some future period. Therefore, what is essential in the estimation is to determine how actually to measure $V_{h,t+1}$.

The task of measuring vulnerability to poverty would necessitate knowing the following information for each household:

i) what resource endowments they will possess in the coming year/ period, including assets like land, educational endowments as well as skills and expertise; ii) what type of risky factors households are faced with such as prolonged lack of rainfall/ drought, price increases for essential consumption items, the morbidity of family members, among others; the likelihood of occurrence for each combination of risk factors that they face ("states of the world"); and the expected effect that each of the combinations of risk factors is likely to have on their resources. This assumption is critical in our estimation since it is the one that allows us to incorporate the impact of climate change/variability into the vulnerability equation; and iii) the ability of the household to deal with each combination of risks—for example, by depleting food supplies, counting on backup social networks provided by the family system, credit access and/or borrowing finances/ money, or increasing the hours of work to increase earnings. This is what examines household and individual coping strategies.

Three pieces of information are necessary to complete this modelling: i) the household's expected individual level of consumption in the future period, represented by $E(c_{h,t+1})$. The future estimated level of (expected) consumption follows a normal distribution, and the distribution is known, for example, the Gaussian distribution; ii) the variation of the household's expected individual level of consumption in the future time period is denoted by σ^2 ; iii) and the poverty level, Z .

Haughton and Khandker (2016) extend this by assuming that the future consumption level follows a normal/ Gaussian distribution. Therefore, with shocks to individual consumption that is normally distributed, households may still be susceptible even though their future consumption is predicted to be high if the variation in consumption is substantial enough. As a result, poverty vulnerability might result from either low consumption or large consumption variability. Even though a household's future consumption is uncertain, it is possible to obtain a representative

approximation/ measure by initially building a model of factors that determine the level of consumption, after which the model can be applied to estimate future/ next period level of consumption.

Consequently, the consumption of a household at a present period of time t can be represented by equation 3 as:

$$c_{h,t} = c(X_h, \beta_t, \alpha_h, \varepsilon_{ht}) \tag{3}$$

X_h is a set indicating noticeable characteristics of a household, such as the age of the head of the household and their level of education, and the size of the particular household, among several others; β_t is a vector of macroeconomic variables which measures the impacts of macroeconomic shocks, such as changes/ variability in climate, unfavourable business cycles in the form of economic depressions (financial crisis or a radical/political conflict and/or a revolution) that a household faces; α_h represents any unobserved household-specific variables and/or factors that do not change with time, for example, the individual abilities and inabilities of household members; ε_{ht} is the error-term which estimates household-specific “idiosyncratic/ distinctive” factors, which are principally shocks that are likely to affect one household without necessarily affecting another household. The error variance may vary significantly among the different households between different periods.

In view of the above and with measurement of that relationship, including the variance of future/subsequent period consumption, then vulnerability can be represented by equation 4 as:

$$v_{h,t} = Pr. (c_{h,t+1} = c(X_h, \beta_{t+1}, \alpha_h, \varepsilon_{h,t+1}) < z \mid X_h, \beta_t, \alpha_h, \varepsilon_{h,t}) \tag{4}$$

Then a modest form of equation (4) can be analysed using data from one cross-section, as Chaudhuri et al. (2002) did. They estimate a household consumption model expressed in equation (5):

$$\ln C_h = X_h b + \varepsilon_h \tag{5}$$

In which

$$\varepsilon_h \sim N(0, X_h \theta) \tag{6}$$

In practice, this entails estimating the log of individual consumption on a vector of independent factors/ variables to obtain the projected coefficients expressed in equation (5). Other modifications are undertaken to obtain a measure of individual-specific variance for each household. In particular, by getting the square root of the residuals from equation 6 and regressing those squared residuals of the same set of independent variables, we can calculate the coefficient θ and thus the estimated variance from X_h θ.

Assuming that the independent/ explanatory variables (education of household head, household size, and many others) do not change significantly between various periods, it is possible to estimate the log of expected consumption (as projected by equation (5)) and the consumption log standard deviation (as forecast by equation (6)) and thus build a measure of susceptibility/vulnerability to poverty for each of the households.

3.2 Empirical model and estimation criteria

The study estimates the empirical model on the effects of climate change (variability in precipitation) on household vulnerability to poverty using the theoretical model presented above.

This being a dummy variable, it is estimated by a binary logistic model specified as follows:

$$P \left(Y_{h,t} = \frac{1}{X} \right) = P \left(X' \beta + \varepsilon > \frac{0}{X} \right) \dots \dots \dots 7)$$

Where Y_{h,t} = 1, if the household is classified as vulnerable and 0, otherwise. The error term is assumed to follow a logistic distribution. As the theoretical model predicted, x is a vector of regressors, including climate change indicators (precipitation variability).

After estimating model 7, marginal effects, $\frac{dP(Y_{h,t}=1/X)}{dx}$ are generated to express the effect of regressors on the probability of a household deteriorating into poverty. Regarding estimation criteria, the study employs the logit regression model to estimate the binary panel. It is preferred because it allows for unobserved time-invariant individual heterogeneity, such as choice variation with an arbitrary distribution (Greene, 2012). The time-dependent correction between the deleted/lost unobserved effects and the error term (unseen heteroscedasticity) is corrected by clustering the robust standard errors at the household level. Furthermore, it accounts for any potential heteroscedasticity that may arise and influence the exactness and accuracy of the estimates of the model. The study analyses the impact of climate change on household per adult equivalent expenditure to test the robustness of our findings. The welfare indicator is simply the expenditure per household consumption.

$$\text{Inc}_{it} = b_1\text{ppt}_{it} + b_2\text{tempt}_{it} + b_3H_{it} + b_4I_{it} + (e_{ht} + \alpha_h) \quad (8)$$

Where c_{it} represents per household consumption of household i at time t ; ppt_{it} represents precipitation recorded at various periods for household i ; tempt_{it} represents temperature recorded at various periods for at least 30 years by household i ; H_h Represents household indicators that would affect consumption; I Represents institution factors that would affect household consumption. Both random and fixed effects can be employed to estimate this model, and the Hausman specification test is used to select the most suitable between the two models.

3.3 Definition and measurement of study variables

This analysis makes use of data from the Uganda National Panel Survey (UNPS) and NASA's "Prediction of Worldwide Energy Resources (POWER)." The UNPS data sets are national in scope and include information on household characteristics, women, agriculture, and community. The UNPS is carried out by the Uganda Bureau of Statistics (UBOS) using World Bank and Food and Agricultural Organisation (FAO) "Living Standards Measurement Study Integrated Surveys on Agriculture (LSMS-ISA)" microdata. It includes 2009/10, 2010/11, 2011/12, 2013/14, 2015/16, and 2018/19. These data include information on poverty and consumption. It also provides GPS data, which combines survey and climatic data.

NASA's "Prediction of Worldwide Energy Resources" provided temperature and precipitation data for Uganda from 1981 to 2019. This website provides reliable meteorological data to help boost renewable energy, improve building energy efficiency, and meet agricultural demands. Using Global Positioning System (GPS) data from a panel survey, two data sets were interpolated at the household level.

3.3.1 Dependent variable

The vulnerability of Household Consumption Expenditure is the dependent variable measured in Uganda Shillings but will be categorised as a binary variable of vulnerable (=1) and non-vulnerable (=0). This is consistent with the Uganda Bureau of Statistics (UBOS) definition of vulnerable, which includes people living below the poverty line and households with less than double the benchmark/poverty line in terms of consumption expenditure per adult. Conversely, non-vulnerable people have a consumption expenditure per adult that is more than twice the poverty line (UBOS, 2018).

3.3.2 Independent variables

Table 1 presents the explanatory variables for the study. The table highlights the variable definition, measurement and expected sign illustrating the possible effect on the dependent variable.

Table 1: Definition of independent variables

Variable	Variable description	Expected sign	Data source
Climate variability	Mean and coefficient of precipitation variation averaged from 1981 to 2020.	-/+	NASA Power data
Education of the household head	Measured by dummies with (1 = Yes, 0 otherwise) for the different levels: No education, some primary completed primary, some secondary, completed secondary and post-secondary levels.	+/-	UBOS
Household residence	1=Urban and 0= Rural	-/+	UBOS
Household head's sex	A dummy variable for the household head's sex is 1= male, 2 = female.	+/-	UBOS
Primary employment sector	= 1 if agriculture; = 2 if industry/manufacturing and self-employed; = 3 if service sector.	+/_	UBOS
Household size	= Number of individuals in a particular household	-/+	UBOS
Access to credit	Dummy 1 = Yes with access, 0, otherwise with no access.	+/-	UBOS
Household assets	= value of total household assets in Uganda shillings	-	UBOS

4. Empirical results

This section presents the descriptive and empirical results following the estimation and data analysis technique. The results and findings thus follow in the subsequent sub-sections. Finally, the section presents the descriptive statistics and the empirical results of the estimated models as described in the methodology section.

4.1 Descriptive statistics

This section presents the summary descriptive statistics of the study variables. Table 2 indicates that Uganda's climate is varying noticeably, given that the coefficient of variation for all climate variables is non-zero. However, precipitation seems to vary more than temperature. This is because the coefficient of variation for precipitation is more significant than that of temperature. The summary statistics also show that the precipitation averages 1398.02mm between 1980 and 2021 across the country.

Table 2: Summary statistics of the study variables

Variable	Observation	Mean	Std. Dev	Min	Max
Climate variability	15,292	0.0499272	0.0174943	0.0250883	0.131883
Mean precipitation	15,292	1398.021	264.914	596.842	1944.63
Value of HH Assets	15,292	691011	2.05E+07	0	1.50E+09
Access to credit	15,292	0.7849202	0.4108911	0	1
Household main employment sector					
Agriculture	15,292	0.7594821	0.427412	0	1
Industry	15,292	0.0432906	0.2035172	0	1
Services	15,292	0.1972273	0.3979184	0	1
HH Head marital status					
Married monogamy	15,282	0.6336867	0.4818123	0	1
Married polygamy	15,282	0.1635257	0.3698567	0	1
Divorced	15,282	0.0637351	0.2442885	0	1
Widow/ Widower	15,282	0.1300222	0.3363389	0	1
Never married	15,282	0.0090302	0.0946006	0	1
HH Size	15,292	10.35528	12.38887	1	65
HH residence (Urban)	15,292	0.1346456	0.3413558	0	1
Sex of HH head (male)	15,292	0.7038321	0.4565809	0	1
Education level of the HH head					
No formal education	15,292	0.1836908	0.3872445	0	1
Some primary education	15,292	0.4083835	0.4915508	0	1
Completed primary	15,292	0.1447162	0.351826	0	1
Some secondary	15,292	0.1413157	0.3483583	0	1
Completed secondary	15,292	0.0577426	0.2332637	0	1
Post-secondary education plus	15,292	0.0641512	0.2450301	0	1
HH head age (years)	15,292	42.98489	18.78721	14	100
HH vulnerability	15,292	0.82	0.38	0	1
Welfare (per household consumption expenditure (UGX))	15,292	75530.27	1019526	3380.598	1.26E+08
Region					
Central	15,292	0.2369213	0.4252075	0	1
Eastern	15,292	0.2554277	0.4361156	0	1
Northern	15,292	0.2616401	0.439542	0	1
Western	15,292	0.246011	0.4306991	0	1
Panel waves					
2009/10	15,292	0.2587628	0.4379693	0	1
2010/11	15,292	0.2616401	0.439542	0	1
2011/12	15,292	0.2261967	0.4183816	0	1
2013/14	15,292	0.0465603	0.210702	0	1
2015/16	15,292	0.159299	0.3659666	0	1
2018/19	15,292	0.0475412	0.2128004	0	1

Regarding access to credit, 78 percent of households had access to credit facilities. Additionally, 76% of household heads were farmers. Only 4% of family heads work in the manufacturing industry. Agriculture suffers significantly from climate change due to its reliance on nature (MFPED, 2010).

The majority of family heads (79%) were either monogamous (63%) or polygamous (16%), and the average household had ten members. Most households (87%) were rural, and 70% of the heads were male. Only 18% of household heads were uneducated, while 82% were. The average age of the head of a household was 41. In addition, 51% of households were highly vulnerable, 32%, and 17% were non-vulnerable.

4.2 The impact of climate change on household vulnerability to poverty

Since household poverty vulnerability is defined as a dummy variable (Vulnerability status = 1 if vulnerable, and zero otherwise), we estimate the model using pooled binary logit regression technique in a panel setting. The analysis explains the likelihood of a household falling into poverty with changes in climate change variables. The findings of this analysis are presented in Table 3.

Table 3: Impact of climate variability on household vulnerability to poverty

Dependent variable: Vulnerability	Coefficients	Marginal effects (dy/dx)
Climate Variability	0.0003** (0.0001)	0.00002** (0.00001)
Household asset value	-0.1260*** (0.0234)	-0.0090*** (0.0017)
Residence (urban)	-1.9241*** (0.1672)	-0.1369*** (0.0110)
Household size	0.0750*** (0.0106)	0.0053*** (0.0007)
Household level education level (base- no education)		
Some Primary	-0.9519*** (0.2018)	-0.0547*** (0.0107)
Completed Primary	-1.2278*** (0.2537)	-0.0736*** (0.0153)
Some secondary	-2.4563*** (0.2572)	-0.1750*** (0.0175)
Completed Secondary	-2.9078*** (0.3147)	-0.2187*** (0.0257)
Post-secondary	-4.6054*** (0.3289)	-0.4019*** (0.0274)
Gender of household head (male)	1.1741*** (0.1503)	0.0835*** (0.0103)
Main household occupation (Base: Agriculture)		
Industrial sector	-0.3934 (0.2937)	-0.0288 (0.0223)
Service sector	-0.4464*** (0.1568)	-0.0328*** (0.0119)
Access to credit	-0.2389** (0.0988)	-0.0170** (0.0070)
Constant	4.4185*** (0.3868)	
Observations	15,147	15,147
Number of Households	4,660	
Wald chi2(13)	507.11***	

Standard errors in parentheses; *** p<0.01, ** p<0.05, and * p<0.1

The results indicate that climate variability significantly affects the probability of a household falling into poverty. A one percentage point rise in precipitation increases the chance of the household's vulnerability by 0.0002% holding other factors constant. These findings are consistent with those of Munyai et al., (2019), who found a significant impact of extreme rainfall variations in the form of floods on household vulnerability and the need for adaptation mechanisms, Descheemaeker et al., (2019) that found smallholder farmers being vulnerable to rainfall variability, and Oyebola et al., (2021) highlights the increased vulnerability of fish farmers to flood-related climate hazards.

A household's poverty risk decreases as its assets increase. The greater the size of a household's assets, the less vulnerable it is. A one percentage point increase in the value of assets increases the probability of vulnerability by 0.009%. These findings are consistent with earlier studies by Chaudhuri (2003). According to the report, a household's current poverty level may not predict its future poverty. The study emphasises the importance of investigating household susceptibility to poverty and how the value of household assets affects this vulnerability because assets serve as insurance against poor vulnerability conditions.

When compared to rural living, urban living reduces the risk of poverty. According to the study, urban households reduce the risk of poverty by 0.1369%. These results are consistent with Nguyen et al., (2015) who investigated the relationship between migration, poverty vulnerability, and rural household welfare in three Central Vietnamese provinces. The authors found that migration, particularly for employment, is a means of coping with agronomic and economic shocks for rural households. It reduced poverty and vulnerability in both migrant and non-migrant households.

Household education (education for the head of the household) reduces poverty vulnerability. When the head of the household has some primary education, poverty vulnerability is reduced by 0.0547%. Compared to no education, primary education reduces the risk of poverty by 0.0736%. The likelihood of being vulnerable to poverty decreases by 0.175% when the household head has some secondary education. The likelihood of being vulnerable to poverty decreases by 0.2187% when the household head has completed secondary school. Compared to no formal education, post-secondary education reduces poverty risk by 0.4019%. The findings on education are consistent with those of Chaudhuri et al., (2002b): households headed by unschooled individuals are at high risk and vulnerable. As a result, increased education reduces the risk of poverty.

Female-headed households are more vulnerable to poverty than male-headed ones. Poverty risk rises by 0.0835% when the household head is a woman; furthermore, for every unit increase in household size increases, household vulnerability to poverty increases by 0.0053%.

The occupation of the household head (farm, industry, or services) influences poverty vulnerability. For example, when the household head works in the services sector, the vulnerability to poverty is reduced by 0.0328% compared to the agriculture sector.

Access to credit has an impact on the vulnerability of households to poverty. Poverty risk decreases by 0.017% for every unit increase in household credit availability. This is beneficial (Koomson et al., 2020). The study looked at the impact of financial inclusion on poverty and vulnerability in Ghanaian families. Increasing a household's financial inclusion (access to credit) reduces its risk of becoming poor by 27% and its exposure to future poverty by 28%.

4.3 Robustness of findings

To check the robustness of our findings, the study estimates the impact of climate change on household per adult equivalent expenditure (See Appendix 1). The Hausman specification test results indicate that the fixed effects model is the preferred model, thus consistent with our data set. According to the results in Table 1 of the appendices, the estimation results are reliable in Table 3 and are indeed robust. Rainfall has an impact on the well-being of households. A change in precipitation affects household per adult equivalent consumer expenditure (household welfare) by 0.0006%. Precipitation shocks reduce agricultural output; therefore, if families cannot insure against this risk in returns, they may reduce consumption. These findings are consistent with those of Oriangi et al., (2020), Twinomuhangi et al., (2021) and Babyenda et al., (2021) and. In addition, this study confirms previous findings that a change in precipitation increases the likelihood of a household being poor and particularly vulnerable to poverty Cooper and Wheeler (2017) and Wichern et al., (2019).

5. Conclusions and policy implications

The primary objective of this study was to analyse the impact of climate change on poverty in Uganda. The study combines NASA's Prediction of Worldwide Energy Resources (POWER) long-term climate data with six waves of data from UBOS's UNPS between 2009 and 2019. Using GPS data from a panel survey, interpolation was performed at the household level. The binary panel is calculated using the pooled binary logit regression model.

The findings suggest that precipitation has an impact on the vulnerability of households to poverty. Poor rainfall

distribution affects a household's vulnerability to poverty. According to the study climate change influences a household's vulnerability to poverty. Poverty vulnerability in Uganda is influenced by household asset value, urban or rural residency, household size, head of household education, work type, and access to credit. The study recommends policies that enable increased investment and popularisation of household risk hedging frameworks to mitigate climate change's influence on household poverty vulnerability. Agricultural insurance is a popular risk-hedging tool. However, more agricultural insurance is needed to limit agriculturists' susceptibility to climate variability. Several Ugandan households face climate risks. Despite frameworks like agriculture insurance, small-scale farmers aren't covered. Farmers must be educated on these frameworks to boost access and use for reduced climate risk. The study recommends measures that enable households to diversify employment from agriculture to services. In particular, policies boost agriculture's commercialisation and lower the number of farm households. According to the study, employment in services and industries improves household poverty vulnerability. As a result, value chain investments that increase the commercialisation of agriculture, increase agro industrialisation and lower the proportion of labour employed in the agricultural sector will be critical in reducing household vulnerability to poverty.

References

- Abiud, J. B. 2022. Welfare Effects of Farming Household's Usage of Combination of Climate Smart Agriculture Practises in the Southern Highlands of Tanzania. *African Journal of Economic Review*, 10(March), 88–100.
- Aduralere, O. Oyelade; O. Maku, E, and Oluwafemi, O. 2022. The Effect of CO 2 Emissions on Quality of Life in Anglophone Countries in West Africa. *African Journal of Economic Review January 2022*, 10(1), 27–41.
- Adzawla, W. Azumah, S. B. Anani, P. Y. and Donkoh, S. A. 2020. Analysis of farm households' perceived climate change impacts, vulnerability and resilience in Ghana. *Scientific African*, 8, e00397. <https://doi.org/10.1016/j.sciaf.2020.e00397>
- Asfaw, S. Arslan, A. and Lipper, L. 2016. *Welfare impacts of climate shock Evidence from Uganda. May 2016*. <https://doi.org/10.13140/RG.2.1.4581.7200>
- Azzarri C. and Signorelli, S. 2020. Climate and poverty in Africa South of the Sahara. *World Development*, Vol. 125, ISSN 0305-750X DOI. <https://doi.org/10.1016/j.worlddev.2019.104691>
- Babyenda, P., Kabubo-Mariara, J., and Odhiambo, S. 2021. *Climate Variability and Household Welfare Outcomes in Uganda Climate Variability and Household Welfare Outcomes in Uganda. August*.
- Bonnie, D; Grajeda E. Phillips P, and Atul, S. 2011. Vulnerability to Climate Change: An Assessment of East and Central Africa. *Climate Change and African Political Stability, August*.
- Chaudhuri, S., Suryahadi, A., and Jalan, J. 2001. *Assessing household vulnerability to poverty from cross-sectional data : a methodology and estimates from Indonesia. May*. <https://doi.org/10.13140/RG.2.1.2126.7360>
- Chaudhuri, S. 2003. Assessing vulnerability to poverty : concepts, empirical methods and illustrative examples. *Department of Economics*, http://info.worldbank.org/etools/docs/library/97185/keny_0304/ke_0304/vulnerability-assessment.pdf
- Chaudhuri, S., Jalan, J. and Suryahadi, A. 2002a. Assessing Household Vulnerability to Poverty from Cross-sectional Data: A Methodology and Estimates from Indonesia. *World*, 0102–52(April), 36.
- Chaudhuri, S., Jalan, J., and Suryahadi, A. 2002b. Assessing Household Vulnerability to Poverty from Cross-sectional Data: A Methodology and Estimates from Indonesia. *World*, 0102–52(April), 36. http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?db=pubmed&cmd=Retrieve&dopt=AbstractPlus&list_uids=6086807498683160254related:vpYxytuyvFQJ
- Christiaensen, L., Boisvert, R., and Hoddinott, J. 2000. Validating Operational Food Insecurity Indicators Against a Dynamic Benchmark: Evidence from Mali. In *World Bank Policy Research Working Paper* (Issue 2471).
- Christiaensen, L. J. and Subbarao, K. 2005. Towards an understanding of household vulnerability in rural Kenya. *Journal of African Economies*, 14(4), 520–558. <https://doi.org/10.1093/jae/eji008>
- Cooper, S. J., and Wheeler, T. 2017. Rural household vulnerability to climate risk in Uganda. *Regional Environmental Change*, 17(3), 649–663. <https://doi.org/10.1007/s10113-016-1049-5>
- Cuevas, S. C. 2011. *Climate change, vulnerability, and risk linkages* (Issue June). <https://doi.org/10.1108/17568691111107934>

- Diwakar, V., Albert, J. R. G., and Flor, J. 2019. *Resilience, near poverty and vulnerability dynamics: Evidence from Uganda and the Philippines*. February.
- Diwakar, V., and Lacroix, A. 2021. Climate shocks and poverty persistence: Investigating consequences and coping strategies in Niger, Tanzania, and Uganda. *Sustainable Development*, 29, 552–570. <https://doi.org/10.1002/sd.2200>
- Elbers, C., and Gunning, J. W. 2003. Vulnerability in a Stochastic Dynamic Model. *Tinbergen Institute, Discussion Paper No. 2003-070/2*.
- Fang, Y.Z.C., Rasul, G., and Wahid M., S. 2016. *Rural household vulnerability and strategies for improvement: An empirical analysis based on time series*. Habitat International.
- Fujii, T. 2016a. Climate change and vulnerability to poverty: An empirical investigation in rural Indonesia. *The Asian "Poverty Miracle": Impressive Accomplishments or Incomplete Achievements?* 622, 118–145. <https://doi.org/10.4337/9781785369155>
- Fujii, T. 2016b. *Concepts and Measurement of Vulnerability to Poverty: A review of Literature*. 611.
- Fujii, T. 2016c. Concepts and measurement of vulnerability to poverty and other issues: A literature review. In *The Asian "Poverty Miracle": Impressive Accomplishments or Incomplete Achievements?* <https://doi.org/10.4337/9781785369155>
- Goulden, M. 2008. *Climate Change in Uganda : Understanding the implications and appraising the response Scoping Mission for DFID Uganda July 2008*. July.
- NPA. 2015. Second National Development Plan - Uganda. *National Planning Authority Uganda*, 1(2), 65–70. <https://doi.org/10.1111/j.1475-6773.2006.00624.x>
- Greene, W. H. . 2012. *Econometric analysis* 7th Ed. In *Prentice Hall* (Vol. 97).
- Haughton and Khandker. 2016. *Vulnerability to Poverty*, 231–248. <https://doi.org/10.1057/9780230306622>
- Hisali, E., Birungi, P., and Buyinza, F. 2011. Adaptation to climate change in Uganda: Evidence from micro-level data, *Global Environmental Change*, Volume 21, Issue 4, Pages 1245-1261. <https://doi.org/10.1016/j.gloenvcha.2011.07.005>
- Hill, R., and Mejia-Mantilla, C. 2017. "With a Little Help: Shocks, Agricultural Income, and Welfare in Uganda." Policy Research Working Paper No. WPS 7935. Washington, DC: The World Bank.
- Hoddinott, J., and Quisumbing, A. 2003. *Methods for Microeconometric Risk and Vulnerability Assessments*. 0324.
- Hoddinott, J., and Quisumbing, A. 2010. Methods for Microeconometric Risk and Vulnerability Assessment. *Risk, Shocks, and Human Development*, 0324, 62–100. https://doi.org/10.1057/9780230274129_4
- Hoogeveen, J. G. 2005. Measuring welfare for small but vulnerable groups: Poverty and disability in Uganda. *Journal of African Economies*, 14(4), 603–631. <https://doi.org/10.1093/jae/eji020>
- Irish-Aid. 2018. *Uganda Country Climate Risk Assessment Report*. 1–41.
- Irish Aid. 2017. *Uganda Climate Action Report for 2016*.
- Jalan, J., and Ravallion, M. 2005. Household Income Dynamics in Rural China. *Insurance Against Poverty, November 2001*. <https://doi.org/10.1093/0199276838.003.0006>
- Kamanou, G., and Morduch, J. 2004. Measuring Vulnerability to Poverty - In *Insurance Against Poverty*. *Oxford University Press*, 155–175. <https://doi.org/DOI:10.1093/0199276838.003.0009>
- Koomson, I., Villano, R., and Hadley, D. 2020. Effect of Financial Inclusion on Poverty and Vulnerability to Poverty: Evidence Using a Multi-Dimensional Measure of Financial Inclusion. *SSRN Electronic Journal, January*. <https://doi.org/10.2139/ssrn.3518908>
- Ligon, E., and Schechter, L. 2003. Measuring Vulnerability. *The Economic Journal*, 113(486), C95–C102. <https://doi.org/10.1111/1468-0297.00117>
- Luers, A. L. 2005. The surface of vulnerability: An analytical framework for examining environmental change. *Global Environmental Change*, 15(3), 214–223. <https://doi.org/10.1016/j.gloenvcha.2005.04.003>
- Mansi, E., Hysa, E., and Panait, M. 2020. *Poverty — A Challenge for Economic Development ? Evidences from Western Balkan Countries and the European Union*. 1–24.
- Megersa, D. 2015. *Measuring vulnerability to poverty : An Empirical Evidence from Ethiopian Rural Household Survey*. 904.
- MoFPED. 2010. *Uganda National Report For Implementing the Programme of Action for the Least Developed Countries for the Decade 2001-2010*. Ministry of Finance Planning and Economic Development. 66.

- Ministry of Foreign Affairs of the Netherlands. 2018. *Climate Change Profile for Uganda*.
- Ministry of Water and Environment. 2015. *Uganda National Climate Change Policy*. April.
- Munyai, R. B., Musyoki, A., and Nethengwe, N. S. 2019. An assessment of flood vulnerability and adaptation: A case study of Hamutsha-Muongamunwe village, Makhado municipality. *Jamba: Journal of Disaster Risk Studies*, 11(2), 1–8. <https://doi.org/10.4102/jamba.v11i2.692>
- Nguyen, L. D., Raabe, K., and Grote, U. 2015. Rural-Urban Migration, Household Vulnerability, and Welfare in Vietnam. *World Development*, 71, 79–93. <https://doi.org/https://doi.org/10.1016/j.worlddev.2013.11.002>
- Nkondze, M. S., Masuku, M. B., and Manyatsi, A. 2013. Factors Affecting Households Vulnerability to Climate Change in Swaziland: A Case of Mpolonjeni Area Development Programme (ADP). *Journal of Agricultural Science*, 5(10), 108–122. <https://doi.org/10.5539/jas.v5n10p108>
- Oakes, R., Milan, A., and Campbell, J. 2016. Kiribati: Climate change and migration – Relationships between household vulnerability, human mobility and climate change. Report No. 20. *Qualitative Research Methods in Human Geography*, 20, 106–115.
- Oriangi, G., Albrecht, F., and Baldassarre, G. Di. 2020. *Household resilience to climate change hazards in Uganda*. 12(1), 59–73. <https://doi.org/10.1108/IJCCSM-10-2018-0069>
- Oyebola, O. O., Efitre, J., Musinguzi, L., and Falaye, A. E. 2021. Potential adaptation strategies for climate change impact among flood-prone fish farmers in climate hotspot Uganda. *Environment, Development and Sustainability*, 23(9), 12761–12790. <https://doi.org/10.1007/s10668-020-01183-1>
- Personal, M., and Archive, R. 2012. *Munich Personal RePEc Archive Estimating household vulnerability to poverty from cross-section data : empirical evidence from Ghana*. 39900.
- Pritchett, L., and Sumarto, A. S. S. 2000. Quantifying Vulnerability to Poverty. *The World Bank*, 2437(September), 36.
- Rodgers, J. R., and Rodgers, J. L. 2009. Contributions of longitudinal data to poverty measurement in Australia. *Economic Record*, 85(SUPPL. 1). <https://doi.org/10.1111/j.1475-4932.2009.00587.x>
- Rodgers, J. R., Rodgers, J. L., The, S., Resources, H., Winter, N., Rodgers, J. R., and Rodgers, J. L. 2018. *Chronic Poverty in the United States* Stable URL : <https://www.jstor.org/stable/146087> *Chronic Poverty in the United States*. 28(1), 25–54.
- Stringer, L. C. 2013. *Characterising the nature of household vulnerability to climate variability : empirical evidence from two regions of Ghana*. 903–926. <https://doi.org/10.1007/s10668-012-9418-9>
- Sullivan, A., Mumba, A., Hachigonta, S., Connolly, M., and Sibanda, L. M. 2013. FANRPAN Policy Brief. *The Food, Agriculture and Natural Resources Policy Analysis Network*, XIII(1), 1–4.
- Toshihiro, A; and Gary, M. 2001. *Economic Growth and Poverty Reduction in Sub-Saharan Africa*. IMF working paper.
- Tschay, A. S., and Bauer, S. 2012. Poverty and vulnerability dynamics: Empirical evidence from smallholders in northern highlands of Ethiopia. *Quarterly Journal of International Agriculture*, 51(4), 301–332. <https://doi.org/10.22004/ag.econ.155481>
- Turyahabwe, N., Kakuru, W., Tweheyo, M., and Tumusiime, D. M. 2013. *Contribution of wetland resources to household food security in Uganda*. 1–12.
- Twinomuhangi, R., Sseviiri, H., Mulinde, C., and Mukwaya, P.I. Nimusiima, A. and Kato, M. A. 2021. *Perceptions and vulnerability to climate change among the urban poor in Perceptions and vulnerability to climate change among the urban poor in Kampala City, Uganda*. June. <https://doi.org/10.1007/s10113-021-01771-5>
- UBOS 2021. Uganda Bureau of Statistics. *Statistical Abstract*.
- UBOS. 2019. Uganda Bureau of Statistics. *Statistical Abstract*.
- United States Agency for International Development (USAID). (2011). *Climate Change Adaptation in Uganda*. USAID African and Latin American Resilience to Climate Change (ARCC). (2013). *Uganda Climate Change Vulnerability Assessment*. 0–77.
- World Bank. 2016. “Farms, Cities and Good Fortune: Assessing Poverty Reduction in Uganda from 2006 to 2016.” The Uganda Poverty Assessment Report. Washington, DC: World Bank.
- Wichern, J., Descheemaeker, K., Giller, K. E., Ebanyat, P., and Taulya, G. 2019. *Vulnerability and adaptation options to climate change for rural livelihoods – A country-wide analysis for Uganda* *Vulnerability and adaptation*

options to climate change for rural livelihoods – A country-wide analysis for Uganda. November.

<https://doi.org/10.1016/j.agsy.2019.102663>

Wichern, J., Descheemaeker, K., Giller, K. E., Ebanyat, P., Taulya, G., and Van Wijk, M. T. 2019. Vulnerability and adaptation options to climate change for rural livelihoods – A country-wide analysis for Uganda. *Agricultural Systems*, 176(July), 102663. <https://doi.org/10.1016/j.agsy.2019.102663>

APPENDICES

Appendix 1: Table 1: Estimation results on the impact of climate change on household per adult equivalent expenditure and robustness tests.

Per adult household consumption expenditure	FE	RE
Precipitation	-0.00006*** (0.00002) (0.00285)	-0.00007*** (0.00002) (0.00272)
Household asset value	0.00100 (0.00323)	0.01487*** (0.00287)
Residence (urban)	0.33921*** (0.04414)	0.37837*** (0.02633)
Household size	-0.00481*** (0.00051)	-0.00703*** (0.00048)
Household level education level (base- No education)		
some Primary	0.04505 (0.03907)	0.12335*** (0.02694)
Completed primary	0.08606* (0.04770)	0.20123*** (0.03292)
Some secondary	0.24523*** (0.05327)	0.40276*** (0.03490)
Completed secondary	0.17056*** (0.05875)	0.38053*** (0.04224)
Post-secondary	0.51750*** (0.06768)	0.79413*** (0.04462)
Age of household head	0.00056 (0.00078)	-0.00343*** (0.00047)
Gender of household head (male)	-0.08243** (0.03895)	-0.14936*** (0.02132)
Main household occupation (Base: Agriculture)		
Industrial sector	0.06710 (0.04543)	0.08008** (0.03580)
Service sector	0.06695*** (0.02526)	0.11583*** (0.01999)
Access to credit	0.01131 (0.00992)	0.02350** (0.00960)
Precipitation	10.74192*** (0.10174)	10.69152*** (0.08785)
Observations	15,147	15,147
R-squared	0.05939	
Wald chi2(15)		2873.86***
Number of households	4,660	4,660
Hausman test (chi2(14))	1112.93***	

Source: Author Computations