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Climate variability and agricultural productivity in Uganda

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Abstract

Uganda's climate is changing in terms of rising temperatures and altered precipitation patterns, leading to extreme meteorological conditions such as prolonged drought, floods and landslides. Yet the majority (68%) of Ugandans rely largely on rain-fed agriculture, which is affected by climate variability. This study therefore investigates the effect of climate variability on agricultural productivity in Uganda by combining long-term climate data, sourced from the United States National Oceanic and Atmospheric Administration (NOAA), and six waves of the Uganda National Panel Survey (UNPS) spanning the period 2009 to 2019. Trends and the regression analysis estimated with panel data confirm the existence of climate variability, as well as the vulnerability of farming households across Uganda. The empirical results indicate a significant U-shaped impact of precipitation variability on agricultural productivity. This tends to suggest that, as variability in precipitation intensifies, farming households will adapt to the changing precipitation and thereby improve their productivity. The regional and crop-specific analysis show that, relative to other regions of the country, Eastern Uganda is likely to be the region affected the most, while beans and banana are likely to be affected more by climate variability compared to other crops such as maize and cassava. The study thus recommends measures aimed at encouraging farmers to adapt and increase agricultural productivity. There is a need to strengthen the provision of extension services and inform farmers about climate variability.[1]

Key words: climate variability, agricultural productivity, maize, panel data, Uganda

[1] The data is available from the authors upon request.

1. Introduction

The nexus between agriculture and variations in climate continues to give rise to debate among different stakeholders, including scholars, across the globe. It is projected that climate variability is likely to affect agricultural productivity in developing nations, where the majority of farming households are involved in rain-fed agricultural activities (Kahsay & Hansen 2016; Huong *et al*. 2018; Masson-Delmotte *et al*. 2018; Kontgis *et al*. 2019). The impact may be felt less in developed countries due to their ability to quickly forecast and adapt to changing climatic conditions, their technology and the appropriate safety nets for their citizens to rely on livelihoods other than agriculture (Mubiru *et al*. 2018).

For developing countries such as Uganda, where 68% of farming households are engaged in traditional subsistence farming (Uganda Bureau of Statistics [UBoS] 2018), variations in climate might have a substantial impact on agricultural productivity (Mwaura & Okoboi 2014). This is because climate variability is expected to increase the frequency of extreme precipitation conditions, prolonged dry seasons and floods (Banerjee *et al*. 2019), which greatly influence agricultural outcomes, especially in subsistence agriculture (Lee *et al*. 2012; Sheng & Xu 2019). Therefore, understanding the effect of climate variability on agricultural productivity is important to back up the design of policies that stimulate the adoption of long-term adaptation mechanisms (Reed *et al*. 2017; Huong *et al*. 2018). This also facilitates the assessment of the degree of vulnerability of the country's economy, as well as of the farming households and their dependants to variability in climate and its associated effects. It also fits well in the planning aspirations of the farmers, government and all those stakeholders engaged in agricultural activities.

Despite its declining GDP share, the agriculture sector is still Uganda's economic backbone and the chief employer of most Ugandans (World Bank 2019). The sector employs around 70% of Uganda's total labour force, contributes around 25% to GDP, and accounts for about 45% of the country's total exports (Uganda Bureau of Statistics [UBoS] 2017). Agriculture as a sector therefore has the potential to steer Uganda's development agenda, as outlined in Uganda's vision 2040 and the corresponding National Development Plans (I, II and III;[2] NPA 2015). It provides opportunities for economic inclusion, especially for women and the youth, who are the main participants in the sector (UBoS 2018). However, the sector remains vulnerable to climate shocks, such as prolonged drought and unreliable rainfall patterns (Mwaura & Okoboi 2014; Abidoye *et al*. 2017a).

In addition, farming households in the subsistence sector lack timely climate and weather forecast information, and the skills and resources required to mitigate or adapt to climate variability (Guloba 2014). Thus, it is vital to understand the effects of climate variability on the productivity of Uganda's agricultural sector to generate evidence to design appropriate measures to minimise and mitigate its risks. Failure to do so may expose farming households to food insecurity and poverty, given the limited non-farm opportunities, especially in rural Uganda, coupled with the growing population size (Mwaura & Okoboi 2014; Ochieng *et al*. 2016). Through the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF), Uganda's government designed and started the implementation of the National Adaptation Plan for the Agricultural Sector (NAP-Ag) in 2018 (Adade *et al*. 2019; Mubiru *et al*. 2018). This was aimed largely at minimising the effects of variability in climate on farmers across the country (MAAIF 2018). It was done in response to increasing instances of intense and prolonged dry spells in some areas of the country, along with droughts, floods, and an increase in temperature and higher incidence of pests and diseases as a result of the varying climatic conditions

[2] These are five-year national development plans, designed in line with the country's vision 2040 (NPA 2015). The country is currently implementing National Development Plan (NDP) III (2020 to 2025).

in the country (Mubiru *et al*. 2018; UBoS 2019). In addition, the performance of Uganda's agricultural sector has been varying over time (UBoS 2018; World Bank 2019). Climate variability in Uganda is largely attributed to the continuous destruction of the environment and nature by human activities such as deforestation,[3] wetland reclamation, and the use of poor farming techniques by some farmers (Abid *et al*. 2016; UBoS 2019). Other causes include increasing industrialisation in the country, poor disposal of plastics and polythene bags, increasing electronic waste, and oil exploration activities in the Albertine region (Ministry of Water and Environment [MoWE] 2015; Masson-Delmotte *et al*. 2018).

Several scholars have carried out studies on the effect of climate variability on agriculture across the world, including in Africa. Among these are: Mendelsohn and Nordhaus (2010), Mendelsohn (2011), Ludena and Mejia (2012), Kontgis *et al*. (2019). The majority of these studies have been conducted in developed countries, although they are currently on an increase in developing nations, including African states (Kabubo-Mariara *et al*. 2016). This shows the value attached to the analysis of the impact of climate variability on agriculture by various stakeholders, governments and scholars all over the world. In addition, most of them (see, for example, Mendelsohn & Nordhaus 2010; Mottet *et al*. 2017) have concentrated largely on analysing the effect of climate variability on agricultural yields and incomes, as opposed to analysing the agricultural productivity implications of climate variability following the declining land per capita and increasing population size. Even more so, the effects of climate variability are likely to vary across countries and from one crop to another, hence the need for country-specific studies. Thus far, the lack of an in-depth and countrywide study that combines household-level and long-term climate data to analyse the impact of climate variability on agricultural productivity has curtailed the decision-making and planning process among the farming households, government and other participants in the sector. This study fills these gaps by estimating agricultural productivity by way of a Ricardian model in a panel setting at the national and regional level and for the four common crops grown across Uganda – maize, beans, banana and cassava.

2. Literature review

Nature-dependent sectors such as agriculture are highly sensitive and susceptible to climate variability and its effects (Food and Agriculture Organization of the United Nations [FAO] 2008; Wang *et al*. 2009; Massetti & Mendelsohn 2017). This is largely because agriculture involves natural processes that require specific amounts of nutrients, and specific temperatures and precipitation for the proper growth of both crops and animals (Van Vuren *et al*. 2009; Gornall *et al*. 2010; Mamane Bello & Malam Maman 2015). According to Nastis *et al*. (2012), Limantol *et al*. (2016) and Ali and Erenstein (2017), climatic attributes that are anticipated to have a direct effect on agricultural productivity include variability in temperature and changes in the occurrence and intensity of precipitation, such as rainfall. Others are variability in incidences of dangerous weather conditions (for example prolonged dry seasons, water overflows and landslides), and changes in carbon dioxide (CO_2) levels available for the process of plant photosynthesis.

Crop production varies strongly with variability in temperature, wind and rainfall amounts received in a given area (Baya *et al*. 2019; Sheng & Xu 2019). This relationship depends on the crop type and the location where the particular crop is grown (Ayinde *et al*. 2017; Rötter *et al*. 2018). Altered rainfall patterns not only affect crop growth, but also decrease the amount of water available for irrigation by some farming households (Mwangi & Kariuki 2015; Arshad *et al*. 2017). Variations in temperature and moisture levels indirectly affect crops' capacity to absorb manure and other soil reserves that are

[3] Uganda's forest cover has decreased drastically since independence, from 42% in 1962 to about 9% in 2016 (UBoS 2018), largely due to the need for more land for agriculture, settlement and industrialisation.

important in influencing crop output (Cotter *et al*. 2010; Alam *et al*. 2014). Variability in climate is likely to influence the kinds, incidences and occurrences of crop pests and diseases; affect accessibility, timing and availability of water for irrigation; and increase cases of soil erosion (Ochieng *et al*. 2016; Arslan *et al*. 2017; MAAIF 2018).

Climate variability is projected to increase yields of some crops (Debaeke *et al*. 2017; Seo & Mendelsohn 2008) – for instance, by increasing the regularity and amount of rainfall in some areas, thereby lengthening crop seasons. Rising concentrations of carbon dioxide as a result of climate variability can raise the productivity of agroecosystems – but also vice versa (Wang *et al*. 2009). However, the overall global impact of climate variability on productivity is projected to be negative, and the negative impact will be felt more in developing countries (Silvestri *et al*. 2012; Urgessa 2015; Kumar *et al*. 2016; Ayinde *et al*. 2017; Huong *et al*. 2018; Kontgis *et al*. 2019; Sheng & Xu 2019). This paper therefore establishes the actual effect of variability in climate on agricultural productivity and the yields of selected crops.

In an empirical study, Kabubo-Mariara and Karanja (2007) studied the economic effects of climate change on crop agriculture in Kenya, using a seasonal Ricardian model and a crop simulation model in 38 out of 46 former districts and now counties of the country. The study used several data types, including long-term precipitation and seasonal temperature averages; long-term monthly average hydrological data; soil types; and a cross-sectional household survey. Their findings indicate that variability in climate affects crop revenues, with a rise in temperatures from June to August leading to increased crop revenues, while a rise in temperatures from March to May contributes to a reduction in crop revenues. Their study further uncovered a non-linear impact of climate change (temperature and precipitation) on crop revenues. Their findings corroborate with those of some recent studies, such as Abidoye *et al*. (2017a) and Kurukulasuriya and Mendelsohn (2017).

However, studies that use the traditional Ricardian approach and rely only on cross-sectional data have been criticised on the grounds that their estimated coefficients are unstable over time (Massetti & Mendelsohn 2011). This led to the modification of the traditional Ricardian approach to one that is estimated using panel data (Massetti & Mendelsohn 2011; Galindo *et al*. 2015; Kabubo-Mariara *et al*. 2016). For example, Galindo *et al*. (2015) estimated a Ricardian model with panel data in Mexico to establish the effect of climate variability on agricultural activities. They found that farms that depend on irrigation are vulnerable to variability in temperature, while rainfed farms are vulnerable to precipitation variability and extreme climatic events such as floods. The study by Galindo *et al*. (2015), however, based its analysis only on farm revenues and ignored productivity concerns, which are of greater interest given the rising population:land ratio. On the other hand, Kabubo-Mariara *et al*. (2016) concentrated on food and nutrition security. This study therefore addresses these gaps by focusing on the productivity effects of climate variability in Uganda using panel data and estimating the total factor productivity derived from the estimated stochastic production function.

The second category consist of those studies that have applied crop-simulation models. Example are a world study by Rötter *et al*. (2018) and another by Van Oort and Zwart (2018). Rötter *et al*. (2018) analysed the impact of climate variability on five crops – maize, rice, wheat, potatoes and vegetables. Their study found that variation in climate led to a reduction in the yields of all five crops, and yet these are key food crops consumed globally. The study further predicted that the trend would worsen across the world by the year 2050 if nothing was done currently to tame the varying climate and its effects. However, the key limitation of Rötter *et al*.'s (2018) study, and other studies that use crop-simulation models such as that by Van Oort and Zwart (2018), is that they base their analysis only on simulated data obtained using assimilation methods grounded in cross-section models and remote sensing, instead of real data estimated using economic models. For more robust and concrete evidence to guide accurate policy formulation, cross-sectional simulation models need to be combined with models that are based on economic theories and principles.

The third category of the existing empirical studies involves those that have estimated stochastic production functions in the form of the Cobb-Douglas production function. These include, among others, Nastis *et al*. (2012), Kumar *et al*. (2016), Ademe *et al*. (2017) and Geng *et al*. (2019). For instance, Nastis *et al*. (2012) estimated a production function using secondary time-series data and ordinary least squares (OLS) with Newey-West standard errors for 28 years (1980 to 2007) in Greece. The findings of their study indicate that variability in both temperature and precipitation negatively affects agricultural yields. However, their study omitted the socio-economic household and farm-specific characteristics in its analysis. The omission of such variables might cause a problem of endogeneity, which will affect the accuracy and validity of the model estimates (Greene 2012). On the other hand, Kumar *et al*. (2016) assessed the effect of climate variations on the productivity of land, considering the main food and non-food crops in India using panel data collected over 30 years from 1980 to 2009. They did this for 15 crops in 13 key agricultural states of India. The results show that the productivity of land declines with an increase in yearly mean maximum temperatures. Using simulations, they projected a decrease in land productivity by 48.6% by the year 2100, which will greatly affect farmers' crop productivity and their income levels.

Similarly, Geng *et al*. (2019) applied a structural Cobb-Douglas production function and secondary time-series data from 1981 to 2016 to investigate the effect of variations in climate on wheat yields in northern China during the winter season. The study found that a rise in temperature has a negative effect on per unit wheat harvested. However, these authors concentrated on only one element of climate variability (temperature) and only one crop, ignoring other dimensions of climate variability such as variations in rainfall and other crops that equally can be affected by the varying climate. Secondly, the study focused only on one region of China, thus its findings cannot be generalised across the country. In addition, as noted by Aydinalp and Cresser (2008) and Ayinde *et al*. (2017), the agricultural productivity effects of climate variability might vary across the world, and these authors thus called for country-specific studies investigating the effects of climate variability on agriculture, since the impact might depend largely on existing local conditions.

In Uganda, Mwaura and Okoboi (2014) analysed a time-varying ARCH approach to investigate the effect of climate variability on crop production. This study established that variations in temperature and rainfall from their long-run averages (climate variability) significantly affect crop yields, with an exponential rise in rainfall having the largest negative effect on crop yields in Uganda. The study, however, did not consider the socio-economic, household and institutional factors and yet this is the only national wide study on the subject matter in Uganda. Other existing studies on Uganda, such as those by Egeru (2012), Nabikolo *et al*. (2012) and Shikuku *et al*. (2017), did not cover the whole country and largely used descriptive statistics and trends in their analysis. In addition, these studies ignored productivity concerns and instead concentrated on crop yields. These gaps are what the current study addresses by using a nationally representative dataset to investigate the implications of climate variability on agricultural productivity in Uganda.

From the review of the related literature, there are two arguments regarding the likely effect of climate variability on agricultural productivity. The first argument is that variability in climate might result in an increase in the yields of some crops (Seo & Mendelsohn 2008; Debaeke *et al*. 2017). For example, Debaeke *et al*. (2017) argue that climate variability will lead to an upsurge in the regularity, patterns and amount of rainfall in some areas, leading to longer crop seasons and higher crop yields. However, the study is silent on the effects of climate variability on agricultural productivity. The second argument, which is more popular in the literature, states that climate variability will affect agriculture negatively (see, for example, Silvestri *et al*. 2012; Urgessa 2015; Kumar *et al*. 2016; Ayinde *et al*. 2017; Huong *et al*. 2018; Kontgis *et al*. 2019; Sheng & Xu, 2019). Actually, Ayinde *et al*. (2017) and Huong *et al*. (2018) project that the negative effects are likely to be felt more in less-developed countries due to their overdependence on nature for their agricultural activities, their limited non-farm activities and their lack of adequate capacity to invest in adaptation and mitigation mechanisms, although the impact might vary from one country to another. In Uganda, however, such studies are still in their infancy and scarce, yet agriculture accounts for over 70% of the working labour force and is the backbone of the economy. The few existing studies have either covered a smaller part of the country (see, for example, Egeru 2012), or have not used household-level data (such as Mwaura & Okoboi 2014). The present study thus addresses these gaps in the existing literature by focusing on productivity as opposed to output, on a countrywide basis and over time, and includes some of the adaptation mechanisms adopted.

3. Methodology

The study estimates the total factor productivity (TFP) derived from the stochastic Cobb–Douglas production function (Sheng & Xu 2019). Given that climate variability is not a direct input of agricultural production, estimating the total factor productivity function is the appropriate framework to establish the effect of climate variability on Uganda's agricultural productivity (Kumar *et al*. 2016). The theoretical framework was derived by considering a Cobb–Douglas production function, as below:

$$Y = AK^{\alpha}L^{\beta}Z^{\theta}, \tag{1}$$

where Y is the total agricultural output, and A is the intercept, which is a measure of productivity. K is capital input, L is labour input, while Z is land input. α, β and θ are input elasticities.

Total factor productivity (A), which is defined as the ratio of total output to the weighted input index, is therefore estimated using the following formula:

$$A = \frac{Y}{K^{\alpha}L^{\beta}Z^{\theta}} \tag{2}$$

Taking natural logs on both sides of Equation (2) yields:

$$lnA = lnY - (\alpha lnK + \beta lnL + \theta lnZ) \tag{3}$$

Introducing a time dimension gives:

$$lnA_t = lnY_t - (\alpha lnK_t + \beta lnL_t + \theta lnZ_t) \tag{4}$$

Taking the first difference gives the total factor productivity as:

$$\frac{A_t - A_{t-1}}{A_{t-1}} = lnA_t - lnA_{t-1} = \frac{Y_t - Y_{t-1}}{Y_{t-1}} - \left(\alpha \frac{K_t - K_{t-1}}{K_{t-1}} + \beta \frac{L_t - L_{t-1}}{L_{t-1}} + \theta \frac{Z_t - Z_{t-1}}{Z_{t-1}}\right) \tag{5}$$

Econometrically, this can be estimated as:

$$lnY_t = \hat{\alpha} lnK_t + \hat{\beta} lnL_t + \hat{\theta} lnZ_t + \hat{\gamma} t + \varepsilon_t \tag{6}$$

$\hat{\gamma}$ gives the total factor productivity (TFP) estimates. The estimates obtained are thus used as the dependent variable for assessing the effect of climate variability on agricultural productivity.

Following other studies, such as those by Muendler (2004), Şeker and Saliola (2018) and Sheng and Xu (2019), total factor productivity (TFP) is a function of climate factors (C), household factors (H), socioeconomic factors (S), institutional factors (I) and locational factors (G). Putting these together yields a theoretical model for the study, as follows:

$$TFP = f(C, H, S, I, G) \tag{7}$$

3.1 Empirical model and estimation procedure

Following the theoretical model and other earlier studies such as those of Muendler (2004) and Sheng and Xu (2019), the empirical model is specified as:

$$TFP\ (\hat{\gamma}) = \alpha_0 + \alpha_1 C_{it} + \alpha_2 H_{it} + \alpha_3 S_{it} + \alpha_4 I_{it} + \alpha_5 G_{it} + u_{it}, \tag{8}$$

where C is a vector of climate factors, H is a vector of farming household inputs, S is a vector of socioeconomic factors, I is a vector of institutional factors, and G are locational factors (residential and regional location). A quadratic specification of variability in the precipitation and temperature terms caters for the non-linearity and extreme impacts of variability in climate (Massetti & Mendelsohn 2011; Bozzola *et al*. 2018).

Next, precipitation variability was interacted with the availability of extension services to test whether extension services empower households to overcome climate variability challenges over time.

$$TTF\ (\hat{\rho})_{it} = \alpha_0 + \alpha_1 Temp_{it} + \alpha_2 Ppt_{it} + \delta_1 T^2{}_{it} + \delta_2 Ppt_{it}{}^2 + \alpha_3 H_{it} + \alpha_4 I_{it} + \alpha_5 (Ppt_{it} * Ext_{it}) + \varepsilon_{it}, \tag{9}$$

where Ext_{it} represents the availability of extension services to household i at time t.

This model was estimated using the two panel data models of fixed effects and random effects. To select between fixed effects and random effects, the Hausman specification test is used with the null hypothesis – random effects is the preferred model (Baltagi 2013). The results are also compared with those from the pooled OLS. The study corrects errors for potential heteroskedasticity and tests for multicollinearity using the observed information matrix (OIM). The study further estimates models for each region and for the four commonly grown crops – maize, beans, cassava and banana. These crops were selected because they are the most common crops grown across the country (UBoS 2017, 2018).

3.2 Study variables

The main dependent variable of the study is total factor productivity (TFP), which is obtained by dividing an index of real output by an index of combined units of all inputs or factors (Şeker & Saliola 2018; Sheng & Xu 2019). The same applies for regional and crop-specific estimated models. The explanatory variables used in the analysis were divided into three categories. The first category consists of the climate variability factors (precipitation and temperature). These have been included in the model as a measure of climate variability. The second category includes household characteristics, such as gender, age, marital status, size of the household, education level of household head and location of the household. The last category consists of the institutional variables, and in this study they include the availability of extension services and access to markets for crops.

Table 1: Definition and measurement of variables

Variable	Definition and measurement	Expected sign	Literature source
Total factor productivity	Measures the productivity of the agricultural sector as a whole	Dependent variable	Şeker & Saliola (2018); Sheng & Xu (2019).
Climate variability			
Precipitation variability	Coefficient of variation of precipitation for a period of at least 30 years	±	Alem *et al*. (2010); Arshad *et al*. (2018)
Temperature variability	Coefficient of variation for (minimum and maximum) temperature for period of 30 years	±	Arslan *et al*. (2017); Nkegbe & Kuunibe (2014)
Household characteristics			
Household head age	Complete years	+	Guloba (2014); Hisali *et al*. (2011)
Household head education level	Number of years of school	±	Kabubo-Mariara & Mulwa (2019); Reed *et al*. (2017)
Gender of household head	Dummy: 1 = male, 0 otherwise	+	Ademe *et al*. (2017)
HH head marital status	Dummy: 1 = married, 0 otherwise	±	Zhang *et al*. (2017)
HH equipment value	In Uganda shillings, a measure of capital input	+	Kumar *et al*. (2016)
Household size (labour)	Number of people in the household, a measure of labour input	±	Galindo *et al*. (2015)
Location of a household	Dummy: 1 = urban, 0 otherwise	-	Shikuku *et al*. 2017); Van Passel *et al*. (2017)
Institutional factors			
Extension services	Dummy: 1 = available, 0 otherwise	±	Baya *et al*. (2019)
Access to market	Dummy: 1 = yes, 0 otherwise	+	Zhang *et al*. (2017)

3.3 Data sources

The study used long-term daily climate data (1979 to 2013) sourced from the United States National Oceanic and Atmospheric Administration (NOAA).[4] In this section, the climate data are converted into monthly and then annual data, before obtaining the coefficients of variation for both precipitation and temperature. The study relies on the coefficient of variation of each climate variable as a measure of variability. This dataset has been credited for producing accurate climate observations over time (Massetti & Mendelsohn 2011; Bozzola *et al*. 2018). Information on farming household factors and institutional factors was obtained from the Uganda National Panel Surveys (UNPS), spanning a period of 10 years from 2009 to 2019. Total agricultural output was obtained from the summation of all major crop yields that are captured by the Uganda Bureau of Statistics (UBoS) after standard conversion into one unit of measurement. These datasets are nationally representative, and the study utilises six waves of UNPS (2009/2010, 2010/2011, 2011/2012, 2013/2014, 2015/2016 and 2018/2019), with each covering on average of 2 500 households, giving a total pool of about 15 000 observations. This dataset is large and reliable enough to ensure precision of the model estimates. The Climate data were matched with the household-level data using household GPS information.[5]

[4] More information on this climate data is available at http://www.esrl.noaa.gov/psd. The climate data is made available by NOAA/OAR/ESRL PSD, Boulder CO, USA.

[5] All households without GPS coordinates and those who did not farm any crop were dropped from the dataset.

4. Empirical findings

4.1 Descriptive statistics

Figure 1 shows an increasing trend in both average precipitation and temperature, with the annual increase in average temperature being much smaller than that of average precipitation. A similar trend in Uganda's climate was established by Lazzaroni (2012) and Guloba (2014), who also found an upward trend in the country's climatic variables of precipitation and temperature. However, although average rainfall is rising, the pattern is unreliable, varied and unevenly distributed across the country (Egeru 2012; UBoS 2018). It is clear from Figure 1 that both precipitation and temperature vary, as shown by the three line graphs and a non-zero coefficient of variation. The trend analysis across the various regions of the country between 1978 and 2014 is shown in the maps (see Figures A1, A2 and A3 in Appendix 1). The trends clearly support the existence of climate variability in Uganda; for example, the coefficient of variation ranges between 0.3 and 1.3 for precipitation variability.

Extreme variability in precipitation is observable in the areas of the Karamoja, Southwestern (Kigezi and Kasese) and Albertine regions of Uganda, with the highest variability in precipitation experienced in Karamoja region between 1981 and 2013. The coefficient of variation ranged between 1.00 and 1.60 in Karamoja region during this period. No area had a precipitation coefficient of variation below 0.1 (the threshold), hence confirming precipitation variability in Uganda (Arshad *et al*. 2017). High variability in temperature was experienced in the areas surrounding Lake Victoria (Wakiso, Mpiji and Mukono) and the Kabaale areas in Southwestern Uganda. This can be attributed largely to the changing rainfall patterns, swamp reclamation and deforestation in these areas (Egeru 2012; Guloba 2014).

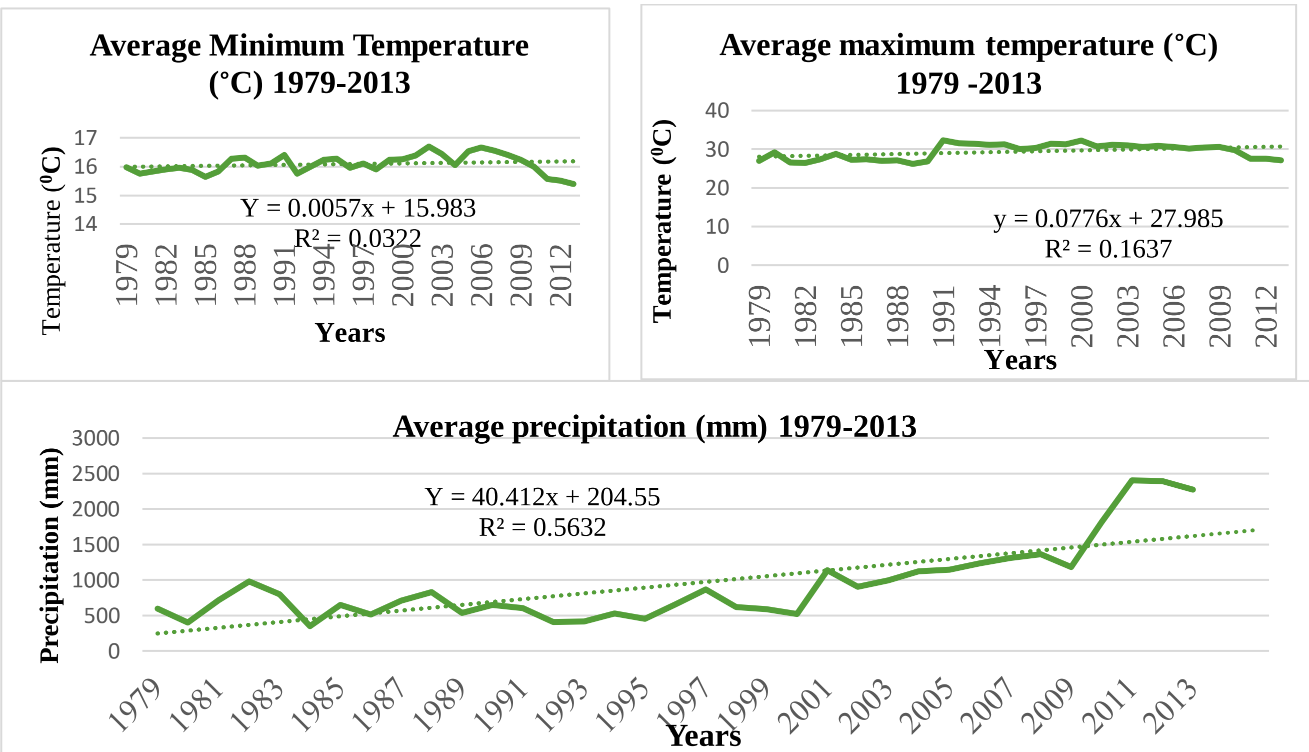

Figure 1: Trend analysis of the Uganda's historical climate variables from 1979 to 2013
Source: Author's own calculations based on global weather data downloaded from NOAA (2019)

For the rest of the country, the variability ranged between 0.01 and 0.18. The variability in the maximum temperature was slightly lower than that of the minimum temperature, although an overall non-uniform trend in temperature variability can be observed across the country.

The summary statistics for all study variables used in this study are presented in Table 2 below.

Table 2: Summary statistics

Study variables	Mean	Std dev.	Min	Max
Total factor productivity	2.99	3.57	1.72E-06	36.81
Precipitation variability	0.33	0.17	0.002	1.55
Minimum temperature variability	0.05	0.02	0.02	0.19
Maximum temperature variability	0.08	0.01	0.05	0.16
Access to extension services	0.44	0.50	0	1
Access to market	0.81	0.40	0	1
Household head age	48.42	15.01	14	100
Gender of HH head (1 = male)	0.70	0.46	0	1
Location (1 = urban, 0 = rural)	0.13	0.33	0	1
Marital status (1 = married)	0.74	0.44	0	1
Education (years of education)	5.34	3.82	0	17
Household size (labour input)	11.09	13.02	1	72
Household assets (capital input)	48 039.78	252 531.4	0	16 700 000

Source: Author's calculations based on UNPS datasets (2009 to 2019) and world climate data

The summary statistics show that the climate variability variables (precipitation and temperature) have non-zero means, implying that there indeed is variability in the climate data, as shown earlier in the trend analysis (Figure 1). On average, the farming household heads in the dataset had attained at least five years of education, which is equivalent to some primary education. The majority of the farmers (56%) did not have access to agricultural extension services, given that only 44% had access to extension services. This is of great concern, given the importance of extension services in agriculture and their perceived role in empowering farmers to improve their productivity and build resilience against climate variability and its effects (Lazzaroni 2012).

This means that there is a need for more effort to be made in the delivery of extension services by the government through the Ministry of Agriculture, Animal Industry and Fisheries. A total of 81% of the households had access to markets for their crop products. The statistics also show that the majority of the farming household heads (76%) were married, with 70% of the households being headed by a male.

The correlation matrix (Appendix 2) shows that the study variables do not suffer from multicollinearity and thus are suitable for inclusion in the empirical analysis.

4.2 Empirical results

The effect of variability in climate on agricultural productivity is presented in Table 3. The standard errors have been corrected for any suspected serial correlation and heteroscedasticity. The results of the observed information matrix confirm the absence of multicollinearity among the regressors, as shown by the correlation matrix in the appendices. The Chow test results indicate that the estimated models are statistically significant, implying that the variables that have been included jointly explain changes in agricultural productivity as measured by total factor productivity. The Roy-Zellner test results shows that the error term is spherical, implying that the random error term is uncorrelated with the model regressors (Baltagi 2013). This therefore confirms that our model estimates are robust, consistent and efficient and hence reliable and valid for policy recommendations.

Table 3: Regression results

Dependent variable (total factor productivity)	Fixed effects	Random effects	Pooled OLS
Precipitation variability	-4.22***	-4.14***	-4.14***
	(1.42)	(1.35)	(1.42)
Precipitation squared	2.24**	2.36**	2.36**
	(1.10)	(1.04)	(1.11)
Min temp variability	11.80*	13.61**	13.61**
	(6.67)	(6.43)	(6.19)
Minimum temp squared	-75.70	-92.30	-92.30*
	(59.59)	(57.40)	(54.17)
Max temp variability	-25.60*	-25.32*	-25.32
	(15.54)	(14.94)	(15.78)
Max temp squared	144.45	146.42*	146.42
	(92.62)	(88.90)	(95.18)
Household age	-0.02	0.03	0.03
	(0.03)	(0.02)	(0.02)
Household age squared	-0.00	-0.00*	-0.00
	(0.00)	(0.00)	(0.00)
Gender of household head (male)	0.72***	0.22*	0.22
	(0.20)	(0.13)	(0.17)
Location (1 = urban, 0 = rural)	-0.62***	-0.77***	-0.77***
	(0.21)	(0.13)	(0.16)
Marital status (married)	0.80***	0.59***	0.59***
	(0.21)	(0.14)	(0.18)
Education of household head (years)	0.10***	0.03**	0.03*
	(0.02)	(0.01)	(0.02)
Access to extension services	0.02**	0.02	0.02
	(0.03)	(0.23)	(0.25)
Access to market	0.06	0.05	0.05
	(0.07)	(0.07)	(0.07)
Precipitation variability*extension services	0.98**	0.84**	0.84**
	(0.42)	(0.40)	(0.42)
Constant	5.78***	3.73***	3.73***
	(1.14)	(0.87)	(0.95)
Observations	12 706	12 706	12 706
Number of households	2 947	2 947	2 947
Houseman test (chi^2(14))	101.83***		
F(2946, 9744)	3.91***		

Note: Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1
Source: Author's calculations based on UNPS datasets (2009 to 2019) and world climate data

4.3 Discussion of results

The Hausman specification test results suggest that the results of the fixed-effects model are consistent with the dataset. This is because the test statistic rejects the null hypothesis that the random-effects model is the preferred model at the 1% level of significance, and hence only the results of the fixed-effects model are interpreted and discussed.

The results show a significant nonlinear link between precipitation variability and agricultural productivity in Uganda. This is because both the linear and the quadratic terms of precipitation are statistically significant. The coefficient of the linear precipitation variability term is negative and statistically significant. This suggests that variability in precipitation reduces agricultural productivity in the initial stages, but, as variability increases, the farmers' productivity starts to increase, given that the coefficient of the squared precipitation variability term is positive and statistically significant. The turning point is observed when the coefficient of precipitation variability is 1.88. This U-shaped relationship between variability in precipitation and the total agricultural factor productivity is consistent with the results of earlier studies (such as Mendelsohn 2014; Abidoye *et al*. 2017b; Ademe *et al*. 2017; Baya *et al*. 2019). For example, Baya *et al*. (2019) argue that, as precipitation variability increases, farming households come to understand the weather changes and start to practise adaptation measures or strategies to minimise the effects of a varying climate, although this is sometimes unintended. Similarly, Ali and Erenstein (2017) note that, as climate varies, farmers resort to early planting, and sometimes planting alternating crops that are tolerant to precipitation variability. They also construct dams in valleys and other water catchment areas. Thus, just as our study findings tend to imply, it appears that that some farmers adapt to varying climatic conditions unknowingly (autonomous adaptation), while others adapt knowingly or with intent (planned adaptation).

However, the study findings contradict those of Lazzaroni (2012), who found a non-significant relationship between rainfall variability and agriculture in Uganda. Lazzaroni argues that the adverse effect of deviations in Uganda's rainfall levels is being offset by land productivity, and thus the arguments in the literature – that rainfall variability reduces agricultural productivity – are exaggerated. Her findings are surprising, given the overreliance of Uganda's agricultural sector on natural conditions, with few farming households using irrigation as an alternative in the light of rainfall variability and unreliability. However, this finding could be due to the time scope (one year) of the weather data used, and the fact that the study considered only rainfall as opposed to precipitation, which combines many components other than rainfall, such as humidity, fog and moisture. All of these play a big role in influencing the productivity of the agricultural sector. Our findings also corroborate the predictions of Cuni-Sanchez *et al*. (2011), that variability in precipitation levels is likely to have a substantial negative effect on agricultural productivity in developing countries, which, like Uganda, are located in the tropics and are very sensitive to changes in climate.

The study uncovers a statistically weak significant impact of minimum and maximum temperature variability on agricultural productivity in Uganda. The results are mixed, with the coefficients of variability in minimum temperature suggesting a weak positive impact, while those of maximum temperature suggest a weak negative impact. These findings tend to support those of Arslan *et al*. (2017) in Tanzania. These authors established that changes in temperature only affect agricultural yields or productivity if the increasing temperature exceeds the threshold of crop-specific heat stress. The results further suggest that Uganda's temperature is changing, and that measures therefore should be devised to overcome the likely negative effects on agriculture, which until now has been the largest employer of Ugandans and the main source of foreign exchange.

The study further investigated the effect of key selected household variables on the productivity of the agricultural sector. This follows the argument by Hlahla *et al*. (2019), namely that the agricultural productivity effects due to climate variability are shaped by household-specific and socioeconomic factors, such as the location of the household and the household head's level of education, measured by years spent at school. The results show that agricultural productivity increases with the education level of the household head. This corroborates the findings of previous studies, such as those of Seo and Mendelsohn (2008), Reed *et al*. (2017) and Sheng and Xu (2019), among others. Reed *et al*. (2017) argue that education is important in enabling farming households to adopt better methods of farming, correctly predict climatic conditions, and thus plan accordingly, which in turn increases their productivity in comparison to that of uneducated farmers. More so, education increases the probability of an individual to obtain non-farm employment, such as in the industrial and service sectors, unlike their uneducated counterparts, who have to depend on agricultural or nature-based activities. The study results further indicate that agricultural productivity is likely to be lower if the farming household is in an urban locality compared to being in a rural area. This contradicts the results of the study by Alam *et al*. (2014), who established that urban-based farmers tend to be more productive than those in rural areas due to the use of advanced farming methods, and exposure to and practice of intensive agricultural activities because of the limited available farmland in urban areas. These farming methods are uncommon among rural farmers. In Uganda's case, however, agriculture is largely a rural-based sector, and thus all programmes and interventions aimed at enhancing agricultural productivity target mainly rural farmers (UBoS 2018). This could partly explain why the findings of this study show that farmers based in rural areas are more productive than their counterparts in urban areas. However, the study shows that total factor productivity increases when the farming household head is married as opposed to being unmarried.

The results show that access to extension services increases total agricultural productivity in Uganda by 0.02 percentage points, other factors held constant. This outcome is in line with Reed *et al*. (2017), who argue that the availability of extension services increases farm productivity among farmers. This supports our earlier argument, that Uganda's Ministry of Agriculture, Animal, Industry and Fisheries (MAAIF) should provide extension services to all farmers throughout the country. In addition, the interaction between precipitation variability and access to extension services in the model yields a significant positive impact on productivity. This implies that access to extension services offsets the negative impact of precipitation variability on the productivity of the farming households. This is true following the arguments of earlier authors, such as Urgessa (2015) and Folayan (2017), who state that extension services can help to mitigate the adverse effects of variability in climate through the skills and assistance offered to farmers in the form of extension services. Farmers can easily learn how to improve their productivity, despite the presence of variability in climate.

4.4 Results by region

Separate models were estimated for each of the four main regions of Uganda – Central, Eastern, Western and Northern – with the aim of identifying the region most vulnerable to climate variability with a view to informing targeted aid policy formulation, implementation and planning (see Table 4).

The regional results (Table 5) show that the size of the impact of precipitation variability on agricultural productivity in Uganda is not uniform across the four regions. The results show that the impact is higher in Eastern Uganda, followed by the central region. This implies that, in comparison to other regions, Eastern Uganda is more vulnerable to climate variability. This region occasionally faces severe occurrences of prolonged drought, landslides and floods in comparison to the other regions in the country (Uganda National Meteorological Authority [UNMA] 2019). These severely affect agriculture in terms of the realised yields per hectare (Guloba 2014). The results further show that access to extension services increases farmers' productivity across all regions of the country and, if it is applied well in Eastern Uganda, it would help to offset the effect of variability in precipitation on productivity in the region.

Table 4: Regression results by region (dependent variable: total factor productivity)

Variables	Central	Eastern	Western	Northern
Precipitation variability	-6.11**	-7.50**	-4.73*	-3.40*
	(3.70)	(2.94)	(2.51)	(2.00)
Precipitation variability squared	4.61	3.20	3.27*	2.95*
	(2.90)	(2.29)	(1.87)	(1.54)
Min temp variability	15.20	22.79	1.52	-0.61
	(11.11)	(14.45)	(16.73)	(8.37)
Min temp variability squared	-118.16	-162.97	33.70	-1.87
	(88.01)	(128.52)	(158.61)	(67.85)
Maximum temp variability	-34.60	-71.20**	9.75	-10.92
	(33.67)	(32.78)	(38.20)	(20.74)
Max temp variability squared	196.95	393.32**	-38.81	42.34
	(199.70)	(195.63)	(238.26)	(120.42)
Age of HH head	-0.13	-0.28**	0.16	0.00
	(0.09)	(0.13)	(0.11)	(0.07)
Age squared	0.00	0.00	-0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Gender of HH head (male)	1.03	2.58***	-0.94	0.31
	(0.64)	(0.75)	(0.74)	(0.42)
Household location (urban)	-1.03	1.48***	0.70	-1.00**
	(0.70)	(0.47)	(0.77)	(0.44)
HH head marital status (married)	1.25**	-1.66**	1.64	-0.28
	(0.59)	(0.78)	(1.13)	(0.43)
HH head education level (years)	0.22***	0.02	0.04	0.07
	(0.08)	(0.07)	(0.08)	(0.06)
Access to extension services	0.60**	0.97**	0.58**	0.03**
	(0.46)	(0.51)	(0.50)	(0.30)
Access to market	0.27	-0.14	-0.16	0.19**
	(0.17)	(0.15)	(0.12)	(0.09)
Precipitation variability*extension services	1.24	1.86**	0.18	0.21
	(1.11)	(0.87)	(0.87)	(0.54)
Constant	11.08***	17.53***	-0.53	2.28
	(3.00)	(3.93)	(3.19)	(2.17)
Observations	3 259	3 090	3 181	3 176
R-squared	0.07	0.04	0.03	0.01
Number of households	790	744	764	762

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Source: Author's computations based on UNPS datasets (2009 to 2019) and world climate data

4.5 Results by major crops

The study further estimated separate models for the four common crops grown by the majority of the farmers in Uganda as per the Uganda Bureau of Statistics records. These crops are maize, beans, banana (locally known as *matooke*) and cassava. The dependent variable for each crop is total factor productivity, derived from estimating the stochastic production function of each crop. The standard errors are robust and clustered at the household level to cater for heteroscedasticity.

The results indicate that variability in precipitation has a significant hill-shaped relationship with total factor productivity for beans and banana, a significant U-shaped relationship with total factor productivity for cassava, and no significant relationship with that of maize. These findings are in line with those of Adhikari *et al*. (2015), who note that changes in climate would likely affect crops such as maize, cassava, banana and beans if farmers of these crops fail to adapt to these changes in time. Similarly, our findings support the arguments of Van Asten *et al*. (2011), who noted that bananas, unlike other crops, require a consistent supply of water to sustain their green vegetation and shallow root system. Therefore, a prolonged change in water patterns might negatively affect banana yields, and thus productivity. According to Arslan *et al*. (2017), beans and maize require relatively less water during the flowering period, as more rain or water destroys the flowering process. This greatly affects the yields realised and hence the productivity returns. However, Sheng and Xu (2019) found a large drop in yields of many crops, including maize, due to climate variability in Asia and in China, which contradicts the findings of our study findings, which found a non-significant impact of all climate variability components on maize productivity.

Table 5: Regression results per major crop grown

Variables	Maize	Beans	Cassava	Banana
Precipitation variability	0.79	2.93*	-3.22**	1.55**
	(1.86)	(1.64)	(1.28)	(0.63)
Precipitation variability squared	-0.59	-2.39*	2.34**	-0.81*
	(1.45)	(1.25)	(1.01)	(0.47)
Min temp variability	3.08	0.70	-0.01	-4.03*
	(6.10)	(5.52)	(7.94)	(2.32)
Min temp variability squared	-48.32	-7.14	19.79	38.37*
	(47.48)	(44.20)	(74.65)	(20.13)
Maximum temp variability	-5.68	-15.56	8.39	-7.27
	(19.37)	(16.86)	(14.81)	(6.87)
Max temp variability squared	38.45	67.31	-46.67	31.13
	(116.71)	(101.99)	(88.88)	(41.28)
Age of HH head	0.10*	0.13*	-0.02	0.03
	(0.06)	(0.08)	(0.06)	(0.02)
Age squared	-0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Gender of HH head (male)	-0.29	0.41	-0.01	-0.26*
	(0.42)	(0.32)	(0.43)	(0.15)
Household location (urban)	-0.11	-0.16	-0.50	0.32**
	(0.44)	(0.33)	(0.47)	(0.15)
HH head marital status (married)	0.10	-0.52	0.60	0.28
	(0.46)	(0.37)	(0.37)	(0.23)
HH head education level (years)	0.05	0.00	0.08*	0.01
	(0.05)	(0.04)	(0.05)	(0.02)
Access to extension services	0.01**	0.16**	0.56**	0.37***
	(0.03)	(0.02)	(0.24)	(0.11)
Access to market	-0.13	-0.03	0.04	0.07**
	(0.09)	(0.08)	(0.06)	(0.03)
Precipitation variability*extension services	0.47	0.22	-0.04	0.51**
	(0.52)	(0.48)	(0.42)	(0.20)
Constant	-2.57	-3.32	1.13	-1.34*
	(1.92)	(2.16)	(1.72)	(0.77)
Observations	7 164	7 492	5 731	6 493
R-squared	0.01	0.01	0.03	0.02
Number of households	2 091	2 067	1 779	1 654

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Source: Author's calculations based on UNPS datasets (2009 to 2019) and world climate data

Variability in minimum temperature has a significant U-shaped relationship with banana productivity, but has no significant impact on the productivity of maize, beans and cassava. This implies that variations in minimum temperature only alter banana yields, and not those of maize, beans and cassava. Beans and maize require relatively higher temperatures during the flowering stage, while cassava is relatively tolerant to changes in temperature, including a rise in temperature (Dhakal 2016). The findings on banana productivity due to a variability in minimum temperature are similar to those of Van Asten *et al*. (2011), who established that a rise in temperature as a result of prolonged drought is one of the main causes for banana yield loss in the East African region, which includes Uganda. Similarly, Adhikari *et al*. (2015) found that a rise in temperature might lead to a 10% loss in banana yields. Therefore, the results in this section seem to imply that, as a crop, banana requires relatively higher temperatures to achieve higher yields per hectare.

As predicted in previous studies, access to extension services increased the productivity of all crops under study in this paper. Extension services are important in providing advice and imparting skills and knowledge on various issues to farmers. The results further show that the productivity of all crops under study in this paper are not sensitive to the level of education of the household head, with the exception of cassava. This is quite surprising, given that education is expected to increase the productivity of the farmers in relation to all crops (Dhakal 2016; Arshad *et al*. 2018). However, it should also be noted that the majority of the farmers tend to learn on the job through their experience, and from peers or government agricultural officials such as commercial, production and extension officers. The government of Uganda has introduced many programmes, including a plan for the modernisation of agriculture, national agricultural advisory services and an operation for wealth creation, all aimed at equipping farmers with the necessary skills and information to improve their productivity, especially in the four crops under study in this paper. This could therefore explain why the level of classroom education of the household head does not play a significant role in the yields per hectare realised for beans, maize, cassava and banana.

5. Conclusions and policy implications

The analysis in and findings of this study shed light on the vulnerability of Uganda's farming households, regions and selected key crops to climate variability. The descriptive statistics in this paper show that the farming household heads, on average, had 5.3 years of education (some primary education as per the UBoS classification). However, 56% of the farming households were not accessing agricultural extension services, although 81% of the farming households had access to markets for their crops. This follows the fact that the government of Uganda has built markets across the country and further improved the road network to facilitate the movement of goods and services across the country. On the other hand, the trend analysis supports the existence of climate variability in all regions of Uganda from 1979 to 2013, as shown by a non-zero coefficient of variation for the two components of climate variability – precipitation and temperature. Coefficients of variation are the most recognised statistical measure for variability in most statistical and empirical studies on the topic (Gorst *et al*. 2018).

The results of the empirical regression show that variability in precipitation has a non-linear U-shaped (convex) relationship with Uganda's agricultural productivity, while access to extension services positively increases agricultural productivity and that of the selected crops under study. The regional analysis, on the other hand, indicates a non-uniform impact of climate variability on agricultural productivity across the four regions of Uganda, with the eastern region being the most affected region. The crop-specific results show that beans and bananas are more sensitive to variability in climate compared to maize and cassava. This implies that maize and cassava, in comparison to beans and banana, are more resilient to climate variability and its effects. The availability of extension services and the education level of the household head have positive effects on agricultural productivity, while the effect on urban-based farmers was negative. Gender, marital status and age of the household head had a statistically insignificant impact on productivity. The automatic (or unintended) adaptation to climate variability by some farming households as a result of the changing climate may improve agricultural productivity. The positive significant coefficient of the interaction term (precipitation variability and access to extension services) confirms the positive role that access to extension services plays in offsetting the negative effects of variability in precipitation on agricultural productivity in the country.

This study therefore contributes to the stock of existing literature on the impact of climate variability on agricultural productivity by combining both household-level survey data and long-term climate data. This is important in accounting for agricultural seasonal complexities and solves the model selection bias that may lead to inconsistent, inefficient and unreliable model estimates, which usually result when household-specific characteristics are omitted in the analysis. This study further provides a methodological innovation in which a total factor productivity is derived from estimating a stochastic production function. This is aimed at establishing the actual impact of changes in climate on total agricultural productivity and specific crop productivity in Uganda. The study thus recommends that the government of Uganda should design and adopt policies and measures aimed at combating variabilities in climate and their effects across the entire country. For example, there is a need for deliberate efforts geared at ensuring that all farming households in the country have access to extension services. Secondly, the negative impact of precipitation variability on agricultural productivity and crop yields can be minimised through regular farmer education programmes. This follows the fact that education improves the productivity of farmers (Nagasha *et al*. 2019). Through education, farmers can learn ways of adapting to climate variability, including how to apply irrigation, plant drought-resistant crops and construct valley dams, among others.

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Appendices

Appendix 1: Maps showing trends in climate variability across various regions of Uganda

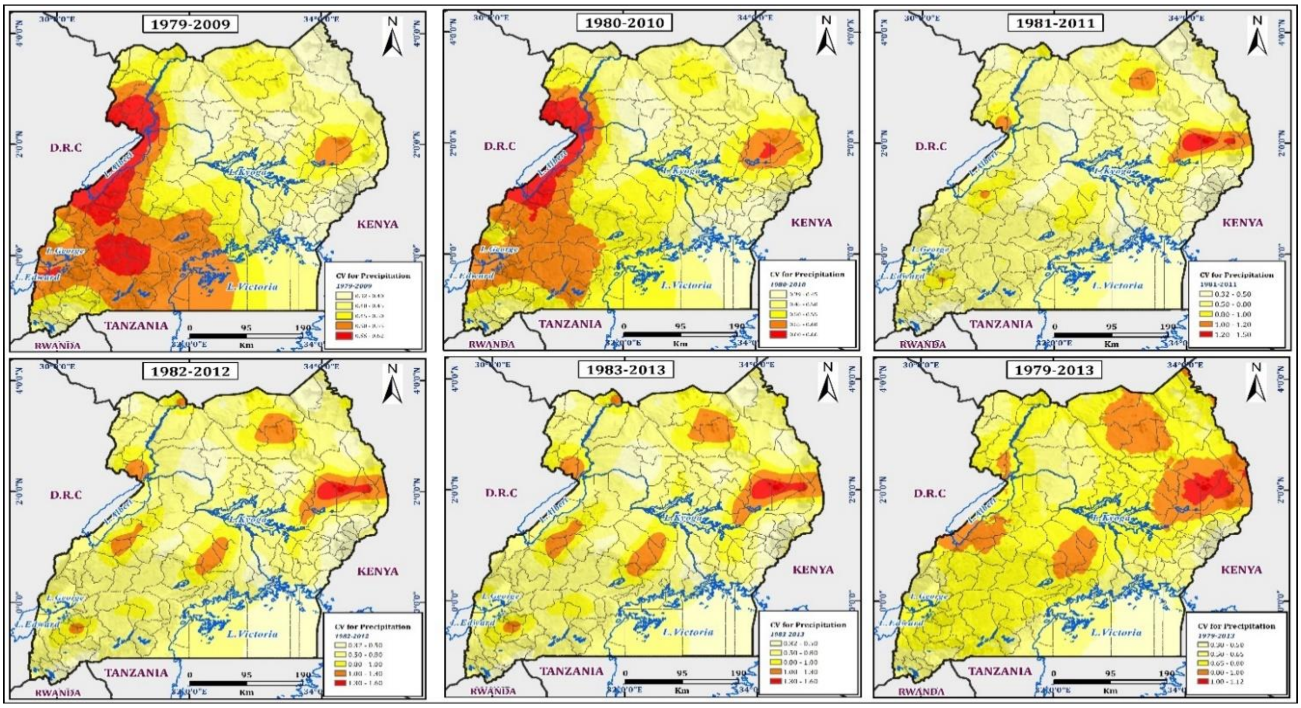

Figure A1: Precipitation variability from 1979 to 2013
Source: National Oceanic and Atmospheric Administration ([NOAA] 2019) reanalysis data

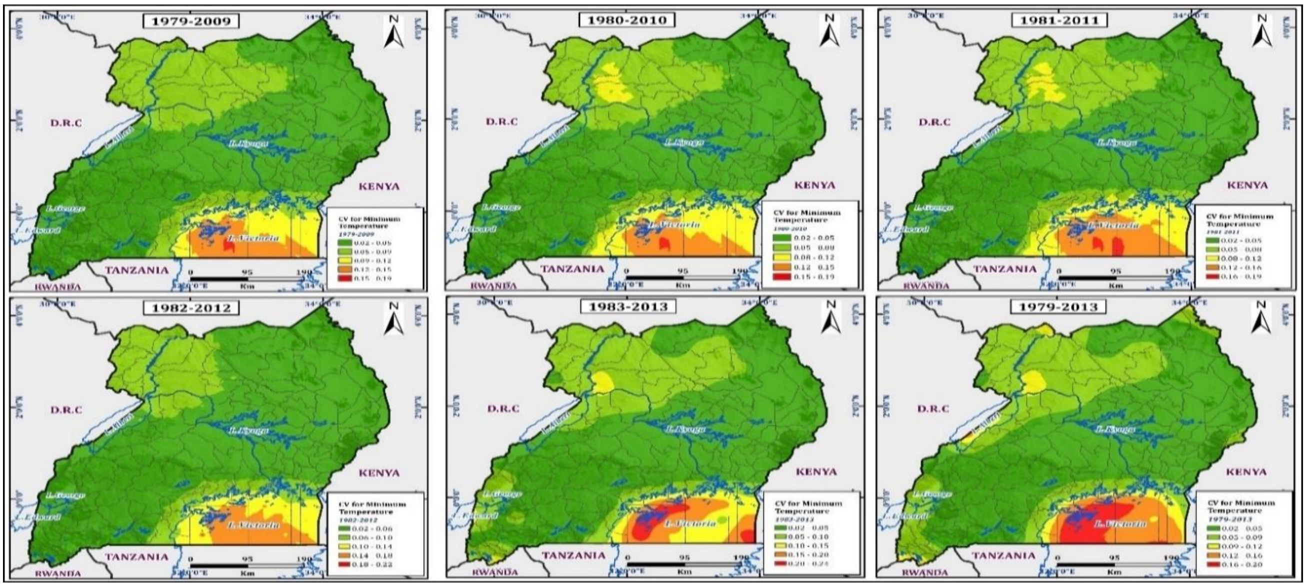

Figure A2: Minimum temperature variability from 1979 to 2013
Source: National Oceanic and Atmospheric Administration ([NOAA] 2019) reanalysis data

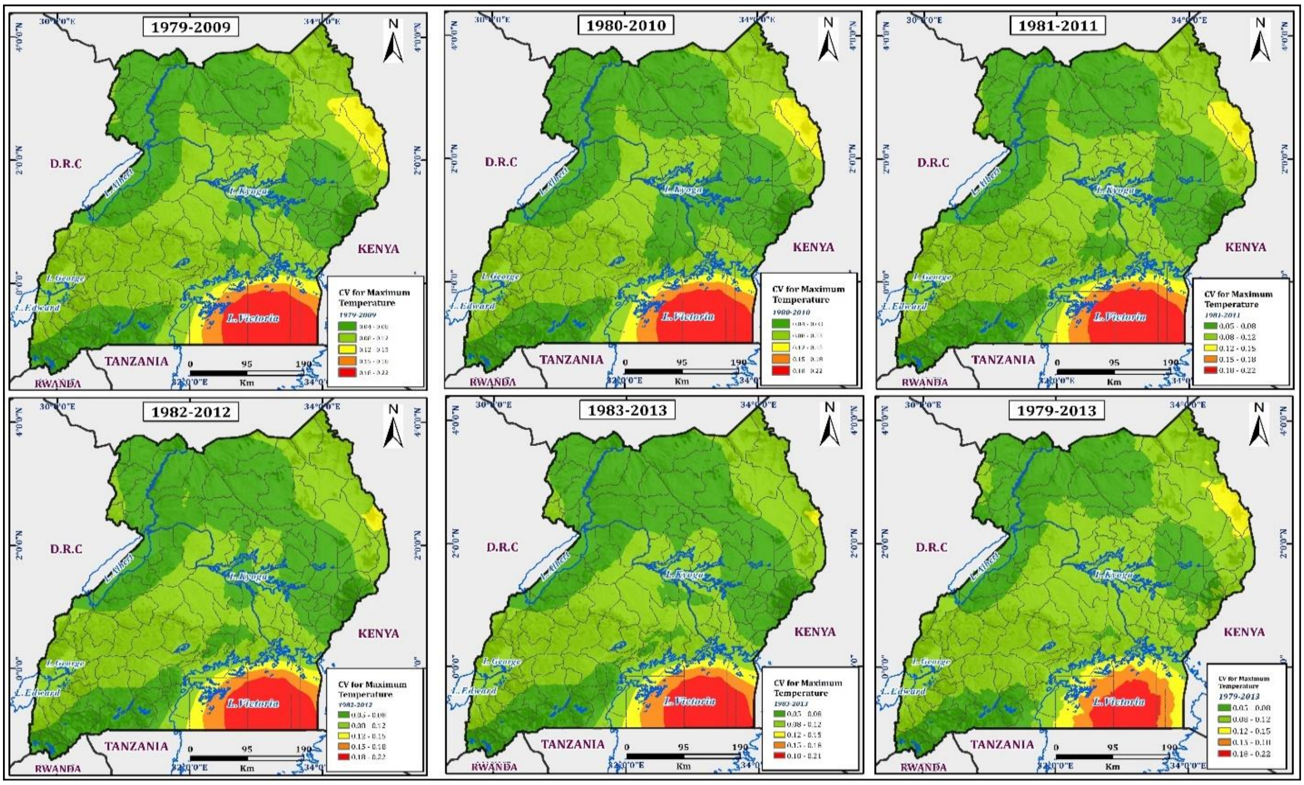

Figure A3: Maximum temperature variability in Uganda from 1979 to 2013

Source: National Oceanic and Atmospheric Administration ([NOAA] 2019) reanalysis data

Appendix 2: Results of correlation matrix

	TFP	**ppt_va~y**	**PPTVar~d**	**mintem~y**	**MinVar~d**	**maxtem~y**	**MaxVar~d**	**hhage**
TFP	1							
ppt_variab~y	-0.027	1						
PPTVariab_~d	-0.0252	0.9887	1					
mintemp_va~y	0.0158	0.0605	0.0362	1				
MinVariab_~d	0.013	0.0311	0.012	0.9682	1			
maxtemp_va~y	-0.0018	-0.0266	-0.0362	0.0649	0.0897	1		
MaxVariab_~d	-0.0006	-0.0268	-0.0356	0.0706	0.1084	0.989	1	
hhage	-0.0226	0.0237	0.0217	-0.0141	-0.0136	0.0043	0.0057	1
hhagsqd	-0.0277	0.0191	0.0173	-0.0151	-0.0144	0.0051	0.0067	0.9858
hhsex	0.0665	-0.0247	-0.0229	0.0126	0.015	0.0112	0.012	-0.1721
urban	-0.0821	0.0526	0.0507	0.0151	0.0122	0.0131	0.0113	0.0259
Marital_st~s	0.0769	-0.0322	-0.0308	0.0073	0.0057	0.0123	0.0126	-0.2696
hhedyrs	0.0776	0.0041	0.0052	0.0143	0.0176	0.0069	0.006	-0.2261
Extension_~s	0.0577	-0.0496	-0.0477	0.0131	0.0111	-0.0108	-0.0085	-0.0027
mkt_access	0.0017	0.0056	0.0047	-0.0215	-0.0227	-0.0147	-0.0149	0.0051
PPT_Ext	0.0541	0.1476	0.1471	0.0308	0.0226	-0.0175	-0.0158	-0.0008
	hhagsqd	hhsex	urban	Marita~s	hhedyrs	Extens~s	mkt_ac~s	PPT_Ext
hhagsqd	1							
hhsex	-0.1581	1						
urban	0.0137	-0.112	1					
Marital_st~s	-0.2622	0.6853	-0.134	1				
hhedyrs	-0.2341	0.3331	0.144	0.2586	1			
Extension_~s	-0.0031	-0.0081	-0.0124	0.0076	-0.0109	1		
mkt_access	0.003	0.001	0.0228	0.0091	0.0002	-0.0067	1	
PPT_Ext	0.0018	0.0078	0.007	0.0064	-0.0109	0.9531	-0.006	1

Source: Author's calculations based on UNPS datasets (2009 to 2019) and world climate data