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Abstract

Rising temperatures due to climate change pose a significant threat to agricultural systems and the livelihoods of farmers across the globe. Identifying farm management strategies that reduce sensitivity to high temperatures is, therefore, critical for moderating the adverse effects of climate change. In this paper, we use spatially granular climate data merged with four waves of household survey data in Uganda to examine empirically the relationships between high temperatures, agricultural production outcomes, and the adoption (including its duration) of three sustainable agricultural practices (organic fertilizer adoption, banana-coffee intercropping and cereal-legume intercropping). We do this using a fixed-effect model, with instrumental variables to address potential endogeneity issues. Our findings indicate that, while exposure to high temperature does reduce farmers' crop income, the adoption of these practices can offset the negative impact of high temperatures on such income. Indeed, we show that the benefits of adopting these practices on the total value of crop production increases monotonically as temperatures increase from their long-term averages. Moreover, the number of years a farmer adopts a practice is associated with higher total value of crop production, and this relationship holds across the full distribution of observed high temperature deviations. Taken together, the results suggest that organic fertilizer adoption, banana-coffee intercropping and cereal-legume intercropping are effective options to adapt to rising temperatures in Uganda, and these benefits increase with the duration of adoption. Adaptation policies and programmes must therefore be designed in ways that help farmers overcome initial barriers to adoption of these practices, as well as to support farmers to sustain adoption over time. This may require longer-term funding horizons for adaptation programmes, and innovative support mechanisms to incentivize sustained adoption.

Keywords: climate change, adaptation, vulnerability, sustainable agriculture, Uganda.

JEL Codes: Q18, Q54, Q55, Q12.

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1 Introduction

It is unequivocal that the earth's surface is warming and anthropogenic causes are driving this trend. Human activities are estimated to have already caused 1.0 °C of global warming above pre-industrial levels, with higher rates of warming occurring in certain regions (IPCC, 2018). Even with significant and immediate reductions in global greenhouse gas (GHG) emissions, the persistence of elevated GHG concentrations in the atmosphere ensures that warming above pre-industrialization levels will continue for centuries to millennia (IPCC, 2018). A hotter future is guaranteed, adapting to this future is, therefore, imperative.

Given its reliance on biological processes and its importance to humanity's wellbeing, the adaptation of agriculture to rising temperatures, and associated weather risks, is of particular importance. Many crops exhibit a non-linear yield response to temperatures (Schlenker and Roberts, 2009; Lobell *et al.*, 2011). Yields typically increase incrementally with temperature up to a certain threshold. Once that threshold is exceeded, yields drop dramatically (Lobell *et al.*, 2011). Moreover, rising temperatures increase the rate of evapotranspiration, and therefore place greater demand on available water, contributing to faster development of water stress in crops during dry spells (Lobell *et al.*, 2011; Osbahr *et al.*, 2011; Hisali *et al.*, 2011). At the same time, rising temperatures can increase the severity and geographic distribution of many agricultural pests and diseases (Thornton *et al.*, 2009).

The magnitude of the challenges posed to agricultural systems and livelihoods by climate change is particularly acute in sub-Saharan Africa (SSA) (IPCC, 2014). In SSA, agriculture serves as the primary source of livelihood for the majority of the population and is a critical driver of the region's economic structural transformation. Despite its importance, the agricultural activity is generally carried out under rain-fed production systems by farmers with few resources and mechanisms to adapt to and cope with climate change. In the predominantly tropical and sub-tropical regions of SSA, warming and drying as a result of climate change may drive down yields from already low levels by 10 to 20 percent by 2050, with some regions experiencing even more drastic declines (Jones and Thornton, 2003; Jones and Thornton, 2009).

In an effort to shed the type of evidence that supports decision-making in climate change adaptation policies and programmes, this paper quantifies the impacts of rising temperatures in Uganda and assesses the effectiveness of various farm practices at reducing climate adverse impacts. To do this, we make use of four waves of panel household survey data, focusing specifically on the impacts of three sustainable agricultural practices, which are anticipated to reduce the sensitivity of farm systems to temperature extremes, namely: the use of organic fertilizers, banana-coffee intercropping systems, and legume-cereal intercropping systems.

The paper makes two important contributions to the evidence on climate change adaption in SSA, and for Uganda in particular. First, we quantify the impacts of adopting different agricultural practices on the sensitivity of smallholder systems to high temperatures. Crop models show that rising temperatures are an important threat to crops and farmers' livelihoods (Lobell *et al.*, 2008; Hassan and Nhemachena, 2008; Jones and Thornton, 2003; Lobell *et al.*, 2011). Identifying farm-level practices to reduce the adverse impacts of high temperatures on smallholders' livelihoods is therefore important to inform policy discussions on climate change adaptation. Second, our analysis pays close attention to the effect of the temporal dimensions of adoption. Policies and programmes often focus on supporting the adoption of improved practices, but rarely consider the importance of sustaining adoption. However, there is reason to believe that sustained adoption of many climate adaptive farming practices is critical for improving the benefits of the practices, due to biological effects that accrue overtime, such as the build-up of soil organic matter and socio-economic benefits that occur through improved knowledge and skills.

Drawing conceptual insights from the literature on climate vulnerability, we examine the effects of adopting these adaptive farming practices on the sensitivity of crop systems to high temperatures using a fixed-effect model on a panel of households, with instrumental variables to address potential endogeneity issues. The instrumental strategy draws from the literature on the role of social and peer learning in the decision to adopt agricultural practices (Conley and Christopher, 2001; Munshi, 2004; Maggio and Sitko, 2019, Arslan *et al.*, 2017). Our results show that in Ugandan smallholder systems, an increase of 1 percent in maximum temperature during the growing seasons reduces the total value of crop production by approximately 7–11 percent. Moreover, the adoption of the three practices under consideration is shown to likely improve crop income, and the magnitude of this positive impact increases monotonically with the severity of the high temperature shock. Finally, we show that an increase in the duration that a farmer applies these practices, measured in terms of number of agricultural seasons, is associated with improvements in crop income, and that such year-by-year improvements hold across the range of high temperature shocks. Taken together, the results suggest that addressing rising temperatures through the promotion of adaptive practices is critical for reducing Ugandan agriculture's sensitivity to climate change, and efforts to do so must consider not only how to overcome initial barriers to adoption, but also how to support farmers to sustain their application over time.

This paper is organized as follows. Section 2 provides background information on the context of this analysis. This is followed in Section 3 with the conceptual framework and in Section 4 with a description of the data and key variables of interest. Section 5 explains the empirical strategy developed in the analysis, while Section 6 discusses the main findings and results. Section 7 provides concluding comments and explores the policy implications of the results.

2 Background

Agriculture in Uganda is a critical component of the overall economy, contributing approximately 23 percent to the country's GDP in 2014 and providing a livelihood for a large share of the population (MAAIF, 2016). Around two thirds of the population are directly engaged in agricultural production, the majority of which takes place under small-scale rain-fed conditions (CIAT and BFS/USAID, 2017).

Uganda observes two agricultural seasons, the first occurs between March to May and the second between September to November.[1] There are climatic differences across the country. North-eastern Uganda is the hottest and driest part of Uganda, making the land suitable only for annual cropping and pastoralism, while crop continuous cultivation are mostly found in the South. According to recent studies, the mean surface temperatures in the country have increased by 1.4 °C since the 1960s (McSweeney *et al.*, 2010), and are projected to rise by as much as 3.2 °C in some parts of the country by 2050 (Duku *et al.*, 2019). Changes in temperature and precipitation due to anthropogenic climate change is already having a significant impact on agriculture in Uganda. Hisali *et al.* (2011), for example, estimate that up to 34 percent of crop damage in the country is caused by climate induced stresses, including low and high rainfall, and increased prevalence of crop diseases and insect damage due to rising temperatures. Thornton *et al.* (2010) estimate that maize and bean yields in Uganda may reduce by up to 18.5 percent by 2050 in humid and arid regions of the country as a result of climate change.

Adapting agriculture to a changing climate through the adoption of appropriate agricultural practices is critical for avoiding major losses in productivity and disruptions in peoples' livelihoods. In this paper we consider three practices that may reduce the sensitivity of cropping systems to climate change, particularly to the adverse effects of rising temperatures: application of organic fertilizer (compost and manure), intercropping bananas with coffee, and intercropping legumes with cereals. These practices were selected for three reasons. First, they are likely to mitigate adverse impacts of rising temperatures on important crops and cropping systems in Uganda. Second these practices are likely to accrue their return over time, due to different underlying mechanisms that will be discussed in the next section. Finally, because data are collected on these practices in all survey waves used in this study.

In Uganda, bananas and maize constitute the primary staples, accounting for 21 percent calories available per day per capita,[2] while coffee is Uganda's major cash crop, providing 20–30 percent of foreign exchange earnings for the country (Wang *et al.*, 2015). The selected practices have the potential for reducing sensitivity of maize and banana systems to high temperatures stresses, and associated impacts on disease, pests, and water stress susceptibility, in various ways that will be discussed below.

Intercropping of legumes with cereal, such as maize, does not specifically address issues related to rising temperatures, but rather is a practice that can improve the overall performance of cropping systems. Given this, we expect that intercropping will be beneficial under a wide range of temperature and agro-ecological conditions (Ladha et al., 2013, Maggio and Asfaw, 2020). That being said, there are three specific attributes of cereal-legume intercropping that

[1] In this study we treat these separate agricultural seasons as a single season. All the variables, including the climatic ones, are calculated as averages of the two seasons excluding the period June–August.

[2] Data retrieved from FAOSTAT database.

address production risks linked to rising temperatures. First, leafy legumes in an intercropping system can generate cooler and moisture micro-climates that are beneficial for cereals under conditions of high temperatures or low rainfall (Raseduzzaman and Jensen, 2017; Rusinamhodzi *et al.*, 2011). Second, it can help to stabilize yields and incomes through what is referred to as the "compensation principle", whereby if one species is affected by a disease or pest, the other may compensate by using available nutrients to stabilize overall yields (Raseduzzaman and Jensen, 2017). Third, it generates complementarities between crops, including different rooting depths, different nutrient requirements, the fixation of atmospheric nitrogen by legumes, and canopy architecture, which can contribute to more stable production in the face of heat stresses (Rao and Wiley, 1980; Frison *et al.*, 2011).

Coffee, particularly Arabica coffee, is sensitive to high temperatures and is typically grown in cooler, high altitude environments in Uganda. As temperatures rise, the suitability of current growing regions for coffee reduces, forcing production to shift upward (Wang *et al.*, 2015). Rising temperatures also increase the incidence of damaging coffee pests, such as coffee leaf rust and coffee twig borer (Craparo *et al.*, 2015). Agronomic research shows that shading coffee with banana helps reduce heat stress and can lower the incidence of leaf rust and twig borer by as much as 50 percent (Alemu, 2015; Craparo *et al.*, 2015). Moreover, this intercropping practice contributes to a build-up of mulch litter, which can further reduce the sensitivity of the crop system to heat and drought stress. Finally, the diversification of production through this practice may help to spread production and market related risks, and thereby reduce the welfare vulnerability of farmers to shocks (Seo, 2010; Asfaw *et al.*, 2019; Arslan *et al.*, 2018). As a result of these attributes, we expect that this practice will have impacts that are most pronounced when temperature risks are highest.

The use of organic fertilizers is a broadly beneficial practice for agricultural production, and it can generate specific benefits under conditions of high temperatures. In particular, high temperatures increase soil and plant evapotranspiration rates, and thus increase water demands by crops (Osbahr *et al.*, 2011; Hisali *et al.*, 2011). The capacity of organic fertilizers to retain soil moisture helps to reduce water stress when temperatures are high and rainfall is limited (Lal 2006). For this reason, we expect that the effects of organic fertilizers will be higher under high temperature conditions than normal temperature conditions (Agehara and Warncke, 2005). A major challenge for the effectiveness of organic fertilizers is that the volumes need to have a measurable effect on soil characteristics is high and may exceed the biomass production capacity of many smallholder systems (Snapp *et al.*, 1998; Place *et al.*, 2003).

In all three cases, we anticipate that the duration that a household has maintained the practices after their adoption will influence the overall impact on the sensitivity of crop systems to higher temperatures. This is due to the biophysical benefits of the practices, such as improved soil organic matter content and improved soil water retention, which build up through sustained adoption (Lal, 2004; Vågen *et al.*, 2005), as well as improved management of the practices which occurs through practice and experience (Marra *et al.*, 2003; Conley and Udry, 2010).[3] Indeed, a reoccurring challenge associated with many improved and more sustainable agricultural practices is that the first years of adoption can entail reductions in yields (Baudron *et al.*, 2012; Giller *et al.*, 2009). Overtime the benefits of these practices increase, relative to conventional practices, but sustained adoption is typically required to realize these benefits.

[3] In addition, for perennial crops, such as bananas and certain types of legumes, the duration is obviously important as it would take time to realize the benefits.

The data used in this study show that organic fertilizer is adopted by between 11 and 16 percent of the farm population, depending on the year, while the average duration of continuous adoption (computed among adopters) ranges from 1.6 to 2.4 years (Table 1). Banana-coffee intercropping is adopted by 18 to 22 percent of the population, with an average duration of adoption between 1.6 and 3 years. As shown in Figure 1, these two practices are spatially concentrated in the southern and south-eastern regions of the country, including the Lake Victoria Crescent, Western and Southern Highlands, and Southern Dryland, which observes lower maximum temperature during the agricultural season. Legume intercropping is more widespread in Uganda, adopted by between 51 and 59 percent of the population with an average duration ranging from 1.7 to 3.1 years.[4] The spatial distribution of adoption of legume intercropping is greater than the other two practices, with non-trivial adoption also observed in warmer regions such as the Mid-Northern and West Nile. In all cases there is no clear change in adoption rates over time.

Table 1. Crop income, and adoption dynamics of sustainable agricultural practices in Uganda between 2010 and 2014

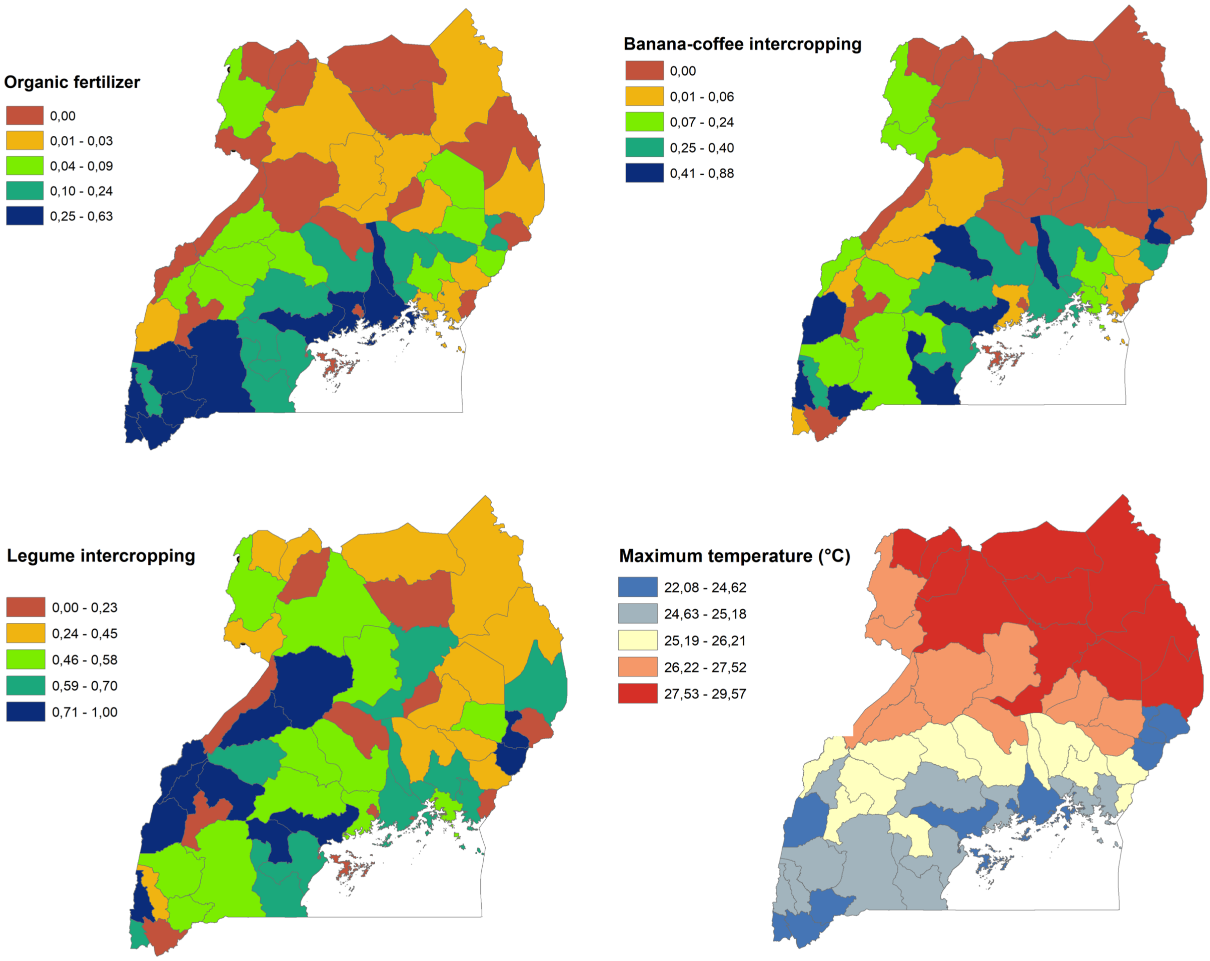
	2010	2011	2012	2014
Total value of crop production (real 2010 USD)	361.56	369.55	484.47	516.30
Households adopting organic fertilizer	16%	16%	16%	11%
Households adopting banana-coffee intercropping	19%	22%	22%	18%
Households adopting cereal-legume intercropping	59%	57%	59%	51%
Duration of adoption organic fertilizer (years)	-	1.6	2.0	2.4
Duration of adoption banana-coffee intercropping (years)	-	1.6	2.3	3.0
Duration adoption legume-cereal intercropping (years)	-	1.7	2.3	3.1

Notes: The duration of adoption for 2010 is not reported because each wave of the survey does not contain info on adoption for the previous years, making impossible to construct the adoption duration for the first wave. Duration of adoption is measured as the number of consecutive years a practice is adopted by a given household. The duration measured in a decimal scale of a year, for example, a value of 0.5 corresponds to 6 months.

Source: Authors' own elaboration.

[4] Some of the legumes under studies are perennials, such as pigeon peas and cowpeas, and thus have increased return from duration also due to the development of the plant itself.

Figure 1. **High temperature risk and the geographic distribution of sustainable agricultural practices in Uganda**



Notes: Average share of adopters of organic fertilizer (above left panel), banana-coffee intercropping (above right panel), crop-legume intercropping (below left panel) and maximum temperature (below right panel) across the country for the period 2010–2014. The map has been realized by using the shape files of the administrative level 2 (district) available in the FAO Hand-in-Hand Geospatial Platform.

Source: Authors’ own elaboration based on Uganda map available in the FAO Hand-in-Hand Geospatial Platform.

3 Conceptual framework: analysing climate vulnerability in Ugandan smallholder systems

Our analysis draws on the vulnerability literature, which focuses on understanding how social-ecological systems respond to stresses or perturbations, including weather and climate related shocks (Adger, 2006; Miller *et al.*, 2010; Janssen and Ostrom, 2006). Vulnerability draws from a diverse epistemic community, including hazard studies in geophysical sciences, economics, political economy, and political ecology (Miller *et al.*, 2010; Downing *et al.*, 2005; Adger, 2006; Ionescu *et al.*, 2009). While there are numerous interpretations of vulnerability, the central idea of vulnerability is the degree to which a system is susceptible to and is unable to cope with adverse conditions, such as those created by climate change (Turner *et al.*, 2003; Adger, 2006). Underlying this definition are the concepts of exposure, sensitivity, and adaptive capacity, which informs the majority of work on vulnerability (Adger, 2006; Kasperson *et al.*, 2005; Miller *et al.*, 2010). More specifically, the concept of vulnerability is concerned with the stress that a system is exposed to (including the magnitude and frequency of this exposure), its sensitivity to that stress, and its capacity to adapt.

An important contribution of the vulnerability literature is its focus on the interactions between exposure to a particular stress or hazards, such as extreme weather events, the capacity of actors or systems to respond to this exposure, and how this affects the well-being of the system (Luers *et al.*, 2003; Ribot, 1995). Thus, analyses of vulnerability focus attention on both the effects of stresses on outcome, as well as mechanisms that may alter this impact (Luers *et al.*, 2003).

In this study we operationalize the concept of vulnerability in the context of smallholder medium landholder households, which are our units of analysis.[5] The weather stress exposure of interest is anomalous high temperatures, which can affect smallholder systems via its effects on agricultural production. We measure the effect of this exposure on smallholder systems along two dimensions. First, we measure the marginal impact of high temperature exposure on the total value of crops harvested, after controlling for a wide range of socio-economic, institutional, and farm management practices. This provides insights into the sensitivity of Ugandan cropping system to high temperatures, which in the absence of effective adaptation or coping strategies can affect household income, food security, and other critical welfare variables. Second, we explore the adaptive capacity conferred to smallholder systems through the adoption and adoption duration of the farming practices considered. This is done by assessing if adoption of the three adaptation practices is associated with a reduction in sensitivity to high temperature exposure of varying severity, and if this adaptive effect varies as a result of the duration that the practice is adopted. As discussed above in the background section, we anticipate that the benefits of the adoption of these practices are likely to be greater under higher temperature conditions, particularly for banana-coffee intercropping and organic fertilizer use, and that adoption duration will improve the impacts of the practices.

[5] While the definition of smallholder households varies depending on the context, there is agreement that these in Uganda are identified by a landholding size lower than 5 hectares (Anderson *et al.*, 2016). In our dataset, about 80 percent of the sample owns less than 5 hectares of land.

Against this conceptual background we hypothesize that: 1) exposure to high temperatures in Ugandan smallholder systems is associated with a reduction in crop income, all else equal. In other words, these systems are sensitive to high temperatures during the growing season; 2) adoption of the agricultural practices reduces sensitivity to high temperatures, suggesting an improvement in adaptive capacity via adoption of the practices, and 3) adoption of the three agricultural practices is associated with higher farm incomes, and this impact increases as the duration of adoption increases.

4 Data and key variables

The analysis contained in this paper comes from household level socio-economic survey data merged with spatially explicit, granular rainfall and temperature data. The socio-economic survey data comes from the Uganda National Panel Survey (UNPS) 2009–10, 2010–11, 2011–12 and 2013–14,[6] which was designed and implemented by the Uganda Bureau of Statistics (UBOS), with support from the World Bank LSMS-ISA project.

The UNPS is representative at the national, urban/rural and regional levels. In each wave, the UNPS collects information about approximately 3 200 households. The UNPS captures a wealth of information on demographics, education, housing, markets and services, employment and agricultural activities, both at household, community and plot-level. The agricultural module includes information on access to land, number of plots, plot area, land use, production quantity and values for a wide range of relevant crops, fruits and legumes, as well as records on the agricultural practices adopted by the households, including the use of organic and inorganic fertilizer, drainage, improved seeds and intercropping.

Since our analysis focuses on the medium-term effects of sustainable agricultural practices, we select the subsample of households observed across all the four waves. This allows us to build a balanced panel database consisting in 1 123 households per year, adopting or dis-adopting the selected agricultural practices multiple times across the time span under analysis.[7]

We construct our dependent variable as the total value of crop production, which is the sum of the real commercial value of all the crops cultivated in a given agricultural season for the household, computed using the median price per crop sold at village level and expressed in real international dollars. Adoption of the three practices of interest, i.e. organic fertilizer, banana-coffee intercropping and crop-legume intercropping, is captured by three dummy variables, equal to 1 if the household adopted that particular practice. To measure the time length of adoption, we construct three further variables that account for the number of years in which each household has adopted that practice. Since the survey does not allow us to reconstruct the duration of adoption for the adopters in the first year, we exclude these adopters from the sample when focusing on the effect of the duration of adoption on total value of crop production. For this reason, the analysis of adoption duration is conducted on three different samples of households who were non-adopters in the first year of the survey. The values of these variables range from 0, if the household never adopted, to 3, if the household adopted that practice in all remaining three survey years (2011, 2012, 2014).[8, 9]

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[6] These data are publicly available and can be retrieved from: http://surveys.worldbank.org/lsms/programs/integrated-surveys-agriculture-ISA/uganda#bootstrap-panel

[7] These observations represent a subset of the overall sample. From the original sample of 2 336 household in 2010, the survey provider track back only 1 459 households in 2014. The sample under analysis, therefore, represents 77 percent of the observations tracked during the fourth wave. Also, a t-test suggests that these two groups of household do not show a statistically significant different crop income households (t=-0.28, P= 0.7741). This suggests that the bias deriving from this sub selection on the dependent variable should be minimal.

[8] Since the survey does not contain retrospective questions on practice adoption, we exclude the first year (2010) from the computation of the “duration” variables, and we assume that in the second year (2011), these variables can only take values from 0–2.

[9] We consider these as consecutive years, thus, if a household has adopted during 2012 and 2014, its adoption duration variable will be equal to two.

Using the geographical location of the households' villages, we merge the survey data with data on local climate conditions observed during and before the years of the survey. Rainfall data employed in this analysis come from the Climate Hazard Center of UC Santa Barbara (CHIRPS), which is a public available dataset of re-elaborated spatial observations from precipitation data observed by the weather stations across the African continent. CHIRPS provides information for decadal (10 days) rainfall at 0.05 degrees of spatial resolution, for the period 1981–2018. Re-elaborated data on temperature derives from the European Center for Medium-Range Weather Forecasts (ECMWF), which delivers records on 10 days maximum, minimum, and average temperature at 0.25 degrees of resolution. In this study we use temperature data from both ECMWF's operational database (1989–2010) and the interim database (2011–2016). These two datasets mainly differ on the model applied to elaborate the temperature data collected by the weather stations. Their usage implies assuming that the sample is unaffected by the change in spatial elaboration in the data.

With these weather data we construct two variables used to identify anomalous temperature and rainfall events during the agricultural production seasons in Uganda. Anomalously high temperature exposure is identified by constructing a variable measuring the positive maximum temperature deviation from its historical average. This is calculated as the difference between the average maximum temperature during the two growing seasons in the year y of the survey, with y = 2010, 2011, 2012, 2014, and the long-term mean of the same seasons in the household's village, divided by the long-term mean, where long-term refers to the period [1989, y] and where negative values of temperature deviations are treated as zero. We use a similar approach to control for anomalous high and anomalous low precipitation (i.e., positive and negative precipitation deviations). For the sake of the interpretation of the coefficient of the negative precipitation deviations, we set to zero the positive values of precipitation deviations and we take the absolute values of negative precipitation deviations.[10] All these variables are computed as percentage variations.

Finally, we control for the level of population density and economic development in the village of farmers' operation extracting information from two other geo-spatial dataset and merging them with farmers' geolocation. Population density comes from the WorldPop platform, which delivers yearly estimates for population density for the African continent at 1 km of spatial resolution (Tatem, 2017). The level of economic development is proxied using the night-time light data delivered by the National Oceanic and Atmospheric Administration with a spatial resolution of about 1 km and widely used by the social science literature on economic and human development (Elvidge et al, 2012; Bertinelli *et al.*, 2016).[11]

[10] Increased levels of the variable, therefore, will correspond to lower level of rainfall with respect to the local average conditions.

[11] The nightlight variable spans between 0–63 with higher values corresponding to more night-time light. This variable enters into the specification lagged as it is available for the period 1992–2013.

5 Empirical strategy

To identify the impact of anomalously high temperatures and the adoption and duration of adoption of farming practices on the total value of crop production, we employ the following panel fixed effect model:

$$TVP_{i,e,y} = \beta_0 + \beta_1 T_{e,y} + \boldsymbol{\beta}_2 \boldsymbol{A}_{i,e,y} + \boldsymbol{\beta}_3 \boldsymbol{X}_{i,e,y} + \alpha_i + \gamma_y + \varepsilon_{i,e,y}, \quad (1)$$

where $TVP_{i,e,t}$ is the total value of crop production (in log) of the household i in year y = 2010, 2011, 2012, 2014 residing in village *e*; $T_{e,y}$ is the temperature deviation computed over the growing seasons in year y and related to village *e*; $\boldsymbol{A}_{i,e,y}$ can be either vector of our three adaptive farming practices (organic fertilizer, banana-coffee intercropping and crop-legume intercropping) measured as a dummy variable equal to 1 if the practice is adopted, or a set of count variables on the duration of the adoption of these practices; $\boldsymbol{X}_{i,e,y}$ is a vector of climatic, demographic and socio-economic time-varying controls that are likely to influence the total value of crop production. The model also includes the household fixed effects α_i, to control for unobservable time-invariant heterogeneity, and the time dummies γ_y, to control for temporal changes or common shocks in a given year, and error terms $\varepsilon_{i,y}$ clusterized at the household level.

As Mundlak (2001) suggests, both adoption of farm inputs and of agricultural practices are potential endogenous to unobserved time-invariant farmer's characteristics, such as skills, access to information and risk aversion. The use of a fixed-effect model addresses this concern, by ruling out these time-invariant causes of endogeneity, and allows to interpret the estimated coefficients as within variation, and in our case as rate of change, for a specific unit of observation. However, fixed-effect estimations might still produce biased estimates for the adoption variables' coefficients due to other unsolved endogeneity issues such as the effect of time-variant unobserved factors (see, among others, Ricker-Gilbert *et al.*, 2011; Mathenge *et al.*, 2014; Manda *et al.*, 2016). We hypothesize three main sources of endogeneity: (i) reverse causality; (ii) self-selection; (iii) omitted variables. Reverse causality refers to the direction of causality. Adoption decisions may be affected by the total value of production in a number of ways. On one side, the adoption of sustainable agricultural practices requires resources to implement them, a condition that leads to a concentration of adoption among better-off farmers (D'souza *et al.*, 1993; Teklewold and Kassie, 2013; Kassie *et al.*, 2009; Marenya and Barrett, 2007). On the other side, the high opportunity cost of adopting some practices may prevent highly productive farmers from adopting (Kassie *et al.*, 2013; Antle and Diagana, 2003; Holden *et al.*, 2004).

The issue of self-selection is strictly related to reverse causality, as adopters and non-adopters may exhibit demographic or socio-economic differences that condition their decision, or may self-select into the adoption of some practices depending on the local climate and agro-ecological condition of their location of operation. For example, a t-test applied to total value of crop production by adoption status indicates that this is lower for non-adopter households than for the adopters, indicating that not accounting for endogeneity may bias the effect of adoption towards the wealthier households (Annex, Table A1).[12] Lastly, estimates of model (1) may also suffer from omitted variable bias, due to time-varying unobservable determinants influencing the

[12] The t-test confirms this difference both for adopters of banana-coffee and of organic fertilizers when compared to non-adopters. Adopters of legume intercropping also report a higher total value of crop production than non-adopters, but the difference is significant only for the part of the sample observed in 2014.

adoption decision of the households, such as extension campaigns about sustainable agricultural practices, program implementation by local and international organizations.

To address these potential endogeneity issues, we employ a two-stage instrumental variable (2SLS-IV) approach. A suitable instrument is a variable correlated with the endogenous regressor (the adoption of an adaptive practice), but not with the errors of the second-stage regression. In our analysis, we employ three instruments, one for each endogenous regressor, based on the economics literature exploiting the important role of social and peer learning in the decision to adopt an agricultural practices (Conley and Christopher, 2001; Munshi, 2004; Maggio and Sitko, 2019; Arslan *et al.*, 2017). For the adoption specification, the instruments measure the share of households adopting one of the three practices and living within 30 km from household i, conditional to their average plot size.[13] Similarly, we instrument the duration of adoption with the average number of years of adoption among neighbours residing within a radius of 30 km from household i, conditional to their average plot size as in the binary case.[14] The exclusion restriction of these instruments holds if the adoption of practices, or its duration, of the neighbours do not influence the total value of crop production of the individual households through any other channel. A potential criticism that can be raised with this instrumental approach is whether more rich farmers are localized into clusters across the country, and therefore the second-step coefficient from the instrumental strategy may be overestimating the impact. To address this and other potential issues, we keep the household-level fixed effects in the specification, which will allow to control for these time-invariant unobserved effect. The first stage of our 2-stage IV model is expressed as follows:

$$A_{i,e,y} = \kappa_0 + \kappa_1 Z_{i,e,y} + \kappa_2 \boldsymbol{X}_{i,e,y} + \alpha_i + \gamma_y + \varepsilon_{i,e,y} \tag{2}$$

where $A_{i,e,y}$ is either the adoption of a given practice or the duration of its adoption, $Z_{i,e,y}$ denotes the instrument for the sustainable agricultural practices, and α_i, $\gamma_y, \varepsilon_{i,e,y}$ are respectively household fixed effects, time dummies and error terms as above. We instrument the adoption variables one by one excluding the other endogenous variables from the instrumented specification.[15] This approach is also consistent with the best available approach that we can implement to test the effect of duration of adoption. Indeed, since in this specification we need to sub-select the sample of non-adopters during the first wave, we will be necessarily studying different samples for each of the practices and instrument them one by one.

The 2-stage IV approach allows us to investigate the effect of both anomalous high temperatures and the adoption of adaptive practices. However, we are also interested in examining whether the impact of adoption on the total value of crop production varies across different temperature levels experienced by the household. We do this for two reasons. First, temperatures typically exhibit a nonlinear effect on agricultural productivity, where adverse

[13] Specifically, we define two land bins: below 1 hectare for smallholder, and above 1 hectare for medium and large land holders. We then calculate the instruments using the share of adopters within the radius of 30 km falling in the same land bin of the household. Given the level of heterogeneity in landholding in the dataset, and the inclusion of household-level fixed effects in the specification, we believe that this is capturing the learning by another channel without influencing the final outcome.

[14] The results remain consistent when testing alternative thresholds of distance and are available in the Annex.

[15] We acknowledge that this may represent a limitation, however, even including all the instruments, the first-stage equation would be exactly identified and therefore it would not be possible to conduct an overidentification test.

effects are observed once temperatures surpass crop-specific thresholds (Lobell *et al.*, 2011; Schlenker and Roberts, 2006, 2009). Second, as climate changes, average temperatures will increase. Examining how these practice effect crop incomes under large deviation from current averages will provide insights into their adaptive capacity under future high temperature conditions. To account for this, we create an interaction term $I_{i,e,y} = A_{i,e,y} * T_{i,e,y}$, equal to the product of adoption and temperature deviation, and we employ a 2-stage IV model, where we simultaneously instrument one practice and its interaction with temperature deviations. The additional instruments for the interaction terms are built as the product of the adoption instruments and the temperature deviations. We then compute marginal effects of the adoption of the practice on crop income for different high temperature deviation percentiles.

Furthermore, we explore whether adopting the practices for more than one year leads to higher values of crop production. We test this hypothesis by computing a variable of adoption duration, which equals the number of years that a household adopts the practice over the last three survey years.[16] We first run a fixed-effect model as our benchmark model (1) where we substitute the duration variables for the binary adoption variables. Then we control for potential endogeneity using a 2-stage IV approach where we instrument the duration variables with the instruments explained above. Finally, to identify differences in terms of crop income for different adoption durations (i.e., one, two or three years) across the range of temperature deviations, we run a fixed-effect model, which includes the interaction of duration and temperature deviation, along with the other variables and controls.

To account for other factors that might influence the total value of crop production, we add several other household and community-level determinants to the main specification.[17] Specifically, to control for demographic characteristics of the household we include the household size, the average number of school years of the household members and a dummy equal to 1 whether the head of the household is female. We also control for a number of agriculture-related variables, including the land size under household cultivation, a dummy equal to 1 if the household accesses land through statutory tenure arrangements and zero if otherwise, an agricultural wealth index computed using the first factor of a principal component analysis on the ownership of different agricultural tools linked to wealth[18], and a set of five dummies equal to 1 if the household irrigates their fields, adopted drainage structures, used improved seeds, planted vetiver bunds, or utilized inorganic fertilizer, respectively. Lastly, to account for service availability and closeness to markets, we employ the population density in the household community, an indicator of nightlights per population density, the distance to the nearest market (in km), and a dummy equal to 1 whether the household lives in an enumeration area classified as urban area. All the continuous variables, including the dependent, are transformed in natural log for the sake of the interpretation of the results.[19]

[16] To measure the duration of adoption in a way that is as consistent as possible across the years and the households, from the duration analysis we do not only exclude the year 2010 (for which we do not have info on adoption history), but we also drop the adopters of the first year (2010) along all the years. This is to avoid considering as, for example, 2-year-adopters also those households who actually adopted from longer, but for which we do not have info prior to the year 2010.

[17] Summary statistics related to these variables are reported in the Annex, Table A2.

[18] This includes ownership of ploughs, panga knives, slashers, wheelbarrows, tractors, watering cans, hoes and livestock.

[19] To keep the zero value observations, we add one before taking the log. Table A4 in the Annex shows that the results do not change when using alternative approaches, such as transforming the continuous variables using the inverse hyperbolic transformation developed by Bellamare and Wichman (2020).

6 Results and discussion

We divide the results section into three sub-sections, corresponding to the hypotheses motivating this article. The first sub-section examines the sensitivity of smallholder production systems to weather risk exposure by measuring the impacts of temperature extremes and precipitation deviations on smallholder crop income. The second sub-section explores the effects of adopting the three agricultural practices on household crop income under different levels of extreme high temperature deviations. This illuminates the extent to which these practices can improve the adaptive capacity of farming systems under increasing temperature conditions. In the final sub-section, the effects of the duration adoption of the practices on crop income is explored.

6.1 Assessing the impacts of climate risks and adaptation strategies on smallholder crop income

High temperature deviations, relative to long term averages, reduce crop incomes in Uganda, and this finding is robust across all specifications. This highlights the sensitivity of Ugandan smallholder systems to rising temperatures. More importantly, the three agricultural practices under analysis have a positive effect on the total value of production and therefore are effective tools to reduce farmers' sensitivity to rising temperatures (see Table 2). In terms of magnitude, the average impact of adopting these practices appear to offset the impact of temperature shocks up to certain levels of temperature deviation. For example, the adoption of cereal-legume intercropping appears to compensate a deviation of 5.34 in temperature, all the other variables kept equal (column 1, Table 2).

In terms of magnitude, we find that on average, an increase of 1 percent in maximum temperature during the growing seasons reduces the total value of crop production by approximately 7–11 percent. Banana-coffee intercropping and crop-legume intercropping are associated with higher crop incomes, and this is confirmed when accounting for endogeneity using the 2SLS-IV strategy (see Table 2). These results are likely linked to the agronomic benefits of the practices and the market related benefits derived from diversification of production systems (Arslan *et al.*, 2016; Pellegrini and Tasciotti, 2014). The adoption of organic fertilizer is also correlated positively with crop income, although the estimated coefficient is significant at a 10 percent level and only for the instrumental strategy specification. The reduced statistical significance of organic fertilizer may be due to high volatility in its application levels among farmers, and the fact that the benefits of organic fertilizer application on soil structure and quality accrue over time through longer term adoption, a point we return to below (Abiven *et al.*, 2009).

Interestingly, the coefficients of all adaptive practices increase in magnitude when instrumented. This indicates that the FE model without instrumenting is likely to under-estimate the effects of adoption on the total value of crop production. In other words, endogeneity associated with the adoption of the practices likely biases the estimates downward.[20] This could be due to issues of reverse causality, such as better natural condition (i.e. soil quality) or higher level of wealth. Among the possible explanations, our interpretation is that farmers adopting these practices are more likely to be richer and their systems are using the input factors at almost their potential.

[20] Since our coefficients are estimating the within-variation for the unit of observation, and this can be interpreted as rate of change, this result suggests that when not instrumenting, then the estimated rate of change is lower than with the instrument.

Assuming that their production function is concave and similar to a Cobb-Douglas function, as modelled through the log-functional specification in (1), the level of growth rate for these systems is naturally lower. Not accounting for these source of endogeneity may therefore underestimate the impact of the practices.

High temperatures are not the only threat to crop income in Uganda. Our results show that precipitation deviations exhibit divergent impacts on crop income. On average, the results show that below normal rainfall is associated with higher average crop incomes, while higher rainfall conditions are associated with lower crop income. In particular, a 1 percent deviation above normal rainfall reduces the total value of crop production by 0.9 to 1.5 percent. This is consistent with qualitative research on smallholder vulnerability in Uganda, which found that heavy rainfall was perceived as the greatest climate threat by farmers (Cooper and Wheeler, 2017). Conversely, a 1 percent reduction in rainfall relative to long-term averages is associated with an increase the total value of crop production by 2.6 to 4 percent. While there is likely to be significant spatial variability between agro-ecological zones, these results suggest that high rainfall levels pose a greater risk to Ugandan crop systems than low rainfall risks. In line with our findings, the negative impact of floods on crop production in Uganda has been also documented in a number of previous studies, such as Mwaura and Okoboi (2014) and FAO and WFP (2008).

Table 2. High temperatures and high rainfall reduce crop income, but this adverse impacts can be reduced by adopting the three sustainable practices

	OLS-Fixed effects	IV model (2nd stage)		
Dependent variable: total value of crop production (ln)	(1)	(2)	(3)	(4)
Organic fertilizer (1=yes)	0.099	0.837**		
	(0.074)	(0.397)		
Banana coffee intercropping (1=yes)	0.322***		2.102**	
	(0.088)		(1.062)	
Cereal-legume intercropping (1=yes)	0.396***			3.126***
	(0.065)			(1.038)
High temperature deviations	-0.073**	-0.068**	-0.067**	-0.108***
	(0.032)	(0.032)	(0.034)	(0.042)
Negative rainfall deviations (abs)	0.026**	0.034**	0.043**	0.003
	(0.013)	(0.014)	(0.017)	(0.018)
Positive rainfall Deviations	-0.011**	-0.010**	-0.009**	-0.015**
	(0.004)	(0.005)	(0.005)	(0.006)
Female head (1=yes)	0.296	0.281	0.288	0.259
	(0.184)	(0.188)	(0.189)	(0.216)
HH size (ln)	0.086	0.075	0.077	0.006
	(0.118)	(0.119)	(0.123)	(0.151)
Avg. education (ln)	0.079	0.083	0.067	0.102
	(0.077)	(0.078)	(0.080)	(0.094)
Land size in ha (ln)	0.393***	0.410***	0.357***	0.340***
	(0.055)	(0.055)	(0.062)	(0.072)
Agr. wealth	0.051**	0.053**	0.056**	0.018
	(0.022)	(0.022)	(0.023)	(0.030)

	OLS-Fixed effects	IV model (2nd stage)		
Access to land (1=yes)	0.295***	0.302***	0.391***	0.140
	(0.076)	(0.079)	(0.091)	(0.111)
Irrigation (1=yes)	-0.087	-0.072	-0.140	-0.061
	(0.181)	(0.189)	(0.192)	(0.231)
Drainage (1=yes)	0.132**	0.101	0.094	0.189**
	(0.064)	(0.067)	(0.071)	(0.089)
Improved seeds (1=yes)	0.159**	0.145*	0.170**	0.240**
	(0.079)	(0.081)	(0.081)	(0.101)
Vetiver (1=yes)	0.178	0.206*	0.233*	0.116
	(0.119)	(0.122)	(0.126)	(0.157)
Inorganic fertilizer (1=yes)	0.502***	0.428***	0.478***	0.583***
	(0.153)	(0.164)	(0.159)	(0.175)
Distance to market (ln)	-0.184	-0.229	-0.359	0.180
	(0.610)	(0.624)	(0.557)	(0.621)
Nightlights per population density	66.973**	71.005**	59.812*	54.279
	(31.351)	(31.628)	(34.298)	(41.723)
Pop. density (ln)	-0.230	-0.265	-0.251	-0.110
	(0.206)	(0.207)	(0.204)	(0.254)
Urban (1=yes)	-0.085	-0.091	-0.114	0.143
	(0.208)	(0.220)	(0.229)	(0.243)
Year dummies	yes	yes	yes	yes
HH fixed effects	yes	yes	yes	yes
Observations	4 398	4 370	4 370	4 370
R-squared	0.121	-	-	-
F-test	-	50.09	18.00	15.98

Notes: Estimates of FE model (1 column) and 2SLS-IV model (2-4 columns, only 2nd stage reported). Variables instrumented: organic fertilizer adoption (column2), banana-coffee intercropping adoption (column3), legume-cereal intercropping adoption (column4). Significance: * p<0.1, ** p<0.05, *** p<0.01. Standard errors are clustered at household level.

Source: Authors' own elaboration.

The other control variables influence crop production value as expected. Table 2 shows that the coefficients of land size, agricultural wealth and land use right are all strongly significant and positive. Similarly, the use of drainage, improved seeds and inorganic fertilizer,[21] as well as the nightlights per population density, have a significant and positive effect on the total value of crop production.

The first stage results of the 2SLS-IV model are found in the Annex (Table A3) and show that each instrument applied to the corresponding adaptive practice significantly explains the adoption of the practice. In addition, the F-test reported at the bottom of Table 4 is well above 10, suggesting we can reject the hypothesis about the weakness of the instruments.

[21] Interestingly, the coefficient associated with inorganic fertilizer has a similar magnitude to the one of organic fertilizer, suggesting the potential for substitution between these two practices in the context under analysis.

Lastly, to confirm the robustness of the main specification to the log-functional form of the dependent variable, we run the same set of specifications after having transformed all the continuous variables using the Inverse Hyperbolic Sine transformation developed by Bellamare and Wichman (2020). The results, shown in Table A4 of the Annex, remain consistent both in terms of magnitude and significance.

6.2 Marginal impacts of the adoption of adaptive practices across the distribution of high temperature exposure

The results show that the adoption of the three practices are effective in reducing sensitivity to even the highest temperature extremes (see Table 3). Indeed, the positive impacts of adoption the practices on the total value of production increases monotonically as high temperature deviations increase for all the three practices under consideration. These results derive from a specification using the 2SL-IV model, where the adoption of the practices is interacted with high temperature deviations at different percentiles of the temperature distribution.[22] The results summarized in Table 3 show that in all three cases the estimated coefficients on the margins are positive and increasing from the lowest to highest deviations. In the case of banana-coffee intercropping and organic fertilizer applications these positive relationships are only significantly different from zero at the top of the high temperature deviation distribution, while for cereal legume intercropping the relationship are significant across the distribution.

Table 3. The three practices are effective in increasing the total value of crop production, even under high temperature deviation (IV approach)

High temperature percentiles	Banana-coffee intercropping	Organic fertilizer	Cereal-legume intercropping
25	1.38	0.58	2.65**
50	1.46	0.73*	2.72***
75	1.84*	1.45***	3.08***
90	2.88***	3.44***	4.06***
95	3.07***	3.78***	4.23***
99	3.46***	4.53***	4.61***

Notes: levels of significance are * p<0.1, ** p<0.05, *** p<0.01. Standard errors clustered at household level. The model estimates are reported in Table A5 in the Annex. The marginal effects are monotonically increasing as both the adoption and the interaction term are positive and significant.

Source: Authors' own elaboration.

6.3 Positive impact of longer-term adoption of the practices

The longer a farmer adopts the practices the greater the impacts are in terms of crop income. These benefits hold under both normal and high temperature conditions. Table 4 presents results of the fixed effects model and the 2SLS-IV second stage estimates.[23] This model focuses only on households that were non-adopters in the first year, so the sample size changes with

[22] We instrument the interaction between temperature deviations and adoption of practices with the interaction between the respective instruments on share of adopters and the temperature deviation, which is exogenous in our model. We report the second stage of the 2SLS-IV model in the Annex, in Table A5.

[23] The first stage results of the 2SLS-IV are presented in the Annex in Table A6, and confirm a significant relationship between the instruments and the adoption duration of the practices.

the practice under consideration. The coefficients of adoption duration of all practices are significant and positive, both in the IV and the fixed effects models. This includes a positive effect of duration of adoption associated with organic fertilizer, which had only a marginal or insignificant effect when measured as a dummy variable (Table 2). The results show that every addition year of adoption is associated with an increase in total value of crop production of between 35.5 percent for organic fertilizer, 37 percent for banana-coffee intercropping, and 56 percent for legume intercropping.[24]

Finally, the analysis finds that for all the practices, adopting three years instead of two, or two years instead of one year, is associated with higher crop incomes when compared at similar temperature deviations. In other words, longer term adoption improves the benefits of the practices under different high temperature scenarios (Figure 2). These results are obtained by adding an interaction term between duration and temperature to the baseline model on adoption duration. Each plot reports the changes in the total value of crop production (in the y-axis, in log) due to an increase of 1 percent in maximum temperature deviation during the agricultural seasons (in the x-axis), for different durations of adoption (one, two or three years). In the case of organic fertilizer adoption and banana-coffee intercropping, we observe crop incomes increase with higher levels of temperature deviations, and the higher the years of adoption the steeper this increase. In the case of crop-legume intercropping, instead, higher levels of temperature deviations are associated with lower crop income values, and this trend is steeper the higher years of adoption, but this trend is present also for farmers adopting only 1 year. The marginal decline in crop incomes at higher temperature deviations for legume intercropping may be due to the sensitivity of some legume species to extremely high temperatures, which reduce their rates of nitrogen fixation when heat stressed (see, among others, Keeiro and Wilson, 1998, Hernandez-Armenta *et al.*, 1989). The selection of heat tolerant legume species, such as cowpeas or pigeon peas, is likely to moderate this trend. Why the slope is steeper with longer adoption requires further exploration.[25]

These findings highlight the importance of developing policies and programmes that are designed not only to promote the adoption of these practices, but also to help farmers to sustain adoption. This is a significant challenge, as so-called "dis-adoption" of improved agricultural practice after the withdrawal of project support is common in SSA (Neill and Lee 2001; Grabowski *et al.*, 2016; Arslan *et al.*, 2014). Because the benefits of these practices accrue over time, and in some cases may not be immediately apparent after adoption or are more apparent only under conditions of climate stress, short term incentives for adopting these practices may be limited (Corbeel *et al.*, 2014; Rusinamhodzi *et al.*, 2011). This challenge is particularly acute in the context of resource constrained farm households, who typically have high temporal discount rates and whose production choices are linked directly to their consumption outcomes (Moser and Barrett 2003; Place *et al.*, 2003; Holden *et al.*, 2006).

[24] These values have been calculated transforming the log coefficient as follows: x=exp(x)-1

[25] This result is not in contrast with what found in Table 3 as this one is looking to the predicted value of income at different thresholds of temperature accounting for the temperature itself, while Table 3 is showing the marginal effects of adoption, therefore the first derivative on cereal-legume adoption of the estimated specification, without accounting for the effect of temperature itself.

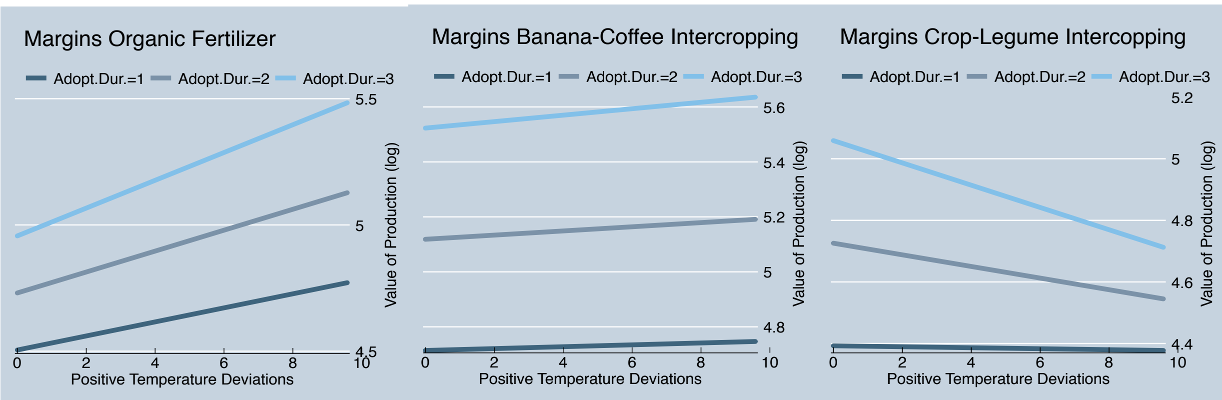
Table 4. Additional years of adoption of sustainable practices improves crop incomes

	IV model (2nd stage)		
Dependent variable: total value of crop production	(2)	(3)	(4)
Duration organic fertilizer (0-3)	2.180***		
	(0.488)		
Duration banana coffee intercropping (0-3)		1.457***	
		(0.384)	
Duration cereal-legume intercropping (0-3)			1.108*
			(0.599)
Socio-economic controls	yes	yes	yes
Climatic controls	yes	yes	yes
Year dummies	yes	yes	yes
HH fixed effects	yes	yes	yes
Observations	2,732	2,641	1,323
F-test	57.11	77.95	48.73

Notes: The table reports the additional effects of the duration of adoption on the total value of crop production. The specification is a 2SLS-IV with instrumental variables equal to the average duration of adoption within a radius of 30 km. The estimated coefficients of the first-stage instruments are reported in Table A6 in the Annex. Table A7 in the Annex reports the full list of coefficients of the second stage and includes a robustness test using the OLS-FE model (column 1).

Source: Authors' own elaborations.

Figure 2. Visualizing how adoption duration influences production at different high temperature deviations



Note: Predictive margins of the total value of crop production (in the y-axis, in log) due to a 1 percent increase in maximum temperature deviation (in the x-axis), for different duration adoption of a particular practice (one, two or three years).

Source: Authors' own elaborations.

7 Conclusions

This article has shown that smallholders' crop systems in Uganda are vulnerable to deviations of temperatures from the long-run averages. Rising temperature due to climate change, therefore, poses a significant risk to crop production systems in the country, and the consumers and producers that rely on these systems. Reducing smallholders' sensitivity to this risk through the adoption of effective, climate adaptive agricultural practices is essential to avoid welfare losses in the sector.

Our analysis shows that organic fertilizers, banana-coffee intercropping, and cereal-legume intercropping are all effective strategies for improving the income of smallholders, and the benefits of these practices are particularly pronounced under conditions of extreme high temperature. Moreover, we show that the benefits derived from adoption increase as the duration of adoption increases.

The results of this analysis suggest that policies and programmes designed to support the adoption of these practices within appropriate farming systems can improve the overall adaptive capacity of farmers and the agricultural sector. However, adoption alone should not be considered an end, but rather the beginning of a holistic adaptation strategy. Addressing the challenge of sustaining adoption is critical. This challenge requires strategies that move beyond traditional technology dissemination approaches, which rely primarily on providing training and input support to overcome immediate adoption barriers, to longer term approaches to help farmer sustain adoption. This will involve longer-term funding horizons and innovative approaches to support farmers through the initial, sometimes difficult years that follow a major change in agricultural management practices. Bundling the promotion of adaptive agricultural management practices with support mechanisms that help farmers manage production and the livelihoods risk posed by changes in management practices and sustaining this support over several years, offers the potential to overcome barriers to sustained adoption and the benefits this brings with it. There is emerging evidence that managing downside consumption and income risks of smallholders through cash or in-kind transfers can improve adoption of climate adaptive agricultural practices and enable farmers to sustain adoption over time (Scognamillo and Sitko, forthcoming; Holden *et al.*, 2006; Pannell *et al.*, 2014). Integrating social protection instruments with the promotion of these practices is, therefore, likely to be an effective approach to enhancing smallholder adaptive capacity. It is hoped that the results presented in this paper contribute to the emerging consensus that holistic, multisector approaches are necessary to address climate related vulnerabilities in smallholder systems.

References

Abiven, S., Menasseri, S. & Chenu, C. 2009. The effects of organic inputs over time on soil aggregate stability – A literature analysis. *Soil Biology and Biochemistry*, 41(1): 1–12.

Adger, W.N. 2006. Vulnerability. *Global Environmental Change*, 16(3): 268–281.

Agehara, S. & Warncke, D.D., 2005. Soil moisture and temperature effects on nitrogen release from organic nitrogen sources. *Soil Science Society of America Journal*, 69(6): 1844–1855.

Altieri, M.A., Nicholls, C.I., Henao, A. & Lana, M.A. 2015. Agroecology and the design of climate change-resilient farming systems. *Agronomy for Sustainable Development*, 35(3): 869–890.

Antle, J.M. & Diagana, B. 2003. Creating incentives for the adoption of sustainable agricultural practices in developing countries: the role of soil carbon sequestration. *American Journal of Agricultural Economics*, 85(5): 1178–1184.

Alemu, M.M. 2015. Effect of tree shade on coffee crop production. *Journal of Sustainable Development*, 8(9): 66.

Anderson, J., Learch, C. & Gardner, S., 2016. *National survey and segmentation of smallholder households in Uganda*. *Understanding their demand for financial, agricultural and digital solutions.*

Arslan, A., Cavatassi, R., Alfani, F., Mccarthy, N., Lipper, L. & Kokwe, M. 2018. Diversification under climate variability as part of a CSA strategy in rural Zambia. *The Journal of Development Studies*, 54(3): 457–480.

Arslan, A. Belotti, F. & Lipper, L., 2017. Smallholder productivity and weather shocks: Adoption and impact of widely promoted agricultural practices in Tanzania. *Food Policy*, 69: 68–81.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S. & Cattaneo, A. 2014. Adoption and intensity of adoption of conservation farming practices in Zambia. *Agriculture, Ecosystems & Environment*, 187: 72–86.

Asfaw, S., Scognamillo, A., Di Caprera, G., Sitko, N. & Ignaciuk, A. 2019. Heterogeneous impact of livelihood diversification on household welfare: Cross-country evidence from Sub-Saharan Africa. *World Development*, 117: 278–295.

Bandiera, O. & Rasul, I. 2006. Social networks and technology adoption in northern Mozambique. *The Economic Journal*, 116(514): 869–902.

Baudron, F., Tittonell, P., Corbeels, M., Letourmy, P. & Giller, K.E. 2012. Comparative performance of conservation agriculture and current smallholder farming practices in semi-arid Zimbabwe. *Field Crops Research*, 132: 117–128.

Bellemare, M.F. & Wichman, C.J., 2020. Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, 82(1): 50–61.

Bertinelli, L., Mohan, P. & Strobl, E., 2016. Hurricane damage risk assessment in the Caribbean: An analysis using synthetic hurricane events and nightlight imagery. *Ecological Economics*, 124: 135–144.

Beyene, A.D. & Kassie, M., 2015. Speed of adoption of improved maize varieties in Tanzania: An application of duration analysis. *Technological Forecasting and Social Change*, 96: 298–307.

Challinor, A., Wheeler, T., Garforth, C., Craufurd, P. & Kassam, A. 2007. Assessing the vulnerability of food crop systems in Africa to climate change. *Climatic Change*, 83(3): 381–399.

Conley, T.G. & Udry, C.R. 2010. Learning about a new technology: Pineapple in Ghana. *American Economic Review*, 100(1): 35–69.

Conley, T. & Christopher, U. 2001. Social learning through networks: The adoption of new agricultural technologies in Ghana. *American Journal of Agricultural Economics*, 83(3): 668–673.

Cooper, S.J. & Wheeler, T. 2017. Rural household vulnerability to climate risk in Uganda. *Regional Environmental Change*, 17(3): 649–663.

Corbeels, M., De Graaff, J., Ndah, T.H., Penot, E., Baudron, F., Naudin, Andrieu, N., Chirat, G., Schuler, J., Nyagumbo, I. *et al.* 2014. Understanding the impact and adoption of conservation agriculture in Africa: a multi-scale analysis. *Agriculture, Ecosystems & Environment*, 187: 155–170.

Craparo, A.C.W., Van Asten, P.J., Läderach, P., Jassogne, L.T. & Grab, S.W. 2015. Coffea arabica yields decline in Tanzania due to climate change: Global implications. *Agricultural and Forest Meteorology*, 207: 1–10.

Dadi, L., Burton, M. & Ozanne, A., 2004. Duration analysis of technological adoption in Ethiopian agriculture. *Journal of Agricultural Economics*, 55(3): 613–631.

Deressa, T.T., Hassan, R.M. & Ringler, C. 2011. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science*, 149(1): 23–31.

Downing, T.E., Patwardhan, A., Klein, R. J., Mukhala, E., Stephen, L., Winograd, M. & Ziervogel, G. 2005. *Assessing vulnerability for climate adaptation*. Cambridge University Press.

D'souza, G., Cyphers, D. & Phipps, T. 1993. Factors affecting the adoption of sustainable agricultural practices. *Agricultural and Resource Economics Review*, 22(2): 159–165.

Duku, C., Groot, A., Demissie, T., Oroma, G. & Osumba, J. 2019. *Soybean Uganda: Climate change risks and opportunities.*

Elvidge, C.D., Baugh, K.E., Anderson, S.J., Sutton, P.C. & Ghosh, T., 2012. The Night Light Development Index (NLDI): a spatially explicit measure of human development from satellite data. *Social Geography*, 7(1): 23–35.

Falkenmark, M. & Rockström, J. 2008. Building resilience to drought in desertification-prone savannas in Sub-Saharan Africa: The water perspective. *Natural Resources Forum,* 32(2): 93–102. Oxford, UK, Blackwell Publishing Ltd.

FAO & World Food Programme (WFP). 2008. *FAO/WFP assessment of the impact of 2007 floods on food and agriculture in Eastern and Northern Uganda*. FAO global information and early warning system on food and agriculture world food programme. Special Report (available at: www.fao.org/3/ah878e/ah878e00.htm).

Frison, E. A., Cherfas, J. & Hodgkin, T. 2011. Agricultural biodiversity is essential for a sustainable improvement in food and nutrition security. *Sustainability*, 3(1): 238–253.

Giller, K.E., Witter, E., Corbeels, M. & Tittonell, P. 2009. Conservation agriculture and smallholder farming in Africa: the heretics' view. *Field Crops Research*, 114(1): 23–34.

Grabowski, P.P., Kerr, J.M., Haggblade, S. & Kabwe, S. 2016. Determinants of adoption and disadoption of minimum tillage by cotton farmers in eastern Zambia. *Agriculture, Ecosystems & Environment*, 231: 5467.

Hassan, R.M. & Nhemachena, C. 2008. Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *African Journal of Agricultural and Resource Economics*, 2(311-2016-5521): 83–104.

Hernandez-Armenta, R., Wien, H.C. & Eaglesham, A.R.J. 1989. Maximum temperature for nitrogen fixation in common bean. *Crop Science,* 29(5): 1260–1265.

Hisali, E., Birungi, P. & Buyinza, F. 2011. Adaptation to climate change in Uganda: evidence from micro level data. *Global Environmental Change*, 21(4): 1245–1261.

Holden, S., Barrett, C. B. & Hagos, F. 2006. Food-for-work for poverty reduction and the promotion of sustainable land use: can it work? *Environment and Development Economics*, 11(1): 15–38.

Holden, S., Shiferaw, B. & Pender, J. 2004. Non-farm income, household welfare, and sustainable land management in a less-favoured area in the Ethiopian highlands. *Food Policy*, 29(4): 369–392.

International Center for Tropical Agriculture (CIAT) & Bureau for Food Security, United States Agency for International Development (BFS/USAID). 2017. *Climate-Smart Agriculture in Uganda. CSA Country Profiles for Africa Series*. Washington, DC.

Ionescu, C., Klein, R.J., Hinkel, J., Kumar, K.K. & Klein, R. (2009). Towards a formal framework of vulnerability to climate change. *Environmental Modeling & Assessment*, 14(1): 1–16.

Intergovernmental Panel on Climate Change (IPCC). 2018. *Global warming of 1.5 °C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty* [V. Masson-Delmotte, P. Zhai, H. O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J. B. R. Matthews, Y. Chen, X. Zhou, M. I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, T. Waterfield (eds.)]. In Press.

IPCC. 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. Geneva, Switzerland.

Janssen, M. & Ostrom, E. 2006. Resilience, vulnerability, and adaptation: A cross-cutting theme of the International Human Dimensions Programme on Global Environmental Change. *Global environmental change*, 16(3): 237–239.

Jones, P.G. & Thornton, P.K. 2009. Croppers to livestock keepers: livelihood transitions to 2050 in Africa due to climate change. *Environmental Science & Policy*, 12(4): 427–437.

Jones, P.G. & Thornton, P.K. 2003. The potential impacts of climate change on maize production in Africa and Latin America in 2055. *Global environmental change*, 13(1): 51–59.

Kasperson, R.E., Dow, K., Archer, E., Caceres, D., Downing, T., Elmqvist, T., Eriksen, S., Folke, C., Han, G., Iyengar, K. *et al.* 2005. Vulnerable peoples and places. *Ecosystems and human wellbeing: Current state and trends*, 1: 143–164.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P. & Erenstein, O. 2015. Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land Use Policy*, 42: 400–411.

Kassie, M., Zikhali, P., Manjur, K. & Edwards, S. 2009. Adoption of sustainable agriculture practices: Evidence from a semi-arid region of Ethiopia. *Natural Resources Forum*, 33(3): 189–198). Oxford, UK, Blackwell Publishing Ltd.

Keerio, M.I. & Wilson, J.M. 1998. Effects of high temperature on nitrogen fixation in soybean cultivars. In *Nitrogen Fixation with Non-Legumes*, pp. 99–102. Springer, Dordrecht.

Kikoyo, D.A. & Nobert, J. 2016. Assessment of impact of climate change and adaptation strategies on maize production in Uganda. *Physics and Chemistry of the Earth, Parts A/B/C*, 93: 37–45.

Ladha, J.K., George, T. & Bohlool, C. 2013. *Biological Nitrogen Fixation for Sustainable Agriculture: Extended Versions of Papers Presented in the Symposium, Role of Biological Nitrogen Fixation in Sustainable Agriculture at the 13th Congress of Soil Science, Kyoto, Japan, 1990* (Vol. 49). Springer Science & Business Media.

Lal, R. 2004. Soil carbon sequestration impacts on global climate change and food security. *Science*, 304(5677): 1623–1627.

Lal, R. 2015. Sequestering carbon and increasing productivity by conservation agriculture. *Journal of Soil and Water Conservation*, 70(3): 55A–62A.

Lobell, D.B., Bänziger, M., Magorokosho, C. & Vivek, B. 2011. Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature Climate Change*, 1(1): 42–45.

Lobell, D.B., Burke, M. B., Tebaldi, C., Mastrandrea, M.D., Falcon, W.P. & Naylor, R.L. 2008. Prioritizing climate change adaptation needs for food security in 2030. *Science*, 319(5863): 607–610.

Luers, A. L., Lobell, D. B., Sklar, L. S., Addams, C. L. & Matson, P. A. 2003. A method for quantifying vulnerability, applied to the agricultural system of the Yaqui Valley, Mexico. *Global Environmental Change*, *13*(4): 255–267.

Ministry of Agriculture, Animal Industry and Fisheries (MAAIF). 2015. Uganda Climate-Smart Agriculture Country Program 2015-2025. MAAIF and Ministry of Water and Environment (MWE), Uganda.

Ministry of Agriculture, Animal Industry and Fisheries (MAAIF). 2016. Agricultural Sector Strategic Plan 2015/16 – 2019/20.

Maggio, G. & Sitko, N. 2019. Knowing is half the battle: Seasonal forecasts, adaptive cropping systems, and the mediating role of private markets in Zambia. *Food Policy*, 89: 101781.

Maggio, G. & Asfaw, S. 2020. Heterogeneous Effects of Sustainable Agriculture Practices: Micro-evidence from Malawi. *Journal of African Economies*.

Manda, J., Alene, A.D., Gardebroek, C., Kassie, M. & Tembo, G. 2016. Adoption and impacts of sustainable agricultural practices on maize yields and incomes: evidence from rural Zambia. *Journal of Agricultural Economics*, 67(1): 130–-153.

Maertens, A. & Barrett, C.B. 2013. Measuring social networks' effects on agricultural technology adoption. *American Journal of Agricultural Economics*, 95(2): 353–359.

Marra, M., Pannell, D.J. & Ghadim, A.A. 2003. The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve?. *Agricultural Systems*, 75(2–3): 215–234.

Mathenge, M.K., Smale, M. & Olwande, J. 2014. The impacts of hybrid maize seed on the welfare of farming households in kenya. *Food Policy*, 44: 262–271.

Marenya, P.P. & Barrett, C.B. 2007. Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. *Food Policy*, 32(4): 515–536.

McSweeney, C., New, M. & Lizcano, G. 2010. *UNDP Climate Change Country Profiles: Uganda*. New York, USA, United Nations Development Programme (UNDP).

Miller, F., Osbahr, H., Boyd, E., Thomalla, F., Bharwani, S., Ziervogel, G., … & Hinkel, J. 2010. Resilience and vulnerability: complementary or conflicting concepts?. *Ecology and Society*, 15(3).

Moser, C.M. & Barrett, C.B. 2003. The disappointing adoption dynamics of a yield-increasing, low external-input technology: the case of SRI in Madagascar. *Agricultural Systems*, 76(3): 1085–1100.

Mundlak, Y. 2001. Production and supply. *In* Gardner, B.L. & Rausser, G.C. (eds.). *Handbook of Agricultural Economics*, vol. 1, pp. 3–85 (Chapter 1). Elsevier.

Munshi, K. 2004. Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution. *Journal of Development Economics*, 73(1): 185–213.

Mwaura, F.M. & Okoboi, G. 2014. Climate variability and crop production in Uganda. *Journal of Sustainable Development*. 7(2):159–172.

Neill, S.P. & Lee, D.R. 2001. Explaining the adoption and disadoption of sustainable agriculture: the case of cover crops in northern Honduras. *Economic development and cultural change*, 49(4): 793–820.

Osbahr, H., Dorward, P., Stern, R. & Cooper, S. 2011. Supporting agricultural innovation in Uganda to respond to climate risk: linking climate change and variability with farmer perceptions. *Experimental agriculture*, 47(2): 293–316.

Pannell, D.J., Llewellyn, R.S. & Corbeels, M. 2014. The farm-level economics of conservation agriculture for resource-poor farmers. *Agriculture, ecosystems & environment*, 187: 52–64.

Pellegrini, L. & Tasciotti, L. 2014. Crop diversification, dietary diversity and agricultural income: empirical evidence from eight developing countries. *Canadian Journal of Development Studies/Revue canadienne d'études du développement*, 35(2): 211–227.

Place, F., Barrett, C.B., Freeman, H.A., Ramisch, J.J. & Vanlauwe, B. 2003. Prospects for integrated soil fertility management using organic and inorganic inputs: evidence from smallholder African agricultural systems. *Food Policy*, 28(4): 365–378.

Ribot, J.C. 1995. The causal structure of vulnerability: Its application to climate impact analysis. *GeoJournal*, 119–122.

Ricker-Gilbert, J., Jayne, T.S. & Chirwa, E. 2011. Subsidies and crowding out: a doublehurdle model of fertilizer demand in Malawi. *American Journal of Agricultural Economics*, 93(1): 26–42.

Rao, I.R. 1980. The distribution of scientific productivity and social change. *Journal of the American Society for Information Science*, 31(2): 111–122.

Raseduzzaman, M.D. & Jensen, E.S. 2017. Does intercropping enhance yield stability in arable crop production? A meta-analysis. *European Journal of Agronomy*, 91: 25–33.

Rusinamhodzi, L., Corbeels, M., Van Wijk, M.T., Rufino, M.C., Nyamangara, J. & Giller, K.E. 2011. A meta-analysis of long-term effects of conservation agriculture on maize grain yield under rain-fed conditions. *Agronomy for sustainable development*, 31(4): 657.

Schlenker, W. & Roberts, M.J. 2006. Nonlinear effects of weather on corn yields. *Review of agricultural economics*, 28(3): 391–398.

Schlenker, W. & Roberts, M.J. 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37): 15594–15598.

Scognamillo, A. & Sitko, N. forthcoming. *Leveraging social protection to advance climate-smart agriculture: Empirical evidence from Malawi.* FAO Agricultural Economic Development Working Paper. Rome, FAO.

Seo, S.N. 2010. Is an integrated farm more resilient against climate change? A micro-econometric analysis of portfolio diversification in African agriculture. *Food Policy*, 35(1): 32–40.

Shiferaw, B. & Holden, S. 1999. Soil erosion and smallholders' conservation decisions in the highlands of Ethiopia. *World Development*, 27(4): 739–752.

Snapp, S.S., Mafongoya, P.L. & Waddington, S. 1998. Organic matter technologies for integrated nutrient management in smallholder cropping systems of southern Africa. *Agriculture, Ecosystems & Environment*, 71(1–3): 185–200.

Tatem, A.J., 2017. WorldPop, open data for spatial demography. *Scientific Data*, 4(1): 1–4.

Teklewold, H., Kassie, M. & Shiferaw, B. 2013. Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agricultural Economics*, 64(3): 597–623.

Thornton, P.K., Jones, P.G., Alagarswamy, G. & Andresen, J. 2009. Spatial variation of crop yield response to climate change in East Africa. *Global Environmental Change*, 19(1): 54–65.

Thornton, P.K., Jones, P.G., Alagarswamy, G., Andresen, J. & Herrero, M. 2010. Adapting to climate change: agricultural system and household impacts in East Africa. *Agricultural Systems*, 103(2): 73–82.

Thornton, P.K., Jones, P.G., Owiyo, T.M., Kruska, R.L., Herrero, M., Kristjanson, P., Notenbaert, A., Bekele, N., Orindi, V., Otiende, B. *et al.* 2006. *Mapping climate vulnerability and poverty in Africa*. Nairobi, The International Livestock Research Institute (ILRI).

Turner II, B.L., Kasperson, R.E., Matson, P.A., McCarthy, J.J., Corell, R.W., Christensen, L., Eckley, N., Kasperson, J.X., Luers, A. *et al*. 2003. A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences of the United States of America*, 100(14): 8074–8079.

Vågen, T. G., Lal, R. & Singh, B. R. 2005. Soil carbon sequestration in sub-Saharan Africa: a review. *Land Degradation and Development*, 16(1): 53–71.

Wang, N., Jassogne, L., van Asten, P.J., Mukasa, D., Wanyama, I., Kagezi, G. & Giller, K.E. 2015. Evaluating coffee yield gaps and important biotic, abiotic, and management factors limiting coffee production in Uganda. *European Journal of Agronomy*, 63: 1–11.

Annex

Table A1. *t*-test for equality of means of total value of crop production among adopters and non-adopters

	Year = 2010			Year = 2011		
	Total value of crop production non-adopters	Total value of crop production adopters	T-test	Total value of crop production non-adopters	Total value of crop production adopters	T-test
Organic fertilizer	331.86	736.10	***	301.63	730.1	***
Banana-coffee intercropping	362.14	543.39	**	339.96	476.12	**
Cereal-legume intercropping	386.62	402.13		333.33	396.97	

	Year = 2012			Year = 2014		
	Total value of crop production non-adopters	Total value of crop production adopters	T-test	Total value of crop production non-adopters	Total value of crop production adopters	T-test
Organic fertilizer	295.51	675.57	***	267.59	693.68	***
Banana-coffee intercropping	292.66	591.16	***	278.61	499.46	***
Cereal-legume intercropping	337.66	371.98		271.81	361.76	*

Note: Significance * p<0.1, ** p<0.05, *** p<0.01.

Source: Authors' own elaboration.

Table A2. Summary statistics

	2010	2011	2012	2014
Socio-economic variables (UNPS) **Total value of crop production**	361.56	369.55	484.47	516.31
Proportion HH adopting organic fertilizer	0.16	0.16	0.16	0.12
Proportion HH adopting banana-coffee intercropping	0.19	0.22	0.22	0.18
Proportion HH adopting crop-legume intercropping	0.59	0.57	0.59	0.51
Avg. duration adoption organic fertilizer	-	0.07	0.17	0.24
Avg. duration adoption banana-coffee intercropping	-	0.10	0.21	0.30
Avg. duration adoption crop-legume intercropping	-	0.39	0.85	1.20
Proportion HH female head	0.28	0.30	0.31	0.30
Avg. HH size	5.64	7.549	6.05	5.24
Avg. # school years	4.65	3.692	3.56	5.57
Avg. land size	6.07	5.45	4.76	2.86
Avg. Agricultural wealth	0.13	0.35	0.06	0.18
Access to land	0.40	0.35	0.31	0.32

	2010	2011	2012	2014
Proportion HH irrigating	0.02	0.04	0.01	0.02
Proportion HH using drainage	0.26	0.25	0.23	0.09
Proportion HH adopting improved seeds	0.29	0.20	0.29	0.20
Proportion HH adopting vetiver	0.04	0.06	0.06	0.00
Proportion HH adopting inorganic fertilizer	0.05	0.05	0.07	0.05
Distance to nearest market (Km)	33.16	33.22	33.18	33.19
Avg. nightlights per population density	0.00	0.00	0.00	0.00
Population density	300.10	308.87	310.67	328.88
Proportion HH living in urban areas	0.10	0.10	0.10	0.13
Climatic variables				
Maximum Temp. Pos. Deviations	0.61	0.00	0.50	6.43
Rainfall Neg. Deviations (abs.)	1.08	0.01	0.02	1.91
Rainfall Pos. Deviations	6.73	12.64	20.28	3.98

Source: Authors' own elaboration.

Table A3. First stage result of the two-stage instrumental variable model on the adoption of adaptive farming practices

	(1)	(2)	(3)
	Organic fertilizer (1=yes)	Banana coffee intercropping (1=yes)	Cereal-legume intercropping (1=yes)
Share of organic fertilizer adopters (radius=30 km)	0.412***		
	(0.058)		
Share of banana-coffee adopters (radius=30 km)		0.237***	
		(0.056)	
Share of cereal-legume intercropping adopters (radius=30 km)			0.196***
			(0.049)
F-test	50.09	18.00	15.98
Observations	4 374	4 374	4 374

Notes: Climatic, socio-economic, agricultural, market-related controls and year dummies included in the 1st stage IV model. Significance * p<0.1, ** p<0.05, *** p<0.01. Standard errors are clustered at household level.

Source: Authors' own elaboration.

Table A4. Robustness test using the Inverse Hyperbolic Sine Transformation (IHS) on the continuous dependent variables

Dependent variable: total value of crop production (IHS)	OLS-Fixed effects	IV model (2nd stage)		
	(1)	(2)	(3)	(4)
Organic fertilizer (1=yes)	0.098	0.811**		
	(0.073)	(0.390)		
Banana coffee intercropping (1=yes)	0.313***		2.020*	
	(0.086)		(1.041)	
Cereal-legume intercropping (1=yes)	0.384***			3.010***
	(0.063)			(1.008)
High temperature deviations	-0.071**	-0.067**	-0.066**	-0.105***
	(0.031)	(0.032)	(0.033)	(0.040)
Negative rainfall deviations (abs)	0.026**	0.033**	0.041**	0.004
	(0.013)	(0.014)	(0.017)	(0.017)
Positive rainfall deviations	-0.010**	-0.009**	-0.009*	-0.014**
	(0.004)	(0.004)	(0.005)	(0.006)
Female Head (1=yes)	0.284	0.269	0.277	0.249
	(0.180)	(0.184)	(0.184)	(0.210)
HH size (IHS)	0.076	0.068	0.067	0.017
	(0.094)	(0.095)	(0.098)	(0.120)
Avg. education (IHS)	0.055	0.058	0.047	0.074
	(0.059)	(0.060)	(0.061)	(0.072)
Land size in ha (IHS)	0.327***	0.341***	0.298***	0.285***
	(0.043)	(0.044)	(0.050)	(0.057)
Agr. wealth	0.049**	0.050**	0.053**	0.017
	(0.022)	(0.022)	(0.022)	(0.029)
Access to land (1=yes)	0.291***	0.298***	0.383***	0.141
	(0.074)	(0.077)	(0.088)	(0.108)
Irrigation (1=yes)	-0.082	-0.067	-0.133	-0.057
	(0.178)	(0.185)	(0.187)	(0.225)
Drainage (1=yes)	0.130**	0.100	0.094	0.185**
	(0.063)	(0.065)	(0.069)	(0.086)
Improved seeds (1=yes)	0.156**	0.143*	0.167**	0.234**
	(0.077)	(0.078)	(0.078)	(0.098)
Vetiver (1=yes)	0.175	0.202*	0.227*	0.115
	(0.117)	(0.119)	(0.124)	(0.153)
Inorganic fertilizer (1=yes)	0.493***	0.422***	0.470***	0.570***
	(0.150)	(0.161)	(0.156)	(0.171)
Distance to market (IHS)	-0.186	-0.230	-0.356	0.167
	(0.599)	(0.613)	(0.547)	(0.608)
Nightlights per pop. dens.	64.959**	68.762**	58.110*	52.714
	(30.664)	(30.913)	(33.433)	(40.529)
Pop. density (IHS)	-0.223	-0.257	-0.244	-0.109
	(0.201)	(0.202)	(0.199)	(0.247)
Urban (1=yes)	-0.077	-0.082	-0.105	0.142
	(0.202)	(0.214)	(0.223)	(0.235)

Dependent variable: total value of crop production (IHS)	OLS-Fixed effects	IV model (2nd stage)		
	(1)	(2)	(3)	(4)
Year dummies	yes	yes	yes	yes
HH fixed effects	yes	yes	yes	yes
Observations	4 398	4 370	4 370	4 370
R-squared	0.123	-	-	-
F-test	-	50.06	17.91	15.99

Notes: Estimates of FE model (1 column) and 2SLS-IV model (2-4 columns, only 2nd stage reported). Variables instrumented: organic fertilizer adoption (column2), banana-coffee intercropping adoption (column 3), legume-cereal intercropping adoption (column 4). Significance * p<0.1, ** p<0.05, *** p<0.01. Standard errors are clustered at household level.

Source: Authors' own elaboration.

Table A5. Effect of adoption of the selected practices when interacted with temperature deviation

Variables	IV model (2nd stage)		
	(1)	(2)	(3)
Banana coffee intercropping (1=yes)	1.380		
	(1.078)		
Organic fertilizer (1=yes)		0.580	
		(0.434)	
Cereal-legume intercropping (1=yes)			2.647**
			(1.035)
High Temperature Deviations X banana coffee intercropping	0.217***		
	(0.050)		
High Temperature Deviations X organic fertilizer		0.413***	
		(0.105)	
High Temperature Deviations X cereal-legume intercropping			0.205**
			(0.087)
High Temperature Deviations	-0.158***	-0.140***	-0.227***
	(0.042)	(0.040)	(0.069)
Negative rainfall deviations (abs)	0.028	0.011	0.002
	(0.018)	(0.016)	(0.018)
Positive rainfall deviations	-0.005	-0.006	-0.011*
	(0.005)	(0.005)	(0.006)
Female Head (1=yes)	0.226	0.242	0.229
	(0.188)	(0.194)	(0.221)
HH size (ln)	0.077	0.084	-0.017
	(0.122)	(0.123)	(0.155)
Avg. education (ln)	0.070	0.124	0.098
	(0.079)	(0.080)	(0.093)
Land size in ha (ln)	0.327***	0.392***	0.317***
	(0.062)	(0.057)	(0.072)
Agr. wealth	0.052**	0.046**	0.023
	(0.023)	(0.021)	(0.031)

Variables	IV model (2nd stage)		
	(1)	(2)	(3)
Access to land (1=yes)	0.360***	0.288***	0.150
	(0.090)	(0.081)	(0.110)
Irrigation (1=yes)	-0.151	-0.140	0.002
	(0.193)	(0.193)	(0.239)
Drainage (1=yes)	0.141**	0.145**	0.195**
	(0.071)	(0.069)	(0.087)
Improved seeds (1=yes)	0.169**	0.114	0.236**
	(0.080)	(0.083)	(0.101)
Vetiver (1=yes)	0.236*	0.224*	0.135
	(0.124)	(0.123)	(0.152)
Inorganic fertilizer (1=yes)	0.418***	0.393**	0.549***
	(0.158)	(0.177)	(0.177)
Distance to market (ln)	-0.300	-0.239	0.180
	(0.581)	(0.629)	(0.627)
Nightlights per pop. dens.	44.940	25.355	37.447
	(33.361)	(34.687)	(41.548)
Pop. density (ln)	-0.193	-0.224	-0.105
	(0.203)	(0.206)	(0.246)
Urban (1=yes)	-0.015	-0.097	0.217
	(0.230)	(0.238)	(0.256)
Year dummies	yes	yes	yes
HH fixed effects	yes	yes	yes
Observations	4 370	4 370	4 370
F-test	116.34	28.66	50.14

Source: Authors' own elaboration.

Notes: Estimates of F 2SLS-IV model (1-3) columns, only 2nd stage reported. Variables instrumented: organic fertilizer adoption (column2), banana-coffee intercropping adoption (column 3), legume-cereal intercropping adoption (column 4) and their interaction with temperature deviation. Instrumental variables are the share of adoption of each practices within a radius of 30 km and their interaction with temperature deviation, which is exogenous in the model. Significance * p<0.1, ** p<0.05, *** p<0.01. Standard errors are clustered at household level.

Table A6. First stage results of the two-stage instrumental variable model on the duration of adoption of adaptive farming practices

Variables	Duration organic fertilizer (1)	Duration banana coffee intercropping (2)	Duration cereal-legume intercropping (3)
Average duration of adoption of organic fertilizer within 30 km	0.323***		
	(0.043)		
Average duration of adoption of banana-coffee within 30 km		0.419***	
		(0.047)	
Average duration of adoption of cereal-legume intercropping within 30 km			0.341***
			(0.049)
Socio-economic controls	yes	yes	yes
Climatic controls	yes	yes	yes
Year dummies	yes	yes	yes
HH fixed effects	yes	yes	yes
Observations	2 732	2 641	1 323
F-test	57.11	77.95	48.73

Notes: Non-instrumented duration variables as well as climatic, socio-economic, agricultural, market-related controls and year dummies are included in the 1st stage IV model and their estimated coefficients are available upon request. Significance: * p<0.1, ** p<0.05, *** p<0.01. Standard errors are clustered at household level.

Source: Authors' own elaboration.

Table A7. Effect of duration of adoption of selected practices on total value of crop production

Dependent variable: total value of crop production (ln)	OLS Fixed effects	IV model (2nd stage)		
	(1)	(2)	(3)	(4)
Duration organic fertilizer (0–3)	0.304***	2.180***		
	(0.109)	(0.488)		
Duration banana coffee intercropping (0–3)	0.449***		1.457***	
	(0.082)		(0.384)	
Duration cereal-legume intercropping (0–3)	0.316***			1.108*
	(0.088)			(0.599)
High Temperature Deviations	0.019	0.037	-0.027	-0.016
	(0.037)	(0.039)	(0.045)	(0.064)
Negative rainfall deviations (abs)	0.039*	0.015	0.006	0.047
	(0.022)	(0.026)	(0.027)	(0.031)
Positive rainfall deviations	-0.019***	-0.020***	-0.020***	-0.012
	(0.006)	(0.006)	(0.006)	(0.008)
Female head (1=yes)	0.190	0.140	0.132	0.467
	(0.245)	(0.248)	(0.250)	(0.333)
HH size (ln)	0.119	0.138	0.202	0.291
	(0.155)	(0.161)	(0.162)	(0.236)
Avg. education (ln)	0.239*	0.293**	0.151	0.187
	(0.126)	(0.131)	(0.130)	(0.181)
Land size in ha (ln)	0.428***	0.434***	0.376***	0.359***
	(0.074)	(0.081)	(0.077)	(0.103)
Agr. wealth	0.064*	0.082**	0.030	0.067
	(0.037)	(0.039)	(0.030)	(0.053)
Access to land (1=yes)	0.311***	0.282***	0.322***	0.220
	(0.104)	(0.109)	(0.111)	(0.146)
Irrigation (1=yes)	-0.381	-0.542*	-0.468*	0.202
	(0.250)	(0.282)	(0.261)	(0.423)
Drainage (1=yes)	0.194**	0.248**	0.173*	-0.042
	(0.090)	(0.099)	(0.097)	(0.131)
Improved seeds (1=yes)	0.039	0.015	0.115	0.256
	(0.107)	(0.111)	(0.111)	(0.167)
Vetiver (1=yes)	0.414**	0.480***	0.489***	0.358
	(0.163)	(0.181)	(0.179)	(0.265)
Inorganic fertilizer (1=yes)	0.269	0.288	0.380*	0.333
	(0.195)	(0.219)	(0.210)	(0.290)
Distance to market (ln)	0.872	0.933	0.506	0.809
	(1.379)	(1.409)	(1.789)	(1.454)
Nightlights per pop. dens.	51.806	44.777	31.668	-2.452
	(68.315)	(72.358)	(61.361)	(80.246)
Pop. density (ln)	-0.455**	-0.449**	-0.430**	-0.375
	(0.219)	(0.224)	(0.217)	(0.312)
Urban (1=yes)	-0.053	-0.105	0.046	0.282
	(0.272)	(0.286)	(0.281)	(0.351)
Year dummies	yes	yes	yes	yes
HH fixed effects	yes	yes	yes	yes
Observations	2 748	2 732	2 641	1 323
R-squared	0.171	-	-	-
F-test	-	57.11	77.95	48.73

Source: Authors' own elaboration.

Table A8. First-stage results on adoption using alternative radius specification for the instruments (20 and 25 km)

Variables	(1) Organic fertilizer (1=yes)	(2) Banana coffee intercropping (1=yes)	(3) Cereal-legume intercropping (1=yes)	(4) Organic fertilizer (1=yes)	(5) Banana coffee intercropping (1=yes)	(6) Cereal-legume intercropping (1=yes)
Share of organic fertilizer adopters (radius=20 km)	0.353***					
	(0.049)					
Share of banana-coffee adopters (radius=20 km)		0.168***				
		(0.047)				
Share of cereal-legume intercropping adopters (radius=20 km)			0.128***			
			(0.041)			
Share of organic fertilizer adopters (radius=25 km)				0.363***		
				(0.052)		
Share of banana-coffee adopters (radius=25 km)					0.160***	
					(0.052)	
Share of cereal-legume intercropping adopters (radius=25 km)						0.147***
						(0.045)
Socio-economic controls	yes	yes	yes	yes	yes	yes
Climatic controls	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
HH fixed effects	yes	yes	yes	yes	yes	yes
Observations	4 374	4 374	4 374	4 374	4 374	4 374
F-test	52.29	12.68	9.86	48.45	9.32	10.7

Source: Authors' own elaboration.

Table A9. First-stage results on duration using alternative radius specification for the instruments (20 and 25 km)

Variables	(1) Duration organic fertilizer	(2) Duration banana coffee intercropping	(3) Duration cereal-legume intercropping	(4) Duration organic fertilizer	(5) Duration banana coffee intercropping	(6) Duration cereal-legume intercropping
Average duration of adoption of organic fertilizer within 20 km	0.216***					
	(0.039)					
Average duration of adoption of banana-coffee within 20 km		0.391***				
		(0.043)				
Average duration of adoption of cereal-legume intercropping within 20 km			0.244***			
			(0.042)			
Average duration of adoption of organic fertilizer within 25 km				0.269***		
				(0.041)		
Average duration of adoption of banana-coffee within 25 km					0.391***	
					(0.044)	
Average duration of adoption of cereal-legume intercropping within 25 km						0.255***
						(0.045)
Socio-economic controls	yes	yes	yes	yes	yes	yes
Climatic controls	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
HH fixed effects	yes	yes	yes	yes	yes	yes
F-test	31.37	83.31	33.6	42.71	78.98	32.64
Observations	2 732	2 641	1 323	2 732	2 641	1 323

Source: Authors' own elaboration.

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