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Weathering shocks: the effects of weather shocks on farm input use in sub-Saharan Africa

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Abstract: There has been much discussion on climate change and its adverse effects on agriculture, including excessive loss of food production. In regions such as sub-Saharan Africa, where agriculture is the major source of household livelihoods, shocks in weather patterns affect farmers' expectations of farm yield and hence the decision to adopt farm inputs such as fertilizers and pesticides and the extent of their utilization, particularly given the relatively high cost of these inputs. In this study, I explore the relationship between weather shocks and the intensity of inputs use at the plot level using large-scale national panel data from three African countries: Niger, Nigeria, and Tanzania. By combining monthly drought index data with a rich Living Standards Measurement Study-Integrated Surveys on Agriculture dataset, I find that the intensity of chemical fertilizer use reduces much more in drought-prone areas than in less drought-prone areas during growing seasons. I also find that drought during lean seasons is associated with higher pesticide uptake. The evidence suggests that drought induces farmers to purposively reduce farm investments, including yield-enhancing technology such as chemical fertilizer, hence worsening adverse farm yield effects.

Key words: chemical fertilizer, agriculture, climate change, sub-Saharan Africa

JEL classification: Q12, Q54, O13

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1 Introduction

Raising agricultural productivity by increasing technology adoption (mainly hybrid seeds, chemical fertilizers, and pesticides) is the best pathway to promote inclusive economies, ensure food security, and combat poverty in sub-Saharan Africa (Bold et al. 2017; Koussoubé and Nauges 2017; Sheahan and Barrett 2014). African farmers, however, have been slow to adopt modern agriculture technology and a number of reasons for this have been put forward. These include: lack of market information, constrained market access, risk attitudes, missing markets, and farm credits (Karlan et al. 2014; Kebede et al. 1990), limited knowledge and inability to save (Duflo et al. 2006), and poor infrastructure and weak institutions (Aker 2011). Furthermore, most of the agricultural systems in sub-Saharan Africa (SSA) are heavily reliant on rainfall, thus exposing livelihoods to weather shocks. If there are unexpected weather shocks (droughts, flooding), these will not only have a substantial effect on farm productivity (Dell et al. 2014) but also influence farmers' decision to adopt farm technology (Jagnani et al. 2018).

The main objective of this study is to provide evidence of the impact of weather shocks on the adoption and intensity of farm input uptakes by smallholder farmers in SSA. Specifically, this paper addresses the question: how do weather shocks affect the probability of adoption and intensity of farm input use in SSA? Using highly geo-coded data on drought index matched with plot-level (unbalanced) panel data from Living Standards Measurement Study-Integrated Surveys (LSMS-ISA) in three African countries (Niger, Nigeria, and Tanzania), I estimate the causal effect of weather shocks on farmers' adoption decision and intensity of fertilizer use on plots. I define adoption decision of farm technology using two indicators. The first indicator relates to pesticide use and equals 1 if the farmer uses any pesticide on a particular plot and 0 otherwise. The second indicator relates to the use of chemical fertilizer (e.g. NPK, UREA, DAP) and equals 1 if the farmer uses chemical fertilizer on a plot at a given time during the agricultural growth cycle and 0 otherwise. I also construct a continuous outcome variable, measuring the intensity (kg/plot) of chemical fertilizer use on a plot. To allow for the possible correlation of residuals, robust heteroscedastic standard errors are clustered at the enumeration area level, which is the primary sampling unit (PSU) for the household survey. To derive the relationship between drought incidence and farm inputs use, I exploit exogenous variations in the localized weather shocks during each phase of the agricultural growth cycle.

This paper differs from earlier studies of weather shocks in the following ways. First, while the existing literature essentially captures local environmental shocks using either log of rainfall shocks (Levine and Yang 2006) or variations in temperature (Garg et al. 2020), in the current study I investigate the effects of weather shocks on farm input adoption decision by considering simultaneously the effects of variations in both rainfall and temperature. Hence, based on the Standardized Precipitation-Evapotranspiration Index (SPEI), the study considers all aspects of temperature, rainfall, and evapotranspiration of the plants in a particular area at a given time. Using the SPEI also allows me to effectively measure drought severity, including its intensity and duration and, hence, to identify the onset and end of drought episodes. Second, I derive the estimated impacts on intensity of modern farm input (MFI) use from agricultural panel data on three SSA countries: Niger, Nigeria, and Tanzania. Considering different agriculture practice from these three countries (two from West and one from East Africa) allows me to control for the topographic and weather differences between and within countries.

The main results of the study indicate a significant negative effect of drought shocks on chemical fertilizer uptake, especially during the pre-planting stage of the agricultural growth cycle. Specifically, I find that one additional month of drought during the initial crop growth period (pre-planting) is associated with a statistically significant decrease in chemical fertilizer use on a given plot.[1] Specifically, in Niger, Nigeria, and Tanzania, an extra month of drought during the pre-planting period will reduce the probability of using chemical fertilizer by 7, 2, and 42 percentage points, respectively. Further, since farmers normally use pesticides just after pests are detected on the crops, the effects should be greater in the planting, main growth, and lean seasons (growing period) than the pre-planting or harvesting periods. The results show that one extra month of drought during the growing period will increase the probability of using pesticide by 4, 2, and 5 percentage points in Niger, Nigeria, and Tanzania, respectively.

The results further indicate that during the pre-planting period, an additional one month of drought will reduce the intensity of fertilizer use (kg/plot) by 36 per cent in Nigeria, 82 per cent in Niger, and 199 per cent in Tanzania. This reaffirms the possible strong reverse associations between weather shocks and farmers' decision to use farm inputs. The higher effect on the intensity of fertilizer uptake in Tanzania can be explained by the fact that the majority of farmers in Tanzania still rely on traditional farming methods due to landscape[2] and favourable climatic conditions compared with the two other countries (Niger and Nigeria). The results remain unchanged even when the robust heteroscedastic standard errors are clustered at district and district-by-year-of-survey levels to allow the correlation of residuals within district and district-by-year-of-survey respectively.

The remainder of the paper is organized as follows. Section 2 describes the empirical framework and identification strategy. The weather and farm household data sources are given in Section 3. The main findings and discussions are presented in Section 4, and the conclusion and policy relevance are reported in Section 5.

2 Empirical strategy

To achieve the main objective of this study- examining the causal effect of weather shocks on farmers' decision to adopt or not and the intensity of farm input use- I set the following expression:

$$y_{hjvt} = \alpha_{hj} + \lambda X_{hjvt} + \gamma D_{jvt} + \varepsilon_{hjvt} \tag{1}$$

Where y_{hjvt} represents the use of chemical fertilizer/pesticide on plot *j* by household *h*, in enumeration area or village *v*,[3] at time *t*. The study uses three outcome variables: first, the rate of fertilizer use, which takes the value 1 if the farmer applied chemical fertilizer on the plot over the course of the farming season, and 0 if otherwise; second, pesticide use, which is a dummy, taking the value 1 if the farmer used any pesticide (such as insecticides, fungicides, and herbicides) on the plot, and 0 if otherwise; and finally the intensity of chemical fertilizer use, i.e. the total weight in kilograms of chemical fertilizer per plot (kg/plot) that farmers apply during the farming season. The expression X_{hjvt} stands for the farm households/plots and village characteristics, while α_{hj} is a household (village) fixed effect. Our variable of interest is D_{jvt}, a proxy for weather shocks

[1] In the sampled countries, the most used chemical fertilizers are NPK and UREA. Others, such as DAP, are rarely used. I therefore combine all other chemical fertilizers into one variable, 'Others'.

[2] By 2008, in Tanzania, only around 33 percent of arable land is cultivated. This implies that the country still have large reserves of arable lands that can be used in farm expansion (World Bank, 2013). for Malawi and Rwanda

[3] The term village is used interchangeably with enumeration area (EA) in this paper.

(capturing the number of months over which the village experienced a drought during a given year or agricultural growth cycle, and it is considered as a month of drought if SPEI<-1) on a given plot *j*, in village *v*, at time *t*; and finally ε_{hjvt} stands for the idiosyncratic error term with mean zero.

To identify the effect of weather shocks (proxied by drought index) on the adoption and intensity of farm inputs use, I exploit a quasi-random variation in drought incidence over time within a given village. I compare the level of technology adoption and intensity of chemical fertilizer adoption (kg/ha) across drought and non-drought areas, while controlling for the average differences in farm plots and households across villages in a given district.

However, estimating equation (1) without accounting for unobserved heterogeneity between farm households may lead to biased estimates. In fact, many of the farm and demographic characteristics are unobserved, which implies that those characteristics are captured in the error term, ε_{hjdrt}. To derive an effective result for the effects of weather shock on the outcome indicators, I hence augment equation (1) by a set of fixed effects, including household, village, district, and time fixed effects. Then, in deriving the causal effect of drought on the adoption and intensity of farm input use, I estimate the model that captures household, farm, and time fixed effects, specified as:

$$y_{hjvt} = \alpha_{hj} + \lambda X_{hjvt} + \gamma D_{jvt} + \varphi_{dt} + \psi_t + \varepsilon_{hjvt} \tag{2}$$

where I use district-by-survey-year fixed effects, φ_{dt}, to account for unobservable time-variant differences across the districts. The ψ_t stands for survey year fixed effects. In the estimation, I cluster robust standard errors at enumeration area (EA) to account for potential differences across villages. The use of farm inputs (such as chemical fertilizer and pesticides) on the plots by farmers would ideally enable them to produce optimally. In the event of weather shocks, however, farmers may decide against using such improved inputs to avoid greater anticipated losses, causing an adverse effect on farm yields.

Estimating equation (2), I derive the marginal effects (γ) of the changes in SPEI during the pre-planting and growing phases of farming systems. Therefore, a negative estimate of gamma (γ) would suggest that an increase in the number of months of drought is associated with a decline in intensity of farm input use, which would be consistent with the existing literature on climate and farm productivity (Akpalu et al. 2009; Barrios et al. 2010; Garg et al. 2020). I assume that the variations in the level of SPEI faced at a given village during each phase of farming is exogenous to household and farm unobserved characteristics that may vary over time. This assumption is reasonable, given the randomness of weather variations (drought incidence) and the inability of farmers to predict such variations beside common spatial and climate forecasts, which I account for in the village (φ_{vt}) and month-by-year (ψ_t) fixed effects.

3 Description of data sources

This paper draws mainly on a rich farm household panel dataset, the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA), in three sub-Saharan African countries: Niger, Nigeria, and Tanzania.[4] To capture weather shocks, I augment these with the

[4] The LSMS-ISA project collaborates with the World Bank and the national statistical offices of its eight partner countries in SSA (Burkina Faso, Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania, and Uganda) to design and implement systems of multi-topic, nationally representative panel household surveys with a strong focus on agriculture.

Standardized Precipitation-Evapotranspiration Index (SPEI), which reflects a village's climatic water balance at different time scales.

3.1 Plot and household

The data used to construct the dependent variable (intensity of fertilizer use) are drawn from the LSMS-ISA dataset. Figure 1 maps the three countries the study focuses on, namely Niger, Nigeria, and Tanzania. The study uses two waves of the National Household Living Conditions and Agriculture Survey in Niger (2011 and 2014), three waves of the Nigerian General Household Survey (2010/11, 2012/13, and 2015/16), and four waves of the Tanzania National Panel Survey (2008/09, 2010/11, 2012/13, and 2014/15), as indicated in Table 1.

Figure 1: Locations of sampled countries

Source: author's construction using ArcGIS programme with Geo-spatial dataset.

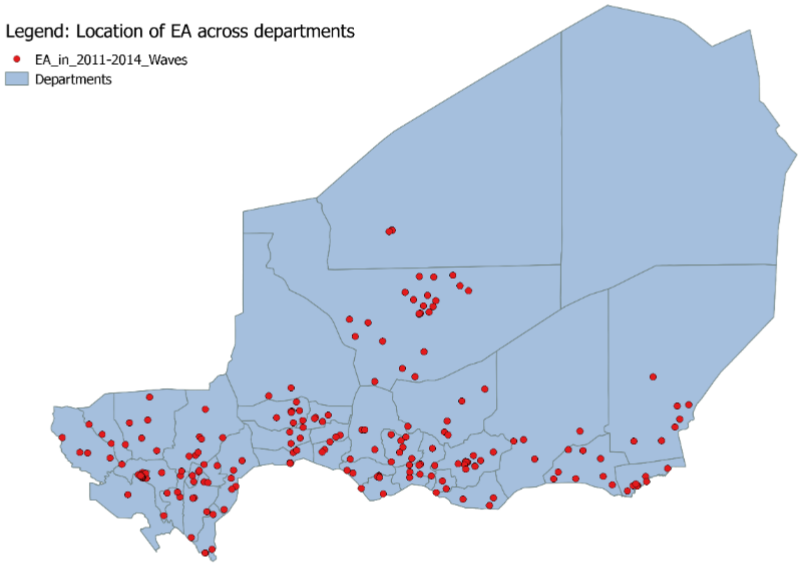
Table 1: The distribution of plot sample sizes and their weights in the data

Country	Year of survey	No. of households in each wave	No. of plots in each wave
Niger	2011 (W1)	2,252	6,011
	2014 (W2)	1,770	4,257
Nigeria	2010/11 (W1)	2,790	5,104
	2012/13 (W2)	2,944	5,911
	2015/16 (W3)	2,653	4,956
Tanzania	2008/09 (W1)	2,283	7,660
	2010/11 (W2)	2,594	8,093
	2012/13 (W3)	3,300	10,203
	2014/15 (W4)	2,090	7,051

Source: author's computation, based on LSMS-ISA dataset.

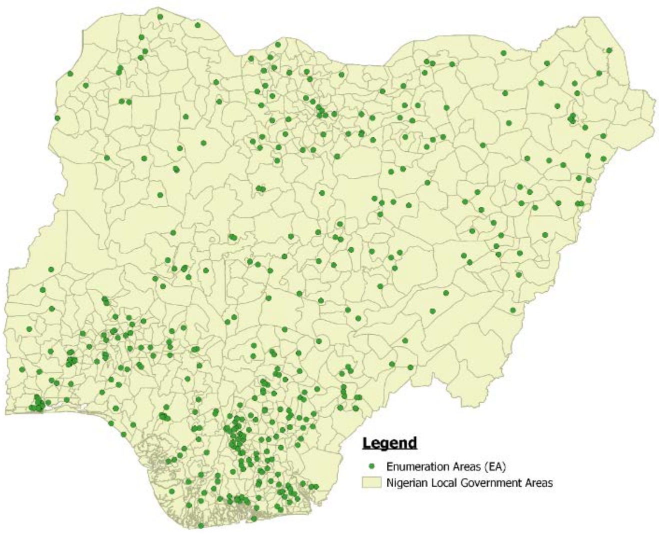
The ability to follow the same farm households over time makes the LSMS-ISA dataset a powerful tool for studying and understanding the role of agriculture in household welfare over time. The surveys provide detailed plot-level data on farm and soil characteristics, including farm inputs, farm yield, soil types and slopes, and land size. In addition, the dataset is geo-coded at the EA level, making it possible to combine it with other datasets. The study uses 200 EAs in Niger, 410 EAs in Nigeria, and 385 EAs in Tanzania that were randomly selected across the countries in all waves. In this study, I use geo-coordinates to merge the SPEI data with LSMS-ISA survey data based on 36 departments in Niger, 774 Nigerian Local Government Areas (LGAs), and 169 districts in Tanzania. Figures 2, 3, and 4 indicate the distribution of the sampled EAs in the three countries.

Figure 2: EAs of waves 2011 and 2014 in Niger



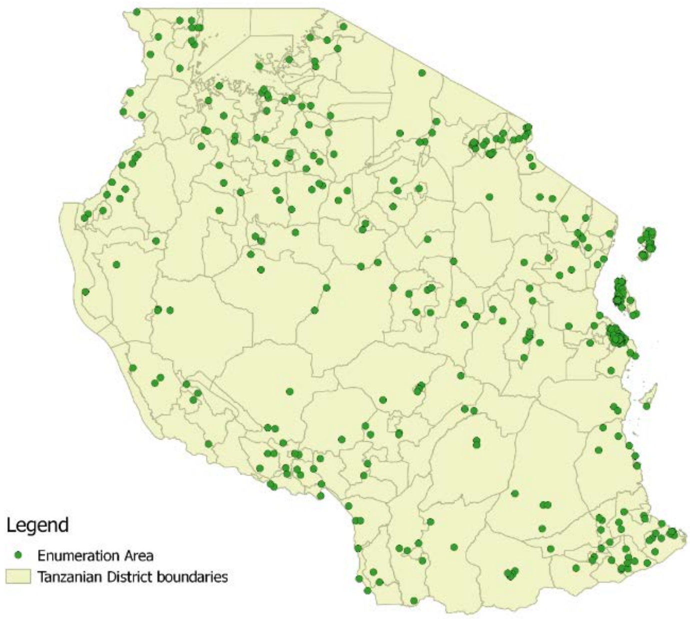
Source: author's construction using ArcGIS programme with Geo-spatial Niger LSMS-ISA dataset.

Figure 3: EAs of waves 2010/11, 2012/13, and 2015/16 in Nigeria



Source: author's construction using ArcGIS programme with Geo-spatial Nigeria LSMS-ISA dataset.

Figure 4: EAs of waves 2008/09, 2010/11, 2012/13, and 2014/15 in Tanzania



Source: author's construction using ArcGIS programme with Geo-spatial Tanzanian LSMS-ISA dataset.

The construction of the panel and the sampling techniques for each country can be found on LSLM-ISA.[5] The study uses an unbalanced panel, as some farm households move into and out of farming, and sell or buy new plots. Table 1 shows the total number of plots per wave in each country.[6] For instance, the total number of plots in the first waves for Niger, Nigeria, and Tanzania are 6,011, 5,104, and 7,660, respectively. In each wave, we observe the intensity of fertilizer and pesticide use at plot level. Table 2 shows the distribution of fertilizer and pesticide use per plot.

The second row of Table 2 indicates that the application of chemical fertilizer ranges between 12 and 20 per cent of the total plots in Niger, between 34 and 37 per cent in Nigeria, and around 11 per cent in Tanzania. The table also shows that the rates of pesticide use and adoption are still low. For instance, in Nigeria, the rate of pesticide use ranges between 14 and 18 per cent of the total plots, while in Niger and Tanzania, its use varies between 6 and 10 per cent.

The dataset also reports farm inputs use, from which we can compute the intensity of chemical fertilizer use (kg/ha), and farm yields at plot level, from which we can compute land productivity across drought and non-drought farm areas. The middle part of Table 2 shows the intensity of chemical fertilizer use during long agricultural rainy seasons. The table indicates that, on average, the intensity of NPK and UREA adoption in Nigeria is higher than their use in Tanzania and Niger. Specifically, the table shows that the intensity of chemical fertilizer use in Nigeria ranges between 80 and 110 kg/plot compared with 38–68 kg/plot and 60–150 kg/plot in Niger and Tanzania, respectively.

[5] The full details can be checked at: http://surveys.worldbank.org/lsms/programs/integrated-surveys-agriculture-ISA.

[6] Although the terms field and parcel are used in the Niger waves, I use the term plot in this paper.

Table 2: Descriptive statistics of plot and farming characteristics in the sampled countries

	Niger		Nigeria			Tanzania			
	W1	**W2**	**W1**	**W2**	**W3**	**W1**	**W2**	**W3**	**W4**
Any fertilizer (binary)	0.35 (0.47)	0.60 (0.48)	0.38 (0.48)	0.37 (0.50)	0.47 (0.49)	0.15 (0.36)	0.16 (0.37)	0.14 (0.34)	0.15 (0.36)
Any inorganic use (binary)	0.12 (0.33)	0.20 (0.40)	0.34 (0.47)	0.34 (0.47)	0.37 (0.48)	0.10 (0.30)	0.12 (0.33)	0.11 (0.31)	0.11 (0.32)
Any organic fertilizer use (binary)	0.31 (0.46)	0.36 (0.48)	-	-	0.46 (0.49)	0.10 (0.31)	0.10 (0.30)	0.11 (0.32)	0.12 (0.32)
Pesticide use (binary)	0.06 (0.23)	0.07 (0.24)	0.14 (0.34)	0.14 (0.35)	0.18 (0.39)	0.10 (0.30)	0.09 ((0.28)	0.09 (0.30)	0.10 (0.30)
Intensity of NPK (kg/plot)	68.9 (191)	38.5 (75.8)	91.1 (86.3)	108 (105.6)	81.1 (79.7)	87.8 (148)	95.2 (135)	73.0 (100)	153 (197)
Intensity of UREA (kg/plot)	66.3 (168)	56.5 (91.7)	93.8 (79.4)	105 (87.67)	78.1 (80.5)	59.1 (92.1)	69.6 (74.0)	72.3 (103)	74.7 (99.6)
Intensity of other chem. (kg/plot)	-	188 ((226)	68.1 (72.2)	99.2 (85.63)	91.6 (71.3)	68.4 (68.3)	72.2 (74.2)	88.0 (109)	88.5 (116)
Maize yield (kg/plot)	-	-	347 (252.4)	323 (269.8)	309 (260.3)	262 (227)	264 (227)	255 (228)	290 (250)
Beans yield (kg/plot)	54 (83.7)	95 (118)	230 (192.5)	240 (200.3)	213 (219.3)	92 (132)	98 (125)	101 (127)	134 (320)
Millet yield (kg/plot)	280 (224)	283 (225)	-	-	-	-	-	-	-
Average distance to the plot (km)	2.1 (5.27)	2.4 (2.46)	1.6 (3.28)	1.3 (2.80)	1.2 (2.40)	2.3 (2.8)	2.6 (3.17)	2.3 (2.93)	2.1 (2.9)
Number of plots per household	4.1 (3.10)	4.3 (3.20)	4.5 (3.08)	2.5 (1.28)	4.8 (2.98)	2.9 (1.5)	3.0 (1.6)	2.4 (1.9)	2.1 (1.7)
Average land hh size (ha)	0.7 (0.51)	0.7 (0.45)	0.5 (0.69)	0.4 (0.59)	0.4 (0.57)	0.6 (0.58)	0.7 (0.60)	0.6 (0.61)	0.6 (0.61)

Source: author’s computation based on LSMS-ISA dataset.

3.2 Weather data: SPEI

To capture the effects of weather shocks on farm inputs use, I also use the Standardized Precipitation-Evapotranspiration Index (SPEI), developed by Vicente-Serrano et al. (2010). The SPEI dataset is based on monthly precipitation and potential evapotranspiration from the Climatic Research Unit of the University of East Anglia.[7] The Global SPEI database, SPEIbase, offers drought conditions at the global scale, with a 0.5 x 0.5 degree spatial resolution. It has a multi-scale character, providing SPEI time scales of between 1 and 48 months. The SPEI is a standardized variable with mean zero and a variance of one that expresses the water balance in units of standard deviations from the long-run average. The index is computed from the current climatic balance on weather, climate, and time-invariant factors (such as latitude) with respect to the long-term balance. A value of zero means that the water balance is exactly at its long-run average, a value of minus one (plus one) means that the water balance is one standard deviation below (above) the long-run average, etc.

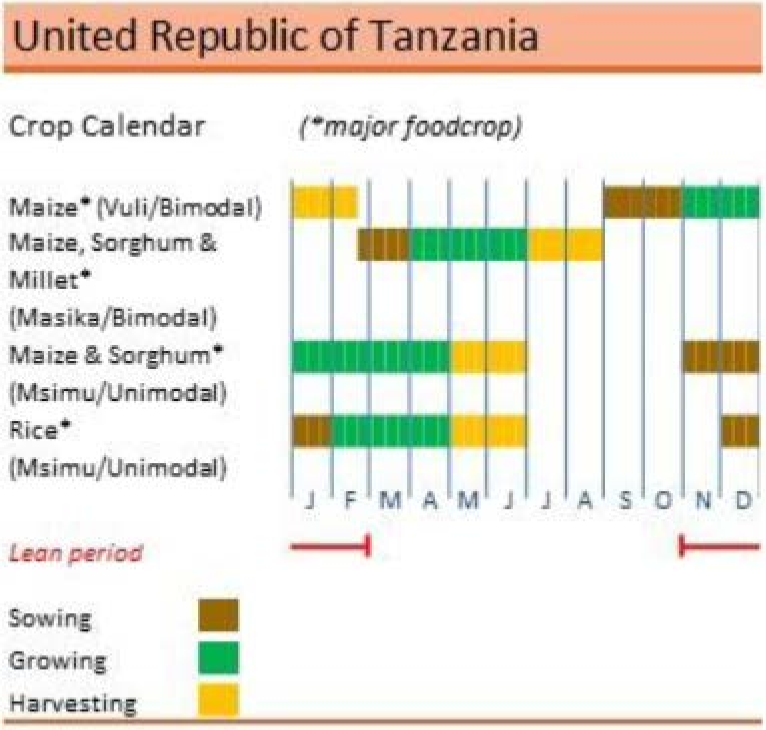
In using SPEI to capture positive and negative weather shocks, we follow the recent contributions to the literature on the nexus of climate changes and agriculture development (Burke and Emerick 2016; Dinkelman 2017; Jagnani et al. 2017; Kurukulasuriya et al. 2011; Mendelsohn 2008). The advantage of using SPEI as a drought index is that not only is it based on precipitation but it also considers the potential evapotranspiration (i.e. evaporation plus plant transpiration), a variable that has a significant impact on local drought conditions. There are other weather shock indices. For instance, Jagnani et al. (2018) use the Global Land Data Assimilation System (GLDAS) in their study on the effects of heat on farming. In the present study, I opt for SPEI due to its high spatial resolution. In an empirical strategy looking at the intensity of farm input use and land productivity in various areas of SSA, the use of highly disaggregated data is a very useful element. Using monthly SPEI data, coupled with agricultural season calendars (Figure 5) and the month for interviews with farmers under LSMS-ISA, I generate the aggregate weather indicators for each stage of the crop growth cycle in each wave, across the sampled countries.[8] From this, I construct three variables of interest: pre-planting (or land preparation), growing (including planting, basal fertilizer application, and lean season), and harvesting (taking crops from the fields). Each of these three variables constitutes the approximate number of months of each crop growing cycle (where it starts and when it ends).

The use of the SPEI also allows us to observe each drought event in relation to the distribution of weather conditions for a given time scale and place. The spatial weather distribution is very useful in farming systems, as the same quantitative rainfall deficit may explain insufficient precipitation in historically wetter villages but not in historically drier villages (Dinkelman 2016), which can be critical for farmers, especially the rain-fed agriculture in SSA. Following the climatology literature (McKee et al. 1993; Vicente-Serrano et al. 2010), I assign $Drought_{it}$ in each village i and month t a value of 1 for all values of the SPEI below -1 and 0 otherwise.

[7] Available at: http://spei.csic.es/database.html

[8] I also consulted other agricultural season calendars, such as the famine early warning systems network for Niger (https://fews.net/west-africa/niger/seasonal-calendar/december-2013) and Nigeria (https://fews.net/west-africa/nigeria/food-security-outlook/october-2018), to obtain weather indicators for each stage of crop growth cycle.

Figure 5: Agricultural season calendar for major food crops in Tanzania

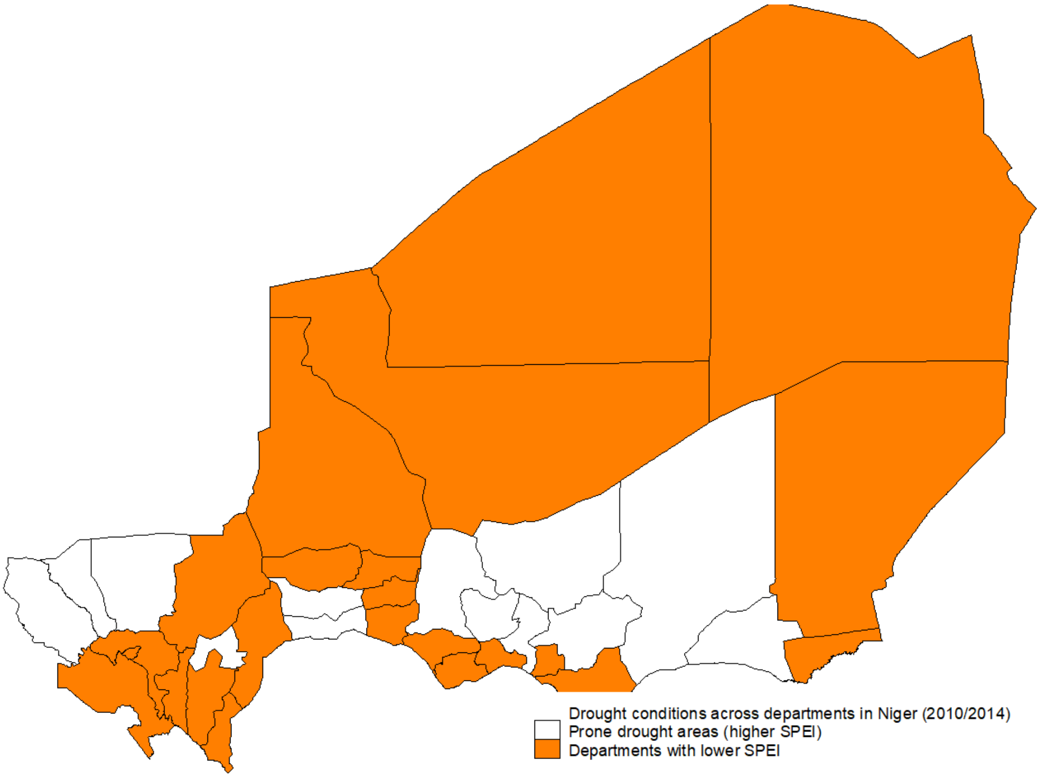


Source: reproduced from FAO (2021), with permission

Using the dummy variables which define the number of months each village might have suffered drought, I then sum the monthly exposures for each of the three phases of the calendar. Figures 6–8 show the distributions of the different districts within which there are villages that have faced drought in each period of the crop cycle for all the EAs considered in LSMS-ISA data.[9]

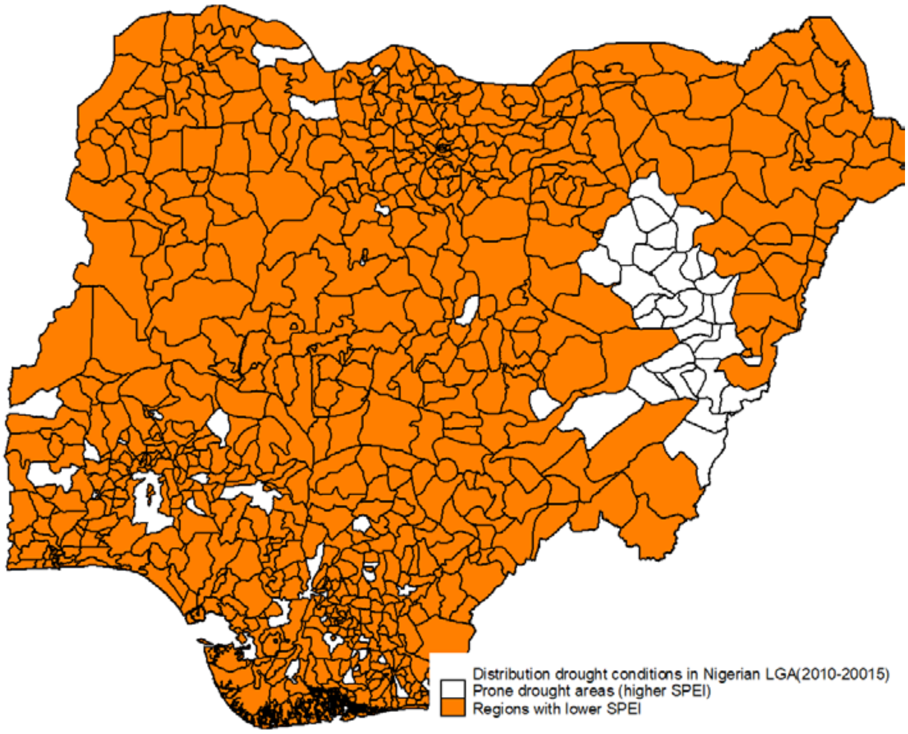
[9] The LSMS_ISA data in Niger do not represent villages in the North-East region, as this is a desert and not fit for habitation.

Figure 6: Fraction of Niger districts (departments) experiencing drought (2011 or 2014)



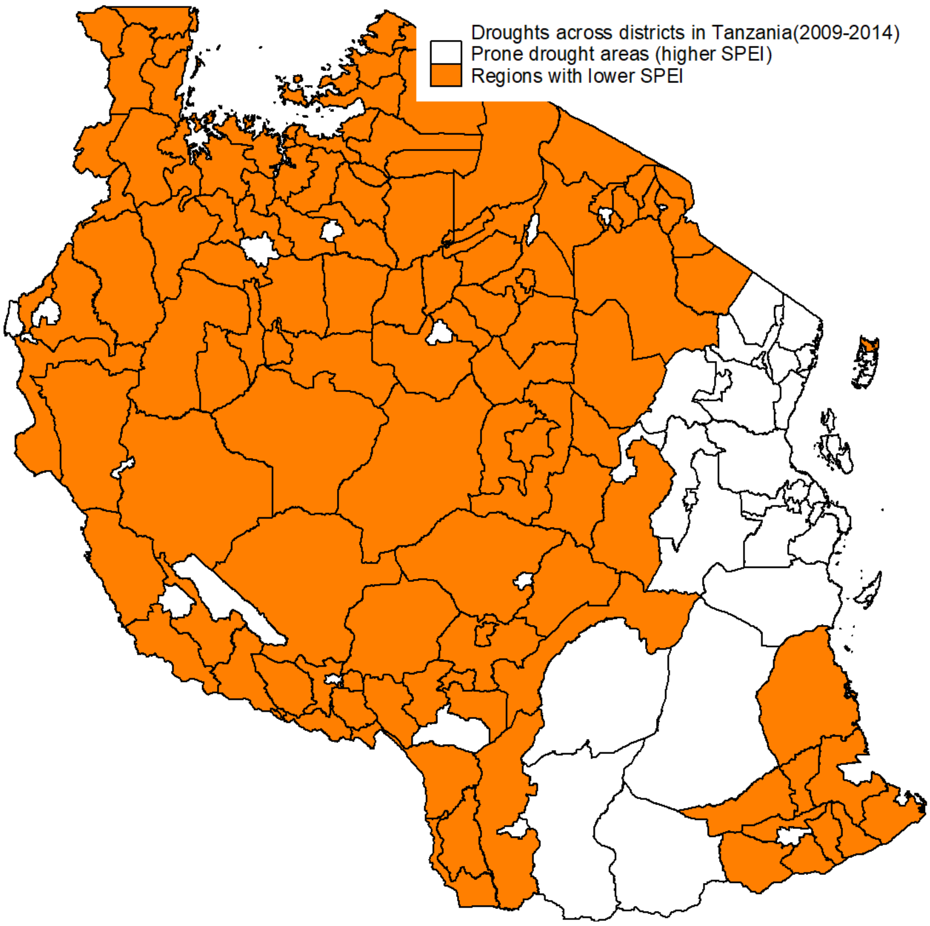
Source: author's construction based on SPEI dataset, using ArcGIS programme.

Figure 7: Fraction of Nigerian districts (LGA) experiencing drought (2010/11, 2012/13, or 2015/16)



Source: author's construction based on SPEI dataset, using ArcGIS programme.

Figure 8: Fraction of Tanzanian districts experiencing drought (2008/9, 2010/11, 2012/13, or 2014/15)



Source: author's construction based on SPEI dataset, using ArcGIS programme.

4 Results and discussion

The main results of the study are shown in Tables 3–5. In addition, the results of some robustness checks are provided. The first columns in Tables 3–5 indicate the associated effects of drought incidence on chemical fertilizer use, while the second columns provide the effects of drought incidence on pesticides use. The third columns indicate the effects of drought incidence on the intensity of fertilizer application on plots.

Table 3: Weather shocks and intensity of chemical fertilizer and pesticide use in Niger

Variables	Fertilizer use	Pesticide use	Fertilizer intensity (kg/ha)
Pre-planting	-0.023 (0.032)	0.002 (0.011)	-0.828*** (0.171)
Growing	0.068** (0.030)	0.026** (0.012)	-0.031 (0.294)
Harvesting	-0.008 (0.019)	-0.010 (0.008)	-0.610*** (0.174)
Parcel controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,186	9,363	2,090
R-squared	0.618	0.510	0.696

Note: sample includes farm households in unbalanced panel from two survey waves (2011 and 2014) in Niger. The table presents the effects of weather shocks (captured via number of drought months during agricultural growth cycle) on agricultural input use. Robust standard errors are in parentheses, clustered by enumeration area. * Significant at 10%. **Significant at 5%. *** Significant at 1%.

Table 4: Weather shocks and intensity of chemical fertilizer and pesticide use in Nigeria

Variables	Fertilizer use	Pesticide use	Fertilizer intensity (kg/ha)
Pre-planting	-0.072** (0.036)	0.052* (0.030)	-0.366* (0.193)
Growing	0.056 (0.043)	0.043 (0.037)	0.491*** (0.177)
Harvesting	-0.005 (0.030)	0.043 (0.028)	-0.108 (0.159)
Parcel controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	12,473	12,523	11,245
R-squared	0.718	0.610	0.659

Note: sample includes households in unbalanced panel from three survey waves (2010/11, 2012/13, and 2015/16) in Nigeria. Other notes as Table 3.

Table 5: Weather shocks and intensity of chemical fertilizer and pesticide use in Tanzania

Variables	Fertilizer use	Pesticide use	Fertilizer intensity (kg/ha)
Pre-planting	-0.420*** (0.107)	0.985*** (0.206)	-1.998*** (0.626)
Growing	-0.163** (0.065)	0.057** (0.024)	-0.751** (0.330)
Harvesting	0.309*** (0.081)	0.005 (0.532)	1.453*** (0.457)
Parcel controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	26,185	26,794	27,266
R-squared	0.769	0.731	0.767

Note: sample includes farm households unbalanced panel from four survey waves (2008/09, 2010/11, 2012/13, 2014/15) from Tanzania. Other notes as Table 3.

Source (Tables 3–5): author's construction.

4.1 Effects of weather shocks on chemical fertilizer and pesticide use

The estimates of the responses of fertilizer use to weather shocks estimated by equation (2) are reported in the first column of Tables 3–5. In all three countries, I find that an additional month of drought during the pre-planting period is associated with a statistically significant decrease in chemical fertilizer use on a given plot. Specifically, in Niger, an extra one month of drought during the pre-planting period leads to a reduction of 0.02 percentage point in chemical fertilizer use. In Nigeria and Tanzania, an additional one month of drought during the pre-planting period induces a decrease of chemical fertilizer use by 0.07 and 0.42 percentage points, respectively. Moreover, noting that the rate of adopting chemical fertilizers approaches 35 per cent in Nigeria, 15 per cent in Niger, and 11 per cent in Tanzania, those point estimates indicate that an additional one month of drought in the pre-planting period result in a probability of a 2 per cent decrease in chemical fertilizer use in Niger, 7 per cent in Nigeria, and 42 per cent in Tanzania.

In the second column of Tables 3–5, I explore the results from equation (2) showing the causal effects of drought on pesticide use on a given plot. In all three countries, the signs of the parameter estimates on drought indices are positive throughout, as expected. It is important to note that farmers generally use pesticides immediately after pests are detected on the crops; hence the effects should be more clearly observed in the growing period than the pre-planting or harvesting periods. Indeed, the results show that, in Niger, one extra month of drought during the growing season is associated with an increase of 0.02 percentage point in pesticide use; and in Nigeria and Tanzania, an additional one month drought incidence leads to approximately 0.04 and 0.05 percentage point increases in pesticide use during the growing season, respectively. These results reaffirm the findings of the study by Jagnani et al. (2018), which showed that when the farmers face drought soon after planting, especially in tropical areas where the incidence of pests is high, they will increase investment in loss-reducing inputs (including pesticides) and thus reduce yield-enhancing investment (including chemical fertilizer).

The estimates from the effects of weather shocks on the intensity of chemical fertilizer use are reported in the last column of Tables 3–5. The results show that during the pre-planting period, an additional one month of drought will reduce the intensity of fertilizer use (kg/plot) by 82 per cent in Niger, 36 per cent in Nigeria, and 199 per cent in Tanzania. This reaffirms the strong reverse associations between weather shocks and farmers' decision on the use of farm inputs. The results are robust even when the heteroscedastic standard errors are clustered at district and district-by-year-of-survey levels to allow the correlation of residuals with district and district-by-year-of-survey, respectively.

4.2 Robustness checks

In estimating equation (2) so far, I have clustered the residuals by village to allow plausible correlations of residuals within the villages. To achieve this, I exploit a random exogenous variation in weather shocks at the village level beyond time-invariant plot and household characteristics and time-invariant administrative and spatial attributes, to derive a causal effect of weather shocks on farmers' decision to use inputs.

To test whether the farm input use residuals remain unchanged with an alternative specification, I clustered the robust residuals at district level, which allows me to control for potential differences across districts. I also cluster the residuals at the district-by-year-of-survey level to allow the correlation of residuals within districts over each year of the household survey. Tables A1–A3 in the Appendix provide the results of these robustness checks, where the derived estimates are clustered at district and district-by-year-of-survey level. Comparing the above results with those reported in Tables 3–5, it is clear that the reported estimates of the effects of weather shocks on farmers' decision to use inputs are still the same despite some indistinguishable differences in the standard errors. This confirms the earlier claim that weather shock plays a significant role in affecting farmers' decision to use or not use farm inputs during the agricultural growth cycle.

5 Conclusion

The low rates of agricultural technology adoption in SSA may be caused by many interlinked factors, including poverty, market imperfection, asymmetric information, and credit constraints. In addition, farming systems in SSA are heavily reliant on rainfall, so that farmers' livelihoods are endangered in the event of weather shocks. This study extends the economic literature on the effects of farm input use decisions in SSA by analysing the effects of local drought shocks on farmers' farm inputs uptake (including chemical fertilizer and pesticides). The study focuses on a unique context of SSA where limited access to coping mechanisms and rates of modern farm inputs use make it difficult for farmers to cope with and avoid threats from weather shocks. Specifically, this study examines the effects of droughts on the intensity of farm inputs use (chemical fertilizer and pesticides) on a given plot. Behavioural economic theory suggests that unexpected droughts may induce farmers to take abrupt decisions regarding farm input use during different stages of the agricultural cycle.

My identification strategy exploits exogenous variations in drought events across different villages over time and controls for farm household and plot characteristics. To capture the effects of droughts on farmers' decisions to use modern agricultural inputs, I use a highly disaggregated monthly drought index (SPEI with 0.25 degree spatial resolution level). This index provides a level of variation of a periodic state of drought in a given village and time from the situation that normally prevails in this village. Coupled with this, I use a set of fixed effects, an approach that makes it reasonable that any effect of drought on the intensity of farm input use I estimate is indeed causal. Using rich panel survey data (LSMS-ISA) from three SSA countries—Niger, Nigeria, and Tanzania—the study explores the relationship between drought incidence and intensity of farm input use by smallholder farmers. I find consistent evidence that drought incidence is strongly correlated with reduced use of chemical fertilizer and positive use of pesticides during different stages of the agricultural cycle. Specifically, the study shows that an additional one month of drought in the pre-planting period results in a 2 per cent decrease in chemical fertilizer use in Niger, a 7 per cent decrease in Nigeria, and a 42 per cent reduction in Tanzania, respectively. On the other hand, the results show that, in Niger, one extra month of drought during the growing period will increase the probability of using pesticides by 2 percentage points, while in Nigeria and Tanzania, an additional month of drought incidence increases the probability of pesticide use during the growing season by roughly 4 and 5 percentage points, respectively.

Given a sufficient sample size in each wave and national-level data representativeness, inclusive of farm household- and plot-level characteristics, the findings of this study seem conclusive. Considering the whole range of responses of farm input use, including chemical fertilizer and pesticides, the paper offers unique insight into how farmers in SSA take their farming decisions sequentially when exposed to drought conditions. These effects show that there is a need to provide effective climate change risk-coping strategies for farmers. The introduction of improved crop disease and drought resistance technologies could allow farmers to maintain their livelihoods regardless of extreme climate events. In addition, it can be argued that quick, accurate, and consistent provision of weather forecasts via mobile phones messages, radio, or television during the agricultural growth cycle, especially in drought-prone areas, would improve farmers' awareness of impending weather conditions and their ability to adjust their farming methods accordingly.

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Appendix: Robustness checks

Table A1: Weather shocks and intensity of fertilizer and pesticide use in Niger

Variables	Clustered at district level			Clustered at district by surveyed year		
	Fertilizer use	**Pesticide use**	**Intensity (kg/plot)**	**Fertilizer use**	**Pesticide use**	**Intensity (kg/plot)**
Pre-planting	-0.023	0.002	-0.828***	-0.023	0.002	-0.828***
	(0.027)	(0.012)	(0.171)	(0.025)	(0.010)	(0.149)
Growing	0.068	0.026	-0.031	0.068	0.026*	-0.031
	(0.049)	(0.018)	(0.324)	(0.042)	(0.015)	(0.285)
Harvesting	-0.008	-0.010	-0.610***	-0.008	-0.010	-0.610***
	(0.028)	(0.010)	(0.133)	(0.025)	(0.008)	(0.123)
Parcel controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,186	9,363	2,090	5,186	9,363	2,090
R-squared	0.618	0.510	0.696	0.618	0.510	0.696

Note: sample includes farm households in unbalanced panel from two survey waves (2011 and 2014) in Niger. The table presents the effects of weather shocks (captured via number of drought months during the agricultural growth cycle) on agricultural input use. I define the three main stages of the agricultural growth cycle as: pre-planting (or land preparation); growing (including planting, basal fertilizer application, and lean season); and harvesting. Robust standard errors are in parentheses, clustered by district and district-by-year of survey respectively. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Source: author's construction.

Table A2: Weather shocks and intensity of fertilizer and pesticide use in Nigeria

Variables	Clustered at district level			Clustered at district by surveyed year		
	Fertilizer use	**Pesticide use**	**Intensity (kg/plot)**	**Fertilizer use**	**Pesticide use**	**Intensity (kg/plot)**
Pre-planting	-0.013***	0.009***	-0.032	-0.013***	0.009***	-0.032
	(0.005)	(0.003)	(0.030)	(0.004)	(0.003)	(0.026)
Growing	0.015*	0.013*	-0.046	0.015**	0.013**	-0.046
	(0.008)	(0.007)	(0.047)	(0.007)	(0.006)	(0.042)
Harvesting	0.006	0.009**	-0.045	0.006	0.009**	-0.045
	(0.006)	(0.005)	(0.038)	(0.006)	(0.004)	(0.033)
Parcel controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,509	12,558	11,290	12,509	12,558	11,290
R-squared	0.623	0.521	0.577	0.623	0.521	0.577

Note: ample includes households in unbalanced panel from three survey waves (2010/11, 2012/13, and 2015/16) in Nigeria. The table presents the effects of weather shocks (captured via number of drought months during the agricultural growth cycle) on agricultural input use. I define the three main stages of the agricultural growth cycle as: pre-planting (or land preparation); growing (including planting, basal fertilizer application, and lean season); and harvesting. Robust standard errors are in parentheses, clustered by district and district-by-year of survey respectively. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Source: author's construction.

Table A3: Weather shocks and intensity of fertilizer and pesticide use in Tanzania

Variables	**Clustered at district level**			**Clustered at district by surveyed year**		
	Fertilizer use	**Pesticide use**	**Intensity (kg/plot)**	**Fertilizer use**	**Pesticide use**	**Intensity (kg/plot)**
Pre-planting	-0.420***	0.012	-1.998***	-0.420***	0.012*	-1.998***
	(0.097)	(0.008)	(0.598)	(0.100)	(0.006)	(0.610)
Growing	-0.163**	0.017**	-0.751*	-0.163**	0.017***	-0.751**
	(0.081)	(0.007)	(0.423)	(0.076)	(0.005)	(0.379)
Harvesting	0.309***	0.001	1.453***	0.309***	0.001	1.453***
	(0.086)	(0.003)	(0.485)	(0.084)	(0.002)	(0.476)
Parcel controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,141	28,255	27,218	26,185	28,255	27,266
R-squared	0.769	0.256	0.767	0.769	0.256	0.767

Note: sample includes farm households in unbalanced panel from four survey waves (2008/09, 2010/11, 2012/13, and 2014/15) from Tanzania. The table presents the effects of weather shocks (captured via number of drought months during the agricultural growth cycle) on agricultural input use.I define the three main stages of the agricultural growth cycle as: pre-planting (or land preparation); growing (including planting, basal fertilizer application, and lean season); and harvesting. Robust standard errors are in parentheses, clustered by district and district-by-year of survey respectively. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Source: author’s construction.