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Luis Guillermo Becerra-Valbuena

PARIS SCHOOL OF ECONOMICS
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Luis Guillermo Becerra-Valbuena†
Paris School of Economics-Université Paris 1 Panthéon-Sorbonne

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Abstract

This article analyses the effects of droughts and climate variability on short-term and medium-term adaptation of Colombian rural households. I measure drought in a Differences-in-Differences (DID) framework, as an alternative to the standard approaches decomposing the effects from climate and yearly weather deviations on agricultural productivity and those using the growing degree days and harmful degree days. In the short-term and medium-term, rural households adapt to the drought of 2010 by increasing the total area planted in crops and livestock, (increasing also the total gross agricultural productivity in value terms) and by working more on the farm. The droughts also increased the use of external sources of water in the farm and made rural households postpone non-housing investments in the farm. I find heterogeneous effects according to the long run mean of temperature in the municipality. Higher temperature affects positively gross agricultural productivity in low-temperature municipalities but negatively high-temperature municipalities. Cereals and coffee seem to benefit from higher temperatures, while vegetables and fruits are more affected.

Keywords: climate change, weather, agriculture, gross productivity, adaptation, rural impacts.
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†48 Boulevard Jourdan, 75014 Paris Cedex 14, France, email: luis.becerra@psemail.eu; lgbecerrav@ucdavis.edu

1 Introduction

Climate change is affecting many aspects of human life, not only through distortions of weather patterns, or increases of the intensity of phenomena such as the El Niño Southern Oscillation (ENSO events or El Niño-La Niña events), but primarily through the impact it has on health, migration and agriculture, among many other aspects. The threat it can pose on food safety and food production of rural households in many countries is undeniable, and one of the most important impacts is on agriculture. In their review of the literature, D'Agostino and Schlenker (2016) note that climate change could reverse the gains in average yields obtained with the Green Revolution, by increasing the volatility of food production. According to Ortiz-Bobea et al. (2021), anthropogenic climate change has reduced global agricultural total factor productivity (TFP) by about 21% since 1961, equivalent to losing the last 7 years of productivity growth. The damaging effect of climate change on TFP has been more severe (a reduction of around 26% to 34%) in warmer regions such as Africa and Latin America and the Caribbean. In spite of the magnitude of the effect, Auffhammer and Schlenker (2014) point out that the main studies of crop responses to climate change have been focused on important food crops and major producers rather than on low income and small producer countries. In this sense, the literature for developing countries and small rural households still remains scarce and particularly focused on U.S, as pointed out by Kolstad and Moore (2020).

Only recently, Aragón et al. (2021) analysed how subsistence rural households respond to extreme heat in Peru. In this case, high temperatures reduce gross agricultural productivity (in value terms), and rural households attenuate the effect on output by increasing the area planted, using more crop mixing and selling livestock. In this article, I study small rural households in Colombia and their adaptation over the medium-term to contribute to this scarce literature on responses to climate change in low-income countries. The article aims to analyse first, how droughts affect agricultural decisions and food production of rural households in Colombia, in the short-term and medium term and for consecutive droughts. To what extent, and by which means, do rural households adapt to these shocks? And what are the differences in rural households' behaviour in the short-term and the medium-term versus the adaptation to consecutive shocks? The analysis also focuses on an important aspect of heterogeneity: the differences between rural households located in municipalities with high average temperature and those located in municipalities with low average temperature in the past.

In order to study rural households' adaptation to these shocks, I use the Colombian panel survey (ELCA) which has very rich information on agricultural production and investments made in the land of rural households. It also has information about the problems faced by the household such as losing crops, weather shocks among others, but I mainly rely on weather data from satellite images in order to avoid the measurement errors that could arise from using subjective self-reported shocks. Since the panel follows the same household over three waves, I can study adaptation such as using more some crops than others, change in the use of inputs or changes towards other types of agricultural activities. This is a main advantage compared to studies such as Aragón et al. (2021), which use repeated cross-section data. Also, the use of panel data to study weather impacts on agriculture allows for a better causal identification, as weather deviations around the mean are random and exogenous (Blanc and Schlenker (2017)).

In terms of agricultural adaptation, Costinot et al. (2016) and Burke and Emerick (2016) show that crop switching could be a possible response to climate change. Rural households might adapt by making investments in the unit of agricultural production, trying to get technical assistance or modifying the use of fertilizers. The information on these adaptive margins are also available in the panel survey ELCA. Similarly, Rosenzweig and Wolpin (1993) also highlight that households could respond to droughts on the intensive margin by increasing off-farm work (see Jayachandran (2006)), selling cattle (see Fafchamps et al. (1998)), or on the extensive margin, through migration (see Cattaneo et al. (2019)), among several others. The roughness, altitude and the different climatic zones are characteristic of the Colombian territory, which have posed some challenges for agricultural production, affecting also transportation. This heterogeneity affects not only weather but also the type of crops that can be produced, and together with the non-linear effects for the agricultural production (see Deschênes and Greenstone (2007) and Schlenker and Roberts (2009)) are additional aspects to consider.

The analysis of the article can be divided in three parts. First, I separate the effect of climate from yearly weather deviations for the Colombian rural households as has been done in the literature (Kelly et al., 2005; Deschênes and Kolstad, 2011; Burke and Emerick, 2016; Bento et al., 2020). Second, I explore different adaptive margins in response to extreme temperature using two measures: the Growing Degree Days (GDD) and the Harmful Degree Days (HDD) (Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007; Aragón et al., 2021). And third, I suggest that an alternative measure of drought can be used in a Differences-in-Differences (DID) framework to analyse how rural households adapt to climate and weather. The DID analyses the short-term and the medium-term adaptation and then, the adaptation with respect to consecutive droughts.

The main findings of the article can be broken down in five. First, with respect to the analysis of climate and yearly weather deviations of section 4.2, gross agricultural productivity (in value terms) is positively affected by the long-run mean temperature, while there is no effect from temperature shocks (deviations from the long-run mean); with respect to the marginal effects, higher temperature affects positively gross agricultural productivity (in value terms) in low-temperature municipalities but negatively in high-temperature municipalities. With the exception of Aragón et al. (2021), the heterogeneous effects of temperature have been explored for the case of U.S. (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009) but less for developing countries. Second, across several of the analyses of the short-term and medium-term (climate-yearly weather deviations, GDD-HDD and the DID), the gross agricultural productivity (in value terms) of cereals and coffee benefit from droughts or when facing higher temperatures. The gross agricultural productivity increases in low-temperature municipalities for cereals and coffee, while those in high-temperature areas are negatively effected. Vegetables seem to be more affected following droughts (DID analysis). Across the different analyses, the gross agricultural productivity (in value terms) of vegetables and fruits present reductions, particularly in low-temperature municipalities (increases in high-temperature municipalities). Third, as regards short-term and medium-term, the drought of 2010 made the rural households re-allocate land by reducing the type of land left fallow and assigning it to production of crops and for livestock. This captures some of the trade-offs proposed in the theoretical model of section 3. It also goes in line with the increase of farm inputs (land and labor) as in Aragón et al. (2021) and with increases in the total gross agricultural productivity (in value terms). The drought of 2010 also affected labor market outcomes, making household heads and his/her partner to work more on the farm. In addition, rural households reduce the investments after droughts, which could be interpreted as postponing investment decisions and a way to smooth consumption. They also increase the use of external sources of water as their own water sources dries up during droughts. Fourth, for the consecutive drought of 2010 and 2013, rural households continue implementing some strategies as in the short-term and medium-term, but the adaptation becomes more difficult once the droughts start to be more frequent. On the one hand, some strategies observed before like working more in agriculture, using external sources of water and smoothing consumption by postponing investments, are less likely to be implemented. On the other hand, the rural households keep using more land available for crops and there is an increase in the land area with investments (excluding housing). In this sense, droughts might make rural households aware of the potential future benefits of making investments, which is compatible with the findings of Burke and Emerick (2016). Fifth, the analysis of the climate-yearly weather deviations of section 4.2 and the DID of section 5.2 gave qualitatively similar findings, with a positive effect of temperature shocks and droughts (short-term and medium-term in the DID) on gross agricultural productivity (in value terms), with a negative marginal effect in high-temperature municipalities, while a positive marginal effect in low-temperature ones. This article thus proposes an alternative manner to examine the short-term and medium-term adaptation decisions of the rural households.

The article contributes in four ways: first, it adds to the scarce literature in low and middle income countries, and proposes an alternative measure to assess climate impact and adaptation in agriculture in the short-term and in medium-term in Colombia. Second, it explores the heterogeneity between households living in high versus low-temperature areas, an aspect not considered yet in the literature. Third, it shows that in the short-term and medium-term, rural households in Colombia adapt by using more available land, which could lead to higher gross agricultural productivity (in value terms). Another novelty is to analyse consecutive droughts. Fourth, it explores in more detail how rural households adapt to droughts by analysing a broader set of crops, vegetables, fruits, cereals and coffee. As pointed out by Hertel and de Lima (2020), the FAO identifies 175 distinct crops but the majority of climate impact studies have focused on changes in yields for four staple crops, maize, wheat, rice and soybeans. These four staple crops account for only one-quarter of the total value of agricultural output. The article gives evidence of climate impacts outside of the staple crop domain and explores other farm inputs such as labor, the use of investments and access to water. According to Hertel and de Lima (2020), the literature should move beyond the yield impact where we have better data and models, and move towards other food products, farm inputs and nutritional impacts.

The article proceeds in the following manner: section 2 describes the ELCA panel survey and the descriptive statistics on gross agricultural productivity; section 3 proposes a simple theoretical framework that helps to explain the mechanisms captured by the empirical findings; section 4.2 analyses the impact of climate and weather deviations on gross agricultural productivity, distinguishing between weather deviations and long-term climate averages; section 4.4 analyses the effect of gradual changes in temperature on gross agricultural productivity (in value terms) to see how rural households adapt in Colombia; section 5 proposes a DID strategy to analyse if there are differences in short-term and medium term adaptation compared to the adaptation with respect to consecutive droughts; and section 6 concludes.

2 Data and Descriptive Statistics

2.1 ELCA 2010-2013-2016

I use the ELCA survey (The Colombian panel survey), a nationally representative panel following the same households for three waves, in 2010, in 2013 and 2016. It is conducted by the University of Los Andes in rural and urban areas, surveying also units of agricultural production, which vary in terms of land size, the type of crops and type of production (crops, livestock, etc.). In the rural areas, it is representative for the small rural households (peasants) of the four micro-regions sampled (Atlantica Media-Cundi Boyacense-Eje Cafetero-Centro Oriental) and the attrition is very low, only 3.6% (see Fuertes et al. (2017)). It covers 17 municipalities and 224 veredas (small rural areas inside a municipality).

The ELCA panel follows the same household for different rounds, with information on the type of crops used by each agricultural unit. It also helps to identify long-term adaptive strategies such as migration, changes in agricultural technology and investment, or dynamic effects of short term responses (changes in the type of crops or effects on the rural labor market).

The panel survey is composed of 10,800 households among which 4,800 are rural households and 6,000 are urban households (see Table 13 in Appendix 3C for the sample per municipality and year). It has a section of questions by household, a section of different land parcels belonging to the household (land section) and another section by crops and livestock that the household produces (production section). Thus, the land section and the production section are aggregated by rural household and merged with the household section. I will focus on the rural sample (44.4% of the total), restricted to households with at least one parcel used in agricultural activities, excluding land given to someone else or sold (the final sample comprises 95% of reported land in 2010, 92% in 2013 and 93.2% in 2016). I also restrict the main sample to households with complete information on land use and investment and I exclude households moving to municipalities outside of the initial sample of 17 municipalities (647 of the total of 12,804 household observations for the three waves in Table 13 of Appendix 3C). I explore in more detail some aspects of migration for the larger sample in the section of results.

Table 1 and Table 2 summarize the descriptive statistics of the outcome variables, the control and weather variables used.[1] For the outcomes, I construct the variable "Per. crops (YEARLY)" as the percentage of annual crops among the total number of parcels that the rural household has. Yearly crops constitutes 61% of the sample, so inter-annual cropping is less frequent in this sample. The ELCA provides detailed information on agricultural costs, sales, total agricultural production (see the description of the construction in the next paragraph), as well as important data on investment. For the latter variables, the survey records a dummy if there was an investment on the parcel of land and I adjust multiplying by the land size of that plot; for example, if a household has two plots, one with two hectares and another one with three hectares, and made an investment in the first one, the variable aggregated by household takes a value of two hectares.[2] The aggregated variable per rural household "Land (ha) ANY INVEST" captures the hectares of parcels in which the household did any investment. Table 1 shows that on average the rural households made investments for housing on 0.32 hectares and investments for structural investments on 0.27 hectares, compared to the average land size of the household of 2.89 hectares. Investments excluding housing were made on 0.69 hectares, which represents 23.9% of the average total land size of the rural households. Other relevant outcomes are "Land size (hectares)" of the household which is separated by the different type of uses (in permanent crops, mixed crops, livestock, etc.). Finally, the ELCA provides data of livestock, which were homogenized in Tropical Livestock Units according to the guidelines of FAO units for international comparison (see Upton (2011)).[3] In terms of labor, the ELCA has information on whether or not the household head (or partner) were employed, or looked for a job, if she or he has an agricultural job, etc. Finally, "Land (ha) (ANY WATER)" is the hectares of land of the household that were declared to have access to water. The descriptive statistics of all outcome variables are shown in Table 1. The ELCA panel survey records the variables of land size and investment questions in a separate section asking the rural household questions by plots, which is another section of the rural agricultural production. Both sections, the agricultural production and the one of parcels are linked only by the rural household number.

For the control variables, Table 2 includes data of the household characteristics such as household size, age of the household head, "N. persons <14" as the number of persons below or equal to 14 years old in the household, and a dependency ratio variable as the ratio between the household members below or equal to 14 years old plus household members above or equal to 64 years old, divided by the household members between 15 to 64 years old. "Percentage crops (DROUGHT problem)" as the percentage of crop parcels for which drought was reported as a problem, "Dummy

[1] I added a value of 1 to all the variables using logarithm in order to avoid missing information for cases when the household reported a production or values of zero, which could make the logarithm of zero to be undefined. The use of logarithm is justified to reduce the variability, avoid extreme values and have outcome variables that resemble better a normal distribution. An alternative was to use the inverse hyperbolic sine (IHS) transformation. Although logarithm and IHS gave similar distributions, I prefer to use the logarithm in order to have a more straightforward interpretation of the results.

[2] The majority of the times, there was only one investment made in each plot. For the cases where the household made more than one investment in the same plot, I divide the number of hectares among the total investments. For a plot of three hectares making two investments, I will assign 1.5 hectares to each investment.

[3] Cattle corresponds to 0.7 Tropical Livestock Units (TLU) in South America, sheep and goats to 0.1 TLU, pigs to 0.25 TLU, asses to 0.5 TLU, horses to 0.65 TLU, mules to 0.6 TLU and chickens to 0.01 TLU.

community prob. (lackwater)" is a question if the community where the household lives faced a problem of lack of water, "PCA 1: HH WEALTH"[4] as the first principal component for the analysis of wealth measures of the household, "Dummy HH has credit" as one or zero if the household has access to credit in that year, "Dummy access cabecera is ok (community)"[5] as a dummy if the community has good access to the town center of the municipality, "Minutes to reach cabecera (community)" for the minutes from the community to reach the town center of the municipality, and finally, "Land (ha) (OWNED)" a variable which the hectares of land that were reported as owned. The descriptive statistics of all control variables are shown in Table 2.

In the estimation section, I only use the dependency ratio (0-14 years old and +65 years old with respect to the household size) variable instead of "HH size", "N. persons <=14", "N. persons 15-64" and "N. persons >=65". I also exclude some potentially endogenous variables in the estimations: "Dummy HH FAMILIAS EN ACCION", "Percentage crops (DROUGHT problem)", "Percentage crops (RAIN problem)", "Dummy community prob. (prices)" and "Dummy community prob. (lackwater)". "Edu. HH head" is excluded for the many missing. However, I include the variables here for illustration.

[4] For the estimations, I create indicator variables for five quintiles in the wealth distribution in 2010 (initial period), in which the household belongs to.

[5] 1 for "Carretera pavimentada en buen estado (paved road in good shape)", "Carretera pavimentada en mal estado (paved road in bad shape)", "Carretera sin pavimentar en buen estado (no paved road in good shape)". 0 for "Carretera sin pavimentar en mal estado (no paved road in bad shape)", "Trocha o carreteable (bad shape road)", "Camino de herradura (bridle path)", "Mar, río o caño (sea or river)."

Table 1: Outcome variables rural households - Descriptive Statistics

	Observations	Mean	SD	Min	Max
Percentage crops (YEARLY)	9056	0.61	0.40	0	1
Percentage crops (SEMIANNUAL)	9056	0.18	0.31	0	1
Percentage crops (QUARTERLY)	9056	0.04	0.14	0	1
Percentage crops (MONTHLY)	9056	0.09	0.21	0	1
Percentage crops (BIMONTHLY-OTHER)	9056	0.08	0.20	0	1
Total Agro costs (Millions Col. Pesos/Ha)	10454	4.70	35.32	0	1580
Agro sale (Millions Col. Pesos/Ha)	10454	2.07	21.90	0	1662
vr prodtot (Millions Col. Pesos/Ha of crops)	3403	21.12	263.55	0	12770
vr prodtot-vegetable (Millions Col. Pesos/Ha of crops)	3403	7.37	93.14	0	2505
vr prodtot-fruit (Millions Col. Pesos/Ha of crops)	3403	4.81	183.98	0	9670
vr prodtot-cereal (Millions Col. Pesos/Ha of crops)	3403	7.49	163.97	0	12770
vr prodtot-coffee (Millions Col. Pesos/Ha of crops)	3403	1.45	11.18	0	425
Land (ha) ANY INVEST	11633	1.01	3.38	0	103
Land (ha) IRRIGATION INVEST	11633	0.05	0.78	0	53
Land (ha) STRUCTURES INVEST	11633	0.27	1.74	0	100
Land (ha) CONSERVATION INVEST	11633	0.12	1.03	0	50
Land (ha) FRUITS INVEST	11633	0.10	0.85	0	35
Land (ha) WOOD INVEST	11633	0.03	0.43	0	30
Land (ha) COMMERC. INVEST	11633	0.03	0.37	0	12
Land (ha) HOUSING INVEST	11633	0.32	1.55	0	40
Land (ha) OTHER INVEST	11633	0.09	0.89	0	40
Land (ha) ANY NO HOUSING INVEST	11633	0.69	2.77	0	103
Land size HH (Ha)	11633	2.89	6.35	0	118
Land PERMANENT crops (Ha)	11633	0.36	1.02	0	21
Land TRANSITIONAL crops (Ha)	11633	0.27	0.92	0	40
Land MIXED crops (Ha)	11633	0.17	0.89	0	30
Land LIVESTOCK (Ha)	11633	1.14	4.27	0	118
Land PASTURE (Ha)	11633	0.15	1.05	0	64
Land FOREST (Ha)	11633	0.13	1.22	0	90
Land OTHER USES (Ha)	11633	0.07	0.44	0	32
Land NO USED (Ha)	11633	0.35	1.73	0	62
Total Area planted (Ha) (perman.+trans.+mixed)	12157	0.78	1.59	0	40
Dummy after moving to another comm inside mpio 2010	12157	0.11	0.31	0	1
Tropical Livestock Units (FAO reference)	11644	6.42	37.66	0	2520
HH head-partner employed	12157	0.67	0.47	0	1
HH head-partner look for job	12157	0.15	0.36	0	1
HH head-partner agro work	12157	0.50	0.50	0	1
HH head-partner no agro work	12157	0.23	0.42	0	1
HH head-partner Ave. wage (Millions Col. Pesos)	4473	0.35	0.32	0	6
HH head-partner Ave. hours worked month	8227	35.76	18.56	1	126
Land (ha) (ANY WATER)	11633	2.14	5.66	0	118
Land (ha) (OWN WATER)	11633	1.27	4.28	0	100
Land (ha) (EXTERNAL WATER)	11633	0.87	2.93	0	118

Source: based on the ELCA panel survey 2010-2013-2016, using expansion factors for 2010 as recommended by the ELCA team.

Table 2: Controls and weather variables rural households - Descriptive Statistics

	Obs.	Mean	SD	Min	Max
Dependency ratio (<=14 + >=65)/(15-64) Per. 2010	12157	83.62	73.69	0	700
HH size	12157	4.59	2.14	1	19
N. persons <=14	12157	1.44	1.41	0	10
N. persons 15-64	12157	2.74	1.42	0	12
N. persons >=65	12157	0.41	0.66	0	4
Dummy HH FAMILIAS EN ACCION	12157	1.51	0.50	1	2
Age HH head	12157	49.76	12.81	16	100
Dummy women HH head	12157	0.21	0.40	0	1
Edu. HH head	9231	4.23	3.31	0	21
Percentage crops (DROUGHT problem)	10411	0.30	0.38	0	1
Percentage crops (PEST problem)	10411	0.26	0.32	0	1
Percentage crops (BRUSH problem)	9518	0.03	0.14	0	1
Percentage crops (RAIN problem)	10411	0.03	0.12	0	1
Percentage crops (SEEDS problem)	9518	0.01	0.07	0	1
Percentage crops (VANDALISM problem)	10411	0.01	0.06	0	1
Percentage crops (OTHER problem)	10411	0.04	0.15	0	1
Percentage crops (NONE problem)	10411	0.47	0.39	0	1
Dummy community prob. (land quality)	11111	0.36	0.48	0	1
Dummy community prob. (transport)	11111	0.70	0.46	0	1
Dummy community prob. (internal abuse)	11111	0.72	0.45	0	1
Dummy community prob. (costs)	11111	0.95	0.22	0	1
Dummy community prob. (armed groups)	11111	0.03	0.17	0	1
Dummy community prob. (lack credit)	11111	0.39	0.49	0	1
Dummy community prob. (others)	11111	0.12	0.32	0	1
Dummy community prob. (selling goods)	11111	4.84	1.47	0	8
Dummy community prob. (lackwater)	11111	0.63	0.48	0	1
Dummy community prob. (prices)	11111	0.95	0.23	0	1
Land (ha) (OWNED)	11633	2.15	5.27	0	118
Land (ha) (OWNED WITH TITLE)	11633	1.66	4.90	0	118
PCA 1: HH WEALTH	12157	0.46	0.24	0	1
PCA 1: HH (LIVESTOCK ASSETS)	12157	0.06	0.84	-1	4
PCA 1: HH (AGR. ASSETS)	12157	-0.01	0.54	-0	6
Dummy HH has credit	12157	0.50	0.50	0	1
Dummy access cabecera is ok (community)	12157	0.28	0.45	0	1
Minutes to reach cabecera (community)	11111	42.47	36.22	1	240
Annual Ave daily Rainfall 1981-2010-CHIRPS (mm) agro-season	12157	4.07	1.10	2	7
Annual Ave daily Temp. 2001-2010 (Celsius MODIS) agro-season	12157	29.16	5.42	19	38
Yearly Ave days with rainfall 1981-2010-CHIRPS (mm)	12157	136.36	30.40	65	176
Yearly Ave days with temp. > 34C 2001-2010 (MODIS)	12157	22.94	15.67	0	52
Rainfall Trend 30 years-MEAN (mm) agro-season	12157	4.32	0.76	3	6
Rainfall deviation from trend-MEAN (mm) agro-season	12157	-0.25	0.81	-2	1
Temperature Trend 15 years-MEAN (Celsius) agro-season	12157	28.85	5.02	20	35
Temperature deviation from trend-MEAN (Celsius) agro-season	12157	0.31	1.06	-2	3
Temperature Trend 15 years-MAX (Celsius) agro-season	12157	31.11	4.30	22	37
Temperature deviation from trend-MAX (Celsius) agro-season	12157	0.25	1.27	-2	3
Temperature GDD-MEAN (Celsius) agro-season	12157	12.78	4.51	4	18
Temperature HDD-MEAN (Celsius) agro-season	12157	1.00	1.13	0	5

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	Obs.	Mean	SD	Min	Max
Temperature GDD-MAX (Celsius) agro-season	12157	15.02	3.07	8	18
Temperature HDD-MAX (Celsius) agro-season	12157	2.74	2.17	0	8
SPI Index 12 months CHIRPS	12157	0.22	1.14	-2	2
SPI Index 12 months CHIRPS(opposite)	12157	-0.22	1.14	-2	2
SPI Index 12 months CHIRPS(opposite)-agro season	12157	-0.55	1.24	-2	2
SPI Index 12 months CHIRPS(opposite)-positive values	12157	0.47	0.72	0	2
SPI Index 12 months CHIRPS(opposite)-negative values	12157	-0.69	0.49	-2	0
Per. months droughts(<=-1)-yearly for SPI Index 12	12157	0.21	0.37	0	1
Per. months droughts(<=-1)-yearly for SPI Index 12-agro season	12157	0.19	0.36	0	1
Per. months droughts(<=-2)-yearly for SPI Index 12	12157	0.08	0.18	0	1
Per. months droughts(<=-2)-yearly for SPI Index 12-agro season	12157	0.03	0.10	0	1
Dummy 1 or more months drought(<=-1)(SPI12)	12157	0.32	0.47	0	1
Dummy 1 or more months drought(<=-1)(SPI12)-agro season	12157	0.23	0.42	0	1
Dummy 1 or more months drought(<=-2)(SPI12)	12157	0.21	0.41	0	1
Dummy 1 or more months drought(<=-2)(SPI12)-agro season	12157	0.15	0.35	0	1

Source: based on the ELCA panel survey 2010-2013-2016, using expansion factors for 2010 as recommended by the ELCA team. "PCA 1: HH WEALTH" is the first principal component and it is already provided in the ELCA. "PCA 1: (LIVESTOCK ASSETS)" and "PCA 1: (AGR. ASSETS)" are also the first principal component but constructed here.

Table 3: Values of gross agricultural productivity by municipality

Municipalities	vr prodtot (ha) Vegetables	vr prodtot (ha) Fruits	vr prodtot (ha) Cereal	vr prodtot (ha) Coffee	vr prodtot (ha) Average
Saboya	1.33	0.84	5.96	0.00	8.13
Cerete	13.63	2.00	8.08	0.00	23.71
Chinu	6.20	0.32	41.94	0.00	48.46
Cienaga de Oro	24.73	2.12	3.74	0.01	30.60
Sahagun	6.93	0.01	14.70	0.00	21.63
Simijaca	0.24	0.39	12.90	0.00	13.53
Susa	25.97	1.55	148.25	0.00	175.77
Tocaima	0.16	1.63	2.14	0.00	3.94
Circasia	27.49	1.46	6.07	4.28	39.30
Cordoba	3.40	0.15	5.49	4.21	13.25
Filandia	5.57	0.24	8.27	3.83	17.92
Belen de Umbria	7.47	2.08	1.73	4.94	16.21
Puente Nacional	0.91	0.59	1.01	1.12	3.63
Sampues	1.59	0.11	4.22	0.00	5.92
Natagaima	1.50	0.76	4.97	0.00	7.23
Ortega	5.54	25.08	4.25	3.33	38.21
Purificacion	4.41	0.69	5.27	0.00	10.37
Average	6.90	4.13	10.73	1.88	23.65

Source: ELCA Panel. The data section describes how the variables were constructed. Each column has the value in million of Colombian Pesos/hectares of household's land in crops. Sample restricted to only crop producers.
Groups of crops:
Vegetables: eggplant, broccoli, onion, green peas, chickpeas, any vegetable, sweet beans, tomato, carrots, cabbage, potatoes, etc.;
Fruits: coconut, avocado, anon, araza, banana, cacao, chirimoya, plum, curuba, guanabana, guava, lemon, etc.; aromatic herbs, palm, wood, others, were included here as the total of them had a very low percentage;
Cereal: beans, soybeans, rice, corn, sorghum, cotton, wheat, etc.;
Coffee: all types of coffee.

The variables of agricultural yields per hectares are calculated in the following manner (see Table 3). The survey in 2010 disaggregates the total production in kilograms for each crop, how many kilograms for consumption and how many kilograms for sale. It also has the sales in Colombian Pesos of the kilograms sold. This allows to infer an implicit price for each crop of the kilograms sold (Price=Value/Quantity), which can be averaged to have a price of different crops inside each municipality. Prices are aggregated by municipality in order to avoid endogeneity when using the implicit price of each crop of the rural household. These prices can then be used to value the total production of each crop by each household in Colombian pesos and sum up all the values to have a measure of yields in pesos per household. As the subsequent surveys in 2013 and 2016 did not disaggregate the total production of kilograms by consumption and sales, I calculate the average implicit prices for 2010 at the level of municipality (or for the whole country) and apply those prices to estimate a measure of yields in Colombian Pesos for the three surveys. I then have a variable in Colombian pesos per household. A drawback of the construction of the gross agricultural production in value (Colombian Pesos) is that it is not able to distinguish exactly price effects and physical yield effects. In the particular case of Colombia and the ELCA panel survey, rural households tend to cultivate several crops, livestock, etc., which can make very hard to sum products that have different units. For this reason, I choose to calculate agricultural yields valued in Colombian Pesos (gross agricultural productivity-value terms), rather than physical units of production. Using total production in physical units can be a better measure of yields in contexts with farmers producing mainly one crop or specializing in a few ones. It is also important to mention that no prices were reported for livestock, and it is not possible to construct a measure of value of livestock production in Colombian Pesos. Therefore, the variables of total gross agricultural productivity (in value terms) do not include livestock.[6] For this reason, the variables of gross agricultural productivity are restricted to only crop producers and capture productivity coming from crops.

Table 3 shows the average value in million of Colombian Pesos/hectares of household's land used in crops for the municipalities of the sample (the gross agricultural productivity). Coffee is mainly produced in Circasia, Córdoba, Filandia, Belén de Umbría and Ortega while cereals are important in Susa and Chinú and Cereté. Vegetables and fruits are produced in the majority of the municipalities. The table also has a description of the crops of each category.

2.2 Weather variables - The Standard Precipitation Index (SPI)

The article uses external data to construct measures of droughts and capture them with more precision. Two measures are extensively used in the literature to capture more adequately droughts, the Standardised Precipitation Index (SPI) proposed by McKee et al. (1993) and the Standardised Precipitation-Evapotranspiration Index (SPEI) of Vicente-Serrano et al. (2010). The SPI is defined as the number of standard deviations by which an observed anomaly deviates from the long-term mean. It can be calculated for any monthly scale (12 or 6 months here), which is the number of months over which water deficits accumulate. It considers the long-term time series of precipitation accumulated over the desired time scale to estimate an appropriate probability density function. Thus, a long period of data is necessary for the calculation (longer than 30 years is desirable). As the rainfall frequency distribution is positive skewed (like Gamma, Pearson III, etc.), the SPI entails a transformation to represent it according to a normal (Gaussian) distribution. Compared to the SPI, the SPEI adjusts by temperature, considering the climatic water balance (the difference between precipitation and potential evapotranspiration (PET) for each month in each location). In both cases, the SPEI and SPI takes values around -3 to 3, and lower values are associated with more intense droughts and higher values with excess water. The SPI and SPEI have started to be used more often in the literature of climatology as in Spinoni et al. (2014) or in agricultural economics as in Branco and Féres (2020). In this sense, Branco

[6] The literature of agricultural economics usually uses measures of "agricultural productivity", which corresponds to either yield by hectare (in physical terms) or some "net profitability" measure after deducting the costs of the inputs used in production. The measure used here corresponds more to gross agricultural productivity in value terms or a gross revenue per hectare.

and Féres (2020) prefer to use the "SPI rather than annual fluctuations of precipitation because its probabilistic nature gives it historical context". In addition, Spinoni et al. (2014) prefer to use the SPI rather than the SPEI or other measures like the Palmer Drought Severity Index (PDSI) (see Palmer (1965)), as the SPEI can mistake a heat wave for a meteorological drought or because the PDSI needs too many input variables.

To construct the measures, I use satellite images of the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) which provide monthly rainfall from 1981 to 2016 at a higher resolution of 0.05 X 0.05 degree - around 5km x 5km at the Equator (Funk et al., 2015). As the average temperature stayed relatively stable during the period of analysis and for the municipalities of the sample (see figure in appendix 3A), I rely mainly on the SPI, without adjusting by temperature.[7]

The construction of the SPI made use of the software ArcGIS and Google Earth Engine to manipulate the raster images, calculate the averages of precipitation by municipality and by month and generate some additional maps with the help of the Python platform inside the software. The drought indices are calculated using the R-software and the package provided by Vicente-Serrano et al. (2010) and Beguería et al. (2014), which allows me to generate the SPI by months and for different locations (municipalities); then, the monthly SPI is collapsed by year. Table 2 gives the descriptive statistics for different types of drought measures. Here, the variable "SPI index 12 months CHIRPS" is the raw measure while the opposite of the SPI is the measure used in the estimations, so that positive values of SPI are associated with more intense droughts. As the interviews of the ELCA were conducted around February-July of 2010, 2013 and 2016, I define the calendar year 2010 as the months of February 2009 to January 2010. In fact, the rural outcome questions ask the rural household about the production during the twelve months before the interview, and defining the calendar year for this period captures much better the agricultural year.

Additionally, I also construct a monthly SPI and collapsed only for the months of the agricultural growing season in Colombia, for example, the average from February to August 2009 is the value for the year 2010. The measure is defined based on the potential growing period for many crops in Colombia.[8] I also include some extra variables ("Per. months droughts (<=-1) yearly for SPI index 12") as the percentage of months during the year that the municipality faced a drought or SPI less than -1. Based on McKee et al. (1993), a moderate drought is defined when the SPI goes below -1 while a severe drought is defined when the SPI goes below -2. Finally, "Dummy 1 month or more with drought(<=-1)-yearly" corresponds to a dummy when there is one month or more of drought (index <=-1) in the municipality and zero otherwise. Appendix 3B shows the

[7]An alternative index could be constructed by using CHIRPS data for precipitation and temperature from MODIS-TERRA dataset from NASA (see Wan et al. (2015)). The construction of the potential evapotranspiration could add noise to the estimation, if it does not include information of wind speed and solar radiation. This gives additional arguments for why I prefer to use the SPI as the main measure to capture droughts.

[8]See FAO link http://www.fao.org/giews/countrybrief/country.jsp?code=COL

SPI index using the CHIRPS data for the monthly scale 12 and 6 months.[9] I also consider an extra variable for consecutive droughts in 2010 and 2013, as a way to measure consecutive impacts.

To sum up, all weather variables are defined according to the crop season, as this has been shown to be important in Auffhammer and Schlenker (2014) and Burke and Emerick (2016), among others.

Table 2 also includes descriptive statistics for the average rainfall and the average temperature per municipality and before 2010. The temperature is calculated using satellite images from MODIS-TERRA dataset from NASA (see Wan et al. (2015)) for the period 2001-2016, using the satellite MOD11A1.006 Terra Land Surface for Temperature and Emissivity Daily Global with a resolution of 0.01 X 0.01 degree - around 1km x 1km at the equator. Additionally, I calculate the yearly average of number of days with rainfall and yearly average of number of days with temperature above 34 degree Celsius. Sections 4.2 and 4.4 use the same data from satellite images described here for rainfall and temperature. I make a detailed description there on how the measures in these sections are built.

3 A theoretical framework for analysing adaptation of rural households in Colombia

Several empirical studies in the literature of adaptation to climate change have relied on reduced-form estimations to assess the effects of climate and weather on total gross agricultural productivity. However, in many cases adaptation is not explicitly described, making it difficult to identify the mechanisms through which weather impacts total agricultural productivity (with exceptions such as Kaminski et al. (2013), Burke and Emerick (2016)[10] and Sesmero et al. (2018)). Several mechanisms could be at work. Weather can affect crop growth, productivity of existing inputs or prices of the outputs and inputs at the same time. It could also change the use of inputs such as land, fertilizers and pesticides and generate a re-allocation of labor. I develop a simple model based on Cui (2020) and Ortiz-Bobea and Just (2013) for a representative rural household who assigns hectares of land to different crops and can use adaptive inputs in the production. The empirical part will capture allocation of land between crop and livestock and the use of adaptive inputs such as investment in irrigation, other non-housing investments and the use of external sources of water for the farm.

The rural household in the municipality allocates land to two crops (A_1, A_2) or prefers not to use land, which is denoted as A_3. Crop production also depends on θ, a variable that gathers

[9] Surveys were collected in the first semester of each year.

[10] Burke and Emerick (2016) define adaptation as switching from one crop variety to another (from a variety that performs better in cooler climates to another one that performs much better in warmer climates). In this sense, the farmer maximizes the expected output by choosing the type of crop variety based on climate and weather realisations.

the effects of the weather conditions for agriculture (weather and climate inputs). This climate variable is one-dimensional and aims to capture "temperature" mainly. Ortiz-Bobea and Just (2013) explore deeper how climate might affect input and production prices. As this is out of the scope of my study, I prefer to assume a price-taking rural household, which helps me to focus more on how the rural household allocates land. The total amount of land is normalized to one and crop prices are p_1 and p_2. The return per unit of the land that is not used is r and the constant marginal cost of each unit of land is s. Hence, the rural household maximizes profit as:

$$\max_{A_1,A_2,A_3,x(\theta)} p_1q_1(A_1,\theta)+p_2q_2(A_2,\theta,x(\theta))-wx(\theta)+rA_3-s(A_1+A_2) \quad s.t. \quad A_1+A_2+A_3=1 \quad (1)$$

Here, crop production for crop 1 and crop 2 are defined as $q_1(A_1, \theta)$ and $q_2(A_2, \theta, x(\theta))$ and are increasing in land use A_1 and A_2, with decreasing marginal returns with respect to land ($\frac{\partial^2 q_1(A_1,\theta)}{\partial {A_1}^2} < 0$ and $\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial {A_2}^2} < 0$). The adaptive input $x(\theta)$ corresponds to the inputs that the rural household use to mitigate the impact of climate on the crop production, with w as its price. This could include investments in irrigation, investments in the land other than housing (from now on called non-housing investments) such as investments in fruit trees or infrastructure, or the use of additional or external sources of water for the farm. I assume that the adaptive input only affects the production of crop 2 and that irregardless of the climate threshold that is introduced later on, it increases the marginal productivity of land for crop 2, $\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial x(\theta)} > 0$.

With respect to climate, I assume that $\frac{\partial^2 q_1(A_1,\theta)}{\partial A_1 \partial \theta} > 0$ if $\theta < \theta_1^*$ and $\frac{\partial^2 q_1(A_1,\theta)}{\partial A_1 \partial \theta} < 0$ for $\theta > \theta_1^*$ and θ_1^* reflects the optimal climate to produce crop 1. The rural household starts producing more crop 1 for low levels of climate until reaching the optimal climate θ_1^*. Similarly, it can be assumed for crop 2 that $\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial \theta} > 0$ if $\theta < \theta_2^*$ and $\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial \theta} < 0$ for $\theta > \theta_2^*$, with θ_2^* the optimal climate to produce crop 2. This reflects that the impact of climate on the marginal productivity of land of crop 2 is positive before the threshold and the rural household has incentives to start to produce crop 2 as the climate variable increases (higher temperature) and up to the threshold. For the adaptive input, I assume that $\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta) \partial \theta} > 0$ if $\theta < \theta_x^*$ and $\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta) \partial \theta} < 0$ for $\theta > \theta_x^*$, with θ_x^* the threshold from which the rural household starts to use the adaptive input. The conditions for optimal land use when the rural household can modify the land left fallow (A_3) are:

$$p_1 \frac{\partial q_1({A_1}^*, \theta)}{\partial A_1} = p_2 \frac{\partial q_2({A_2}^*, \theta, x(\theta))}{\partial A_2} = s + r \tag{2}$$

$$p_2 \frac{\partial q_2({A_2}^*, \theta, x(\theta))}{\partial x(\theta)} = w \tag{3}$$

Equation 2 is obtained by equalising the marginal values of land (MVL) with the cost of land $s+r$ for the two crops, while equation 3 results from equating the marginal value of adaptive input to its price. I calculate the total differentials for both crops from equation 2 and 3 to analyse how climate (θ) affects marginally the optimal choices of land. From equation 2, when MVL of crop 1 equals $s + r$:

$$\frac{d{A_1}^*}{d\theta} = -\frac{\frac{\partial^2 q_1(A_1,\theta)}{\partial A_1 \partial\theta}}{\frac{\partial^2 q_1(A_1,\theta)}{\partial {A_1}^2}} \tag{4}$$

As it was assumed that $\frac{\partial^2 q_1(A_1,\theta)}{\partial {A_1}^2} < 0$, how climate affects the hectares of land allocated to crop 1 depends on the climate impact on its marginal productivity of land (MPL). As long as climate benefits the marginal productivity of crop 1, the rural household starts to use more land available for that crop (allocate A_3 to be used in A_1). This corresponds to the result of Cui (2020). However, the effect on crop 2 depends not only on the marginal productivity of crop 2 with respect to climate, but also, on the use of the adaptive input $x(\theta)$. The total differential from equation 2 when the MVL of crop 2 equals $s + r$ gives:

$$\frac{d{A_2}^*}{d\theta} = -\frac{\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial\theta} + \frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial x(\theta)}\frac{dx(\theta)^*}{d\theta}}{\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial {A_2}^2}} \tag{5}$$

As for crop 1, $\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial {A_2}^2} < 0$. In this case, how climate affects the hectares of land used for crop 2 (A_2) depends on the sign of the numerator. The numerator will be positive if first, climate (θ) benefits the MPL of crop 2 (the first term is positive), and second, if climate increases the use of the adaptive input ($\frac{dx(\theta)^*}{d\theta} > 0$ in the second term); or if the difference between both terms is positive. Notice also that the latter equation depends on $\frac{dx(\theta)^*}{d\theta}$. I can take the total differential of equation 3 to know how climate affects the use of the adaptive input $x(\theta)$ in crop 2:

$$\frac{dx(\theta)^*}{d\theta} = -\frac{\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta) \partial\theta} + \frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta) \partial A_2}\frac{d{A_2}^*}{d\theta}}{\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta)^2}} \tag{6}$$

While equation 4 can be treated separately, equations 5 and 6 form a system that depends on $\frac{dx(\theta)^*}{d\theta}$ and $\frac{d{A_2}^*}{d\theta}$. I use Cramer's rule to solve the system and give the effect of climate (θ) on the use of land for crop 2 and the adaptive input:

$$\frac{d{A_2}^*}{d\theta} = \frac{\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial\theta}\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta)^2} - \frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta) \partial\theta}\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial x(\theta)}}{\left(\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial x(\theta)}\right)^2 - \frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial {A_2}^2}\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta)^2}} \tag{7}$$

and,

$$\frac{dx(\theta)^*}{d\theta} = \frac{\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta) \partial\theta}\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial {A_2}^2} - \frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial\theta}\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial x(\theta)}}{\left(\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial x(\theta)}\right)^2 - \frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial {A_2}^2}\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta)^2}} \tag{8}$$

Given the previous assumptions of the production functions for crops, in equations 7 and 8, $\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial x(\theta)^2} < 0$, $\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial {A_2}^2} < 0$, and $\frac{\partial^2 q_2(A_2,\theta,x(\theta))}{\partial A_2 \partial x(\theta)} > 0$. I use the thresholds over climate defined previously to determine the effect of climate on the use of land for crop 2 and the adaptive input. Those thresholds determine the point until which the land use of the crops is optimal and also the optimal use of the adaptive input. As the denominator in equations 7 and 8 is assumed negative to have a solution and given the previous assumptions, two cases[11] are particularly interesting to explore:

Case A: $\theta_1^* < \theta_2^* < \theta_x^*$

1. $\theta \leq \theta_1^*$ which gives as result $\frac{dA_1^*}{d\theta} > 0$, $\frac{dA_2^*}{d\theta} > 0$ and $\frac{dx(\theta)^*}{d\theta} > 0$
2. $\theta_1^* < \theta \leq \theta_2^*$ which gives as result $\frac{dA_1^*}{d\theta} < 0$, $\frac{dA_2^*}{d\theta} > 0$ and $\frac{dx(\theta)^*}{d\theta} > 0$
3. $\theta_2^* < \theta \leq \theta_x^*$ which gives as result $\frac{dA_1^*}{d\theta} < 0$, $\frac{dA_2^*}{d\theta} \gtreqless 0$ and $\frac{dx(\theta)^*}{d\theta} \gtreqless 0$
4. $\theta_x^* < \theta$ which gives as result $\frac{dA_1^*}{d\theta} < 0$, $\frac{dA_2^*}{d\theta} < 0$ and $\frac{dx(\theta)^*}{d\theta} < 0$

Case B: $\theta_1^* < \theta_x^* < \theta_2^*$

1. $\theta \leq \theta_1^*$ which gives as result $\frac{dA_1^*}{d\theta} > 0$, $\frac{dA_2^*}{d\theta} > 0$ and $\frac{dx(\theta)^*}{d\theta} > 0$
2. $\theta_1^* < \theta \leq \theta_x^*$ which gives as result $\frac{dA_1^*}{d\theta} < 0$, $\frac{dA_2^*}{d\theta} > 0$ and $\frac{dx(\theta)^*}{d\theta} > 0$
3. $\theta_x^* < \theta \leq \theta_2^*$ which gives as result $\frac{dA_1^*}{d\theta} < 0$, $\frac{dA_2^*}{d\theta} \gtreqless 0$ and $\frac{dx(\theta)^*}{d\theta} \gtreqless 0$
4. $\theta_2^* < \theta$ which gives as result $\frac{dA_1^*}{d\theta} < 0$, $\frac{dA_2^*}{d\theta} < 0$ and $\frac{dx(\theta)^*}{d\theta} < 0$

Both cases give the same results, independently of whether the optimal climate for the adaptive input is smaller or larger than the optimal climate for the land used for crop 2. The results show that when $\theta \leq \theta_1^*$, there are incentives for the rural household to increase the land used for crop 1, the land for crop 2 and the use of the adaptive input. Notice that the situation is feasible as the rural household has land not used in the production (A_3). Once the optimal climate for crop 1 is crossed and $\theta_1^* < \theta \leq \theta_2^*$ in case A (or $\theta_1^* < \theta \leq \theta_x^*$ in case B), the rural household reduces the land used for crop 1, but keep using more land for crop 2 and using the adaptive input. As climate increases and reaches the optimal threshold to use the adaptive input in case A $\theta_x^* < \theta$ (or the threshold for crop 2 $\theta_2^* < \theta$, in case B), the results are undetermined. As climate exceeds the thresholds of land to use for crop 2 and for the adaptive input $\theta_2^* < \theta_x^* < \theta$ for case A (or $\theta_x^* < \theta_2^* < \theta$ for case B), the rural household reduces the use of land for crops 1 and 2, as well as

[11] Other cases such as $\theta_2^* < \theta_1^* < \theta_x^*$ or $\theta_x^* < \theta_1^* < \theta_2^*$ are not relevant as I expect that crop 2 is more resilient to extreme climate than crop 1 and the use of adaptive input becomes an option in the production of crop 2 with higher values of the variable of climate, affecting crop 2 and not crop 1.

the use of the adaptive input to produce crop 2. Notice also that $\theta_x^* = \theta_2^*$ is a particular sub-case and gives the same results as in case A and case B (subcategories 1, 2 and 4). Although this does not change the interpretation of the findings, it could be more realistic to assume that the threshold of climate to produce crop 2 is the same as the optimal value to start using the adaptive input.

For case A, when $\theta < \theta_1^*$ and climate increases, the rural household can adapt by using more land available in the production of the farm. If climate increases up to the threshold for crop 2 (θ_2^*), the rural household has incentives to incorporate the adaptive input and focuses mainly on the production of crop 2, with the optimal level of climate for its production determined by θ_2^* for case A and θ_x^* for case B. Once that thresholds are exceeded in each case, climate is far from the optimal and becomes too extreme, affecting the production of crops and the use of the adaptive input. To some extent, some of the strategies used before (increase the land used or using more adaptive inputs) might be harder to implement as they are less profitable for the rural household. This could be the case when the rural household faces extreme droughts or consecutive droughts, which is something I explore in the empirical part.

4 Effects of climate and weather deviations on agricultural productivity

I study the effects of climate and weather on agriculture using three different frameworks. First, I start by separating the effect of climate from yearly weather deviations as in previous studies (Kelly et al., 2005; Deschênes and Kolstad, 2011; Burke and Emerick, 2016; Bento et al., 2020). The results of this can be found in section 4.2. Second, I explore in more detail how rural households adapt on different adaptation margins in section 4.4, using different temperature thresholds. While section 4.2 analyses medium-term and short-term variation in climate and weather, section 4.4 relies more on weather variation. Also, section 4.2 and section 4.4 permit me to have a comparison with the established literature on the effects of climate change on agriculture. Third, in section 5, I propose an alternative approach to study the effects of climate variability on agriculture. I explore if those affected by previous drought events adapt differently to a drought than those who had not experienced drought in the past (the DID approach). This section uses the SPI indices which aim to capture anomalies with respect to the long-term mean.

4.1 Identification Strategy for climate and yearly weather deviations

Burke and Emerick (2016) and Dell et al. (2012), among others, estimate adaptation as the difference between the coefficients estimated using panel data (weather shocks) and the coefficient of a cross-section estimation (climate trends). As mentioned by Blanc and Schlenker (2017), panel data allow for a better causal identification on weather impacts on agriculture, as weather deviations around the mean are random and exogenous. Although, panel models can solve identification problems of cross-sectional approaches, this comes with the cost of poorly approximating the impact of climate change (see Burke and Emerick (2016)). If adaptation is defined as in Burke and Emerick (2016) (switching from a less-tolerant to a more heat-tolerant crop) and a temperature shock occurs during the years of the panel, the estimated coefficient of the impact will be weighted depending on the time that the adaptation happened. If adaptation occurs at the end of the sample, the estimation will weight more the less-tolerant and conventional crop, magnifying equilibrium losses. Bento et al. (2020) and Kolstad and Moore (2020) also point out that the cross-section coefficient can suffer from omitted variable bias; and even in the case that the omitted variable bias does not exist, the coefficients (the one from the cross-section and the one from the panel) come from two different estimating equations. I follow previous studies in the literature in equation 9 that capture climate trends and weather shocks (deviations from those long-term patterns) in the same estimations (Kelly et al., 2005; Deschênes and Kolstad, 2011), in particular Bento et al. (2020)[12]. I use this framework to test the effects of climate and weather deviations on gross agricultural productivity (in value terms) in Colombia, which corresponds to a long-term and short-term analysis.

$$\begin{aligned}\mathbf{Y}_{h,m,r,t} = \mu + \beta_{\mathbf{C}} \times \mathbf{TEMP^C}_{m,t} + \beta_{\mathbf{W}} \times \mathbf{TEMP^W}_{m,t} + \mathbf{\Gamma_C} \times \mathbf{RAIN^C}_{m,t} + \mathbf{\Gamma_W} \times \mathbf{RAIN^W}_{m,t} \\ + \theta_x \times X_{h,m,r,t} + \alpha_r + \alpha_t + \alpha_m + \alpha_h + \xi_{h,m,r,t}\end{aligned} \tag{9}$$

$\mathbf{Y}_{h,m,r,t}$ agriculture outcomes for rural household h (or agricultural unit), of municipality m, region r in year t;

$\mathbf{TEMP^C}_{m,t}$ represents the lagged 30-year annual moving average (MA) of past temperatures;

$\mathbf{TEMP^W}_{m,t}$ represents weather shocks and is defined as the deviation of the annual average of the daily temperature in year t from the lagged 30-year annual MA of past temperatures;

$\mathbf{RAIN^C}_{m,t}$ represents the lagged 30-year annual MA of past rainfall;

$\mathbf{RAIN^W}_{m,t}$ represents rainfall shocks and is defined as the deviation of the annual average of the daily rainfall in year t from the lagged 30-year annual MA of past rainfall;

$X_{h,m,r,t}$ vector of controls for household and community characteristics[13];

α_r, α_t, α_m, α_h dummies by *region*, by *year*, by *municipality* and by *household*.

[12] See also Kolstad and Moore (2020) for a detailed description of other "partitioning approaches" that capture climate and weather together in the same estimations.

[13] Controls for the "Dependency ratio (<=14 + >=65)/(15-64) Per. 2010" of the household in 2010, "Age HH head" for the age of the household head, a "Dummy women HH head" for whether or not the household head is a woman, a "Dummy HH has credit" for whether or not the household has a credit in that year, a "Dummy access cabecera is ok (comm)" at the community level for whether or not the access to the cabecera (center of the town) is reachable and in good shape, the "Minutes to reach cabecera (comm)" for the community, some dummies for reported problems faced by the household or community in that year, two variables "Per. Land (OWNED)" and "Per. Land (OWNED WITH TITLE)" as the percentage of land owned by the household or owned with a title, respectively.

The standard errors are clustered at the municipality level m to account for the correlation within municipality and the estimations use the inverse weights of 2010. I include household fixed effects to account for potential differences in skills of the rural household, or the fact that some of them can be of different types (subsistence versus commercial rural households). The municipality and region fixed effects aim to control for differences in the regional and municipal characteristics, such as the altitude or the fact that the ELCA was designed to collect the rural information representative for some specific regions. The coefficients of interest for temperature are $\beta_{\mathbf{C}}$, $\beta_{\mathbf{W}}$, and for rainfall $\mathbf{\Gamma_C}$ and $\mathbf{\Gamma_W}$. Equation 9 captures both slow-moving cross-section climate effect, and weather deviations. As such, equation 9 relies on estimating a slow-moving cross sectional climate effect (the coefficient $\beta_{\mathbf{C}}$) similar to what has been done in studies such as Deschênes and Kolstad (2011).

4.2 Results of climate and yearly weather deviations

Table 4 summarizes the results of the model estimated using the logarithm of the value of the total production (Millions Colombian Pesos/Ha)[14] explained by the meteorological variables. I use the daily rainfall and temperature data from CHIRPS and MODIS-TERRA satellite images, and I average by month and by year, and then, construct the lagged moving average for 30 years. Rainfall monthly data come from CHIRPS satellite images that are available from 1981 to 2016. However, temperature daily data come from MODIS-TERRA dataset for the period 2001 to 2016 and the measures of long-term temperature constructed here thus capture a shorter period of time. Although some data exist for temperature to capture longer periods of time in the past, I prefer to use the MODIS-TERRA dataset because it has a higher level of resolution (0.01 X 0.01 degree -around 1km x 1km at the equator) that allows to capture much better temperature variability. Using a higher resolution comes with the cost of reducing the time variation, but given the size of the municipalities in Colombia, it should be more pertinent to weight more a better spatial variability and resolution rather than having a longer period of time. Otherwise, I could risk assigning the same value of temperature to many municipalities if data with more time variation and less spatial variation are used. For Kolstad and Moore (2020), some panel approaches use the fact that climate varies over time in a location to estimate short-run and long-run effects in the same panel by including location and period fixed effects. However, the interpretation of the climate term can change, capturing more a medium-run effect. According to Kolstad and Moore (2020), in practice this appears not to matter substantially when the studies use long spans of time of 30 years for example. As in this study the temperature variables were constructed using a shorter period of time, the climate trend should be interpreted as a medium-term impact. Also note that all the estimations for the gross agricultural productivity (in value terms) are restricted to the sample of crop producers only; the variables then capture the gross agricultural productivity of crops. Livestock producers and those producing crop and livestock at the same time are excluded,

[14]As the rural households of the ELCA sample reported to cultivate several crops on their farms, it would be harder to construct a variable to capture agricultural production in terms of units of production. For this reason, I use the variables of total gross agricultural productivity in values (see section 2), as they allow me to sum up all the different crops in values and have a comparable measure for all the rural households.

as it was not possible to recover livestock prices to calculate the income coming from livestock production.

The agricultural year (AGRO YEAR) 2010 is defined from February to August 2009 to capture better the agricultural growing season. I calculate an extra variable for the maximum during the month when I move from the daily to the yearly data. In addition, the histogram of the average temperature shows a bi-modal distribution, with municipalities of high-temperature (above 27 degrees Celsius) and low-temperature (below 27 degrees Celsius) (see Figure 4 in Appendix 3A).[15] Therefore, I interact the variables of temperature with a dummy for municipalities with high and low-temperature in order to see if there are differences between both groups.[16]

Table 4 shows that rainfall trend (AGRO YEAR) and rainfall shocks are beneficial for productivity.[17] Regarding temperature, the long-run mean increases the gross agricultural productivity in columns 1) and 3), while temperature shocks have no effect on productivity in the same estimations. When moving to the estimations with the interaction (columns 2 and 4), in terms of the marginal effects, the increase in the long-run temperature has a positive effect for rural households in municipalities with low-temperature, but no effect for rural households in high-temperature municipalities. However, the marginal effects of the temperature shocks decrease the gross agricultural productivity (in value terms) in high-temperature municipalities, with the net effect (the sum of the marginal effects for low and high-temperature) still negative. This divergence is a new interesting point in terms of the winners or losers from climate and weather shocks. It also has some similarities with Aragón et al. (2021) who find that the coast areas suffer losses for the higher temperatures, while the highlands, with a cooler and wetter climate, would benefit from warmer temperatures. Bento et al. (2020) consider as evidence of adaptation if the difference between the temperature shock and climate is positive.[18] Using this, column 2 and 4 show evidence of adaptation by the rural households facing high temperature, although not statistically significant at conventional levels. However, caution has to be taken in the interpretation, as the

[15]In Appendix 3D, I check if temperature variables could be modelled in squared terms. The squared terms seem to capture some of the relation between temperature and agricultural productivity but the results of column 1) and 4) capture much better the bi-modal distribution of Figure 4 in Appendix 3A. I also include both temperature squared and the interaction of temperature variables with the dummy of high-temperature in columns 3) and 6), to see which one dominates the other. However, the coefficients for the low-temperature municipalities are washed out of the estimations. In this regard, I prefer to use the dummy of high-temperature municipalities as it resembles better the bi-modal distribution of temperature.

[16]High-temperature group: Cereté, Chinú, Ciénaga de Oro, Sahagún, Tocaima, Sampués, Natagaima, Ortega and Purificación. Low-temperature group: Saboyá, Simijaca, Susa, Circasia, Córdoba, Filandia, Belén de Umbía and Puente Nacional.

[17]The large values estimated could be due to the large variations and should be interpreted cautiously as the maximum possible percentage increase is 100%. Log-Lin Models are recommended when the variations are smaller, less than 10% for example.

[18]Other studies such as Burke and Emerick (2016) define adaptation for the case of U.S. agriculture as the difference between a long difference estimate and the estimate from an annual panel model. A positive difference should be interpreted as adaptation, as farmers are adjusting to long-run changes in climate compared to shorter run changes in weather.

variable used is agricultural production in values and it could mix price and volume effects. As mentioned previously, it is harder to construct measures of total production for the rural households of the sample, who cultivate multiple crops.

In order to go further, Table 5 explores climate and weather deviations by groups of crops, using the maximum of temperature during the agricultural growing season (AGRO YEAR). Long-run rainfall and the deviations with respect to the long-run seem to be more beneficial for the gross agricultural productivity (in value terms) of vegetables, cereals and coffee. In terms of temperature, cereals and coffee are the groups that benefit from higher temperature in the long-run and the deviations (columns 1 to 4). The results using the interaction in columns 5 to 8 show that the marginal effect of the long-run temperature affects positively fruits of high-temperature areas, while it damages those in low-temperature areas. The marginal effects of the long run temperature and its deviations increase the gross agricultural productivity of cereals and coffee in low-temperature municipalities, but reduces productivity in high-temperature areas. Interestingly, the net effect (the sum of the low and high-temperature coefficients) of the long run temperature and its deviations are close to zero for fruits and coffee in high-temperature municipalities; only for cereals, the net effect of the long-run mean of temperature is still positive in high-temperature municipalities, and negative with respect to the temperature shocks. There are no statistically significant marginal effects of temperature on the gross agricultural productivity of vegetables. A comparison by type of crops, perennial (fruits and coffee), and annual (vegetables and cereals) yields some interesting results. On the one hand, I should expect that perennial crops in general generate more stable yields than annual crops, and correspond to agricultural production that would be less affected by weather variation. In Table 5, I observe that the marginal effect on perennial crops differs based on the high versus low-temperature municipalities and the type of crop. In low-temperature municipalities, it benefits coffee while reducing the gross agricultural productivity of fruits; in high-temperature municipalities the marginal effect is the opposite and benefits fruits while reducing the gross agricultural productivity of coffee. On the other hand, it should be expected that annual crops are associated with less stable yields, and the agricultural productivity would be more affected by weather variation. However, the results of the marginal effects show in fact that some annual crops such as cereals benefit from higher temperature (long run and shocks). Similar to the case of coffee, they benefit in low-temperature municipalities while the gross agricultural productivity decreases in municipalities with high temperature. It appears that cereals and coffee could take advantage of the higher temperatures in areas at high altitude, which are in general the municipalities with lower temperatures. On the contrary, fruits can take advantage of the higher temperatures in municipalities with high temperature.

Table 4: Climate and Yearly weather deviations

	Value prod. total (Millions Col. Pesos/Ha) ln			
	MEAN TEMPERATURE		MAXIMUM TEMPERATURE	
	NO INTERACTION (1)	INTERACTION (2)	NO INTERACTION (3)	INTERACTION (4)
Rainfall Trend 30 years (MEAN) (AGRO YEAR)	4.362**	4.054**	4.242***	4.358***
	(1.621)	(1.798)	(1.371)	(1.446)
Rainfall Shock (MEAN) (AGRO YEAR)	0.305**	0.250**	0.331***	0.285***
	(0.119)	(0.094)	(0.092)	(0.086)
Temperature Trend 15 years (MEAN) (AGRO YEAR)	1.287**	2.208***		
	(0.556)	(0.645)		
Temperature Shock (MEAN) (AGRO YEAR)	0.032	0.091		
	(0.085)	(0.083)		
High-Temp=1 × Temperature Trend 15 years (MEAN) (AGRO YEAR)		-1.202		
		(0.811)		
High-Temp=1 × Temperature Shock (MEAN) (AGRO YEAR)		-0.204***		
		(0.061)		
Temperature Trend 15 years (MAX) (AGRO YEAR)			1.108***	1.652***
			(0.337)	(0.520)
Temperature Shock (MAX) (AGRO YEAR)			0.060	0.104**
			(0.043)	(0.036)
High-Temp=1 × Temperature Trend 15 years (MAX) (AGRO YEAR)				-0.695
				(0.619)
High-Temp=1 × Temperature Shock (MAX) (AGRO YEAR)				-0.169***
				(0.057)
Observations	1770	1770	1770	1770
r2	0.62	0.63	0.62	0.63
r2_a	0.30	0.30	0.30	0.30

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: based on the ELCA panel survey 2010-2013-2016. The standard errors (in parentheses) are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as agricultural problems of the household (except drought or other weather-related problems). The estimations also include controls for the dependency ratio in 2010, the age of the household head, a dummy for whether or not the household head is a woman, a dummy for whether or not the household has a credit in that year, a dummy at the community level for whether or not the access to the cabecera (center of the town) is reachable and in good shape, and the minutes to reach the cabecera for the community. High-temp is a dummy equal to one for the municipalities with average temperature higher than 27 Celsius degrees, and zero for the other municipalities. Sample restricted to rural households producing uniquely crops (excludes livestock producers or those producing livestock and crops).

Table 5: Climate and Yearly weather deviations-
Maximum monthly Temperature- Agricultural Growing Season

	Value prod. total (Millions Col. Pesos/Ha) ln							
	NO INTERACTION				INTERACTION			
	Vegetables (1)	Fruits (2)	Cereals (3)	Coffee (4)	Vegetables (5)	Fruits (6)	Cereals (7)	Coffee (8)
Rainfall Trend 30 years (MEAN) (AGRO YEAR)	3.690*	0.660	1.023	1.553	3.968**	-0.152	2.338*	1.233
	(1.764)	(1.788)	(1.283)	(0.963)	(1.648)	(1.312)	(1.325)	(0.967)
Rainfall Shock (MEAN) (AGRO YEAR)	0.042	-0.022	0.190*	0.188**	0.079	-0.007	0.183**	0.134**
	(0.102)	(0.098)	(0.103)	(0.068)	(0.081)	(0.077)	(0.072)	(0.056)
Temperature Trend 15 years (MAX) (AGRO YEAR)	-0.419	-0.342	1.546**	0.362**	-0.445	-1.391***	3.089***	0.494
	(0.568)	(0.259)	(0.672)	(0.150)	(0.501)	(0.317)	(0.728)	(0.308)
Temperature Shock (MAX) (AGRO YEAR)	-0.069	-0.162**	0.137**	0.092**	-0.094	-0.199***	0.181***	0.132***
	(0.056)	(0.064)	(0.050)	(0.036)	(0.063)	(0.057)	(0.038)	(0.040)
High-Temp=1 × Temperature Trend 15 years (MAX) (AGRO YEAR)					0.012	1.385***	-2.047***	-0.141
					(0.849)	(0.312)	(0.685)	(0.344)
High-Temp=1 × Temperature Shock (MAX) (AGRO YEAR)					0.076	0.186***	-0.245***	-0.124***
					(0.062)	(0.041)	(0.057)	(0.026)
Observations	1770	1770	1770	1770	1770	1770	1770	1770
r2	0.63	0.51	0.72	0.73	0.63	0.53	0.73	0.73
r2_a	0.31	0.09	0.47	0.49	0.31	0.12	0.49	0.50

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: based on the ELCA panel survey 2010-2013-2016. The standard errors (in parentheses) are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as agricultural problems of the household (except drought or other weather-related problems). It also includes controls for the dependency ratio in 2010, the age of the household head, a dummy for whether or not the household head is a woman, a dummy for whether or not the household has a credit in that year, a dummy at the community level for whether or not the access to the cabecera (center of the town) is reachable and in good shape, and the minutes to reach the cabecera for the community. High-temp is a dummy equal to one for the municipalities with average temperature higher than 27 Celsius degrees, and zero for the other municipalities. Sample restricted to rural households producing uniquely crops (excludes livestock producers or those producing livestock and crops).

4.3 Identification strategy for nonlinear effects of temperature

I follow Aragón et al. (2021) to estimate the effect of weather on gross agricultural productivity as a function of cumulative exposure to temperature and rainfall. In particular, the relationship is modeled by using two measures: the Growing Degree Days (GDD) and the Harmful Degree Days (HDD) (see Deschênes and Greenstone (2007) and Schlenker and Roberts (2009)). GDD measures the cumulative exposure to temperatures between a lower bound θ_{low} and an upper threshold θ_{high},[19] while HDD captures non-linear exposure to extreme temperature (above θ_{high}). With respect to how to model temperature, Deschênes and Greenstone (2007) note that the standard agronomic approach is to convert daily temperatures into degree-days, which represent heating units. In this sense, there is a nonlinear cumulative effect of heat accumulation where temperature must be above a threshold for plants to absorb heat and below a ceiling as plants cannot absorb extra heat when temperature is too high. While the analysis made in 4.2 decomposes the effect of climate variability of temperature in terms of climate trends and weather shocks, the GDD and

[19] Studies like Schlenker and Roberts (2009) use a lower bound of 8 degree Celsius for corn and soybeans.

HDD might capture better the nonlinear effects of temperature on agricultural production and productivity. It is important to notice that the GDD and HDD measures exploit more the yearly weather variation rather a long-term variation, in comparison to section 4.2 that explores climate and weather variation (long-term and short-term variation).

GDD is defined as: $GDD = \frac{1}{n}\sum_d g^{GDD}(h_d)$, with,

$$g^{GDD}(h) = \begin{cases} 0, & \text{if } h \leq \theta_{low} \\ h - \theta_{low}, & \text{if } \theta_{low} < h \leq \theta_{high} \\ \theta_{high} - \theta_{low}, & \text{if } \theta_{high} < h \end{cases}$$

With h_d the daytime temperature in day d and n the number of days during the calendar year or agricultural growing year. The calendar year and agricultural year are defined as in section 4.2. Similarly, HDD is defined as: $HDD = \frac{1}{n}\sum_d g^{HDD}(h_d)$, with,

$$g^{HDD}(h) = \begin{cases} 0, & \text{if } h \leq \theta_{high} \\ h - \theta_{high}, & \text{if } \theta_{high} < h \end{cases}$$

The variable of rainfall corresponds to the average daily precipitation and then, it is averaged by year or agricultural growing year. I include rainfall and rainfall squared in the estimations, to capture non-linear effects and also, to take into account the correlation between temperature and rain. The function relating weather to production corresponds to the variables of rainfall and temperature in the next equation:

$$\begin{aligned} \mathbf{Y}_{h,m,r,t} = \mu + \lambda_1 \times \mathbf{GDD}_{m,t} + \lambda_2 \times \mathbf{HDD}_{m,t} + \lambda_3 \times \mathbf{RAIN}_{m,t} + \lambda_4 \times \mathbf{RAIN^2}_{m,t} \\ +\theta_x \times X_{h,m,r,t} + \alpha_r + \alpha_t + \alpha_m + \alpha_h + \epsilon_{h,m,r,t} \end{aligned} \tag{10}$$

This corresponds to a non-linear version of equation 9, using the same control variables and fixed effects. However, the weather factors are measured with the variables GDD and HDD for temperature, while rainfall is the daily average during the year (or AGRO YEAR) and its square. In this sense, equation 10 captures weather variation rather than climate variation. This is a difference compared to equation 9 which analyses in the same estimation, weather and climate variation.

4.4 Results for nonlinear effects of temperature

An important aspect of the specification in equation 10 is to define the upper threshold θ_{high}, above which temperature starts to have a negative impact on production. In studies like Deschênes and Greenstone (2007) or Schlenker and Roberts (2009) for the U.S. context, this threshold is defined as 29-32 degree Celsius and it is crop and location-dependent.

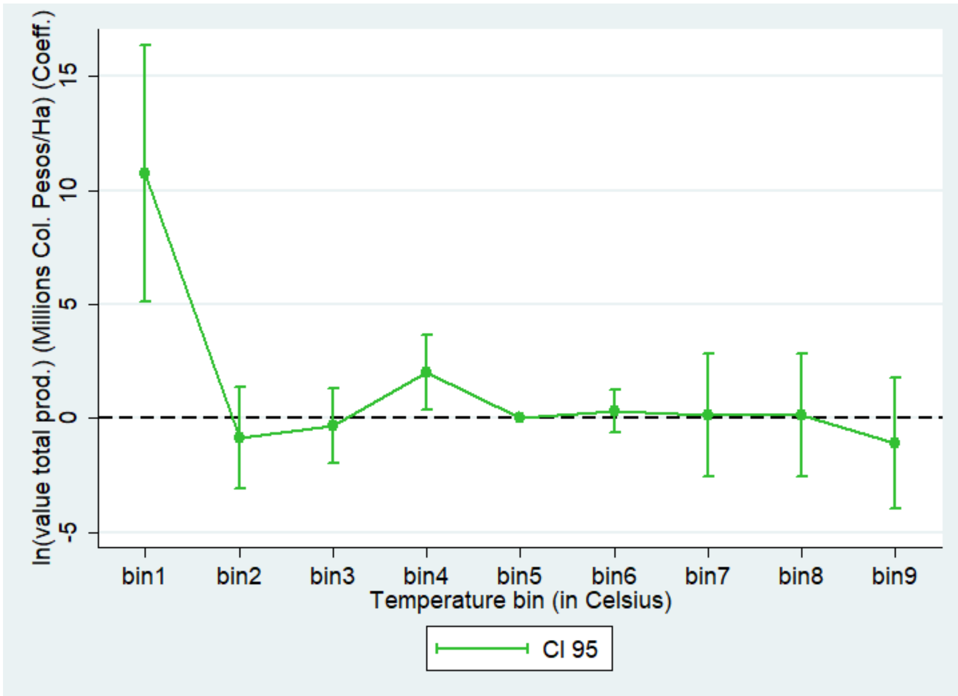
I follow here Aragón et al. (2021) who estimates equation 10, replacing GDD and HDD by a set of temperature bins that measure the proportion of days in the calendar year (or AGRO YEAR) on which the temperature fell in a given temperature bracket. Using the distribution of temperature for my sample (see Figure 4 in Appendix 3A), I define 9 temperature bins: <15C, 15-18C, 18-21C, 21-24C, 24-27C, 27-30C, 30-33C, 33-36C and >36C, with bin 24-27C the baseline category in the estimations.[20] Figure 1 presents the estimation of the coefficients with those bins with a confidence interval at the 95% level. It uses the average temperature during the AGRO YEAR (agricultural growing season). The results show that temperature values above bin 8 (33-36C) start to affect negatively the values of the total production. With this in mind, I determine the upper threshold for my sample as a temperature of 36 degree Celsius and I use it to calculate the measures of GDD and HDD.[21]

Table 6 shows the results of the estimation of equation 10, using the GDD and HDD for the logarithm of the value of the total gross agricultural productivity. Columns 1) and 3) show the results using the mean and the maximum of the temperature without the interaction with the dummy for the high-temperature municipalities. Across all the specifications in the table, there is no statistically significant effect of rainfall or its square or of the GDD-HDD, which could be due to the small sample size (or because the upper threshold of 36 degree Celsius is too high for some municipalities). When analysing the estimations with the interaction of column 2), one extra HDD decreases the gross agricultural productivity in low-temperature municipalities by 15.5%. Regarding the marginal effects, Column 4) shows no negative effect of HDD or GDD on the low or high-temperature municipalities. In column 4), the marginal effects shows that the HDD decrease the total productivity in the high-temperature municipalities but increase it in the low-temperature municipalities, with the results no statistically significant at conventional levels. However, these results go in line with the findings in section 4.2 where the high-temperature municipalities were more affected by higher temperatures.

[20]Rainfall monthly data come from CHIRPS satellite images that expand from 1981 to 2016. Temperature daily data comes from MODIS-TERRA dataset for the period 2001 to 2016.

[21]It is important to notice that the daily measures of temperature for the calculation of the GDD and HDD have several days in which there was no information recorded.

Figure 1: Coefficients estimated for the temperature bins - Average agricultural growing season



Source: estimations based on the ELCA panel survey 2010-2013-2016 and the weather data. The temperature bins are (in degree celsius): <15C, 15-18C, 18-21C, 21-24C, 24-27C, 27-30C, 30-33C, 33-36C and >36C. The baseline category in the estimation is bin 5 (24-27C). Confidence intervals at the 95% level. Sample restricted to rural households producing uniquely crops (excludes livestock producers or those producing livestock and crops).

In Table 7, I explore further the effect of the GDD and HDD on the value of the total production by group of crop and using the maximum of temperature during the agricultural growing season. The increase in rainfall tends to have a positive effect on the value of the production of vegetables (columns 1 and 5 first line), with results statistically significant at the 1% level in column 1). There is a statistically significant effect of rainfall on coffee in column 4). Interestingly, rainfall tends to increase the gross agricultural productivity for cereals and coffee but rainfall squared decreases it. This indicates that these crops might reach a maximum up to which the level of rainfall can benefit the gross agricultural productivity but after some level of rainfall, the extra rainfall can damage the productivity. Columns 1) to 4) show the results of the effect of GDD and HDD without the interaction. There are no statistically significant effects on the different groups of crops.

When separating the effects of GDD and HDD by high and low-temperature municipalities in Table 7, the marginal effects of columns (5) to (8) show that HDD can damage the productivity of vegetables and fruits in low municipality areas while it benefits them in high-temperature municipalities. On the contrary, the marginal effects show that HDD can damage the productivity of cereals and coffee in high-temperature municipalities while it benefits them in low-temperature municipalities. Interestingly, the net effect of the HDD in the high-temperature municipalities is close to zero across the different crops. The analysis of the marginal effects are similar to the findings in section 4.2 where the agricultural productivity of fruits in high-temperature municipalities benefit from higher temperature, while cereals and coffee are the winners in low-temperature areas. An additional GDD seems to benefit more cereals and coffee in high-temperature municipalities while damaging the same crops in low-temperature municipalities. In some sense, cereals and coffee in low-temperature municipalities correspond to the group of crop 2 in the theoretical framework of section 3. The findings of the model show that crop 2 benefits from higher values of climate (higher temperature), compared to crop 1.

Table 6: GDD and HDD for temperature

	Value prod. total (Millions Col. Pesos/Ha) ln			
	MEAN TEMPERATURE		MAXIMUM TEMPERATURE	
	NO INTERACTION (1)	INTERACTION (2)	NO INTERACTION (3)	INTERACTION (4)
Rainfall (MEAN) (AGRO YEAR)	0.337	0.204	0.075	0.254
	(0.288)	(0.440)	(0.330)	(0.310)
Rainfall (MEAN) (AGRO YEAR) × Rainfall (MEAN) (AGRO YEAR)	-0.029	-0.018	-0.008	-0.023
	(0.023)	(0.034)	(0.025)	(0.024)
Temp GDD (average AGRO YEAR)	-0.034	0.009		
	(0.042)	(0.113)		
Temp HDD (average AGRO YEAR)	-0.203	-0.169		
	(0.210)	(0.225)		
High-Temp=1 × Temp GDD (average AGRO YEAR)		-0.080		
		(0.198)		
High-Temp=1 × Temp HDD (average AGRO YEAR)		0.000		
		(.)		
Temp GDD (MAX) (AGRO YEAR)			0.020	-0.099
			(0.066)	(0.110)
Temp HDD (MAX) (AGRO YEAR)			-0.244	16.608
			(0.156)	(11.366)
High-Temp=1 × Temp GDD (MAX) (AGRO YEAR)				0.338
				(0.213)
High-Temp=1 × Temp HDD (MAX) (AGRO YEAR)				-17.069
				(11.411)
Observations	1770	1770	1770	1770
r2	0.62	0.62	0.62	0.63
r2_a	0.30	0.30	0.30	0.30

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: based on the ELCA panel survey 2010-2013-2016. The standard errors (in parentheses) are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as agricultural problems of the household (except drought or other weather-related problems). It also includes controls for the dependency ratio in 2010, the age of the household head, a dummy for whether or not the household head is a woman, a dummy for whether or not the household has a credit in that year, a dummy at the community level for whether or not the access to the cabecera (center of the town) is reachable and in good shape, and the minutes to reach the cabecera for the community. High-temp is a dummy equal to one for the municipalities with average temperature higher than 27 Celsius degrees, and zero for the other municipalities. Sample restricted to rural households producing uniquely crops (excludes livestock producers or those producing livestock and crops).

Table 7: GDD and HDD for temperature-
Maximum monthly Temperature- Agricultural Growing Season

	Value prod. total (Millions Col. Pesos/Ha) ln							
	NO INTERACTION				INTERACTION			
	Vegetables (1)	Fruits (2)	Cereals (3)	Coffee (4)	Vegetables (5)	Fruits (6)	Cereals (7)	Coffee (8)
Rainfall (MEAN) (AGRO YEAR)	-0.385	0.009	0.126	0.236*	-0.359	-0.169	0.428***	0.275*
	(0.220)	(0.344)	(0.285)	(0.129)	(0.247)	(0.514)	(0.141)	(0.133)
Rainfall (MEAN) (AGRO YEAR) × Rainfall (MEAN) (AGRO YEAR)	0.049***	0.013	-0.029	-0.023*	0.047**	0.028	-0.054***	-0.027*
	(0.016)	(0.029)	(0.022)	(0.013)	(0.019)	(0.043)	(0.013)	(0.013)
Temp GDD (MAX) (AGRO YEAR)	0.077	-0.008	-0.047	0.037	0.084	0.106	-0.247***	-0.001
	(0.109)	(0.104)	(0.069)	(0.050)	(0.111)	(0.197)	(0.072)	(0.068)
Temp HDD (MAX) (AGRO YEAR)	-0.190*	0.029	-0.018	-0.107	-68.856***	-2.378	25.238**	38.303***
	(0.105)	(0.158)	(0.147)	(0.068)	(19.097)	(21.720)	(9.184)	(10.809)
High-Temp=1 × Temp GDD (MAX) (AGRO YEAR)					0.178	-0.364	0.578***	0.011
					(0.195)	(0.320)	(0.184)	(0.100)
High-Temp=1 × Temp HDD (MAX) (AGRO YEAR)					68.487***	2.654	-25.630**	-38.386***
					(19.103)	(21.743)	(9.255)	(10.834)
Observations	1770	1770	1770	1770	1770	1770	1770	1770
r2	0.62	0.49	0.70	0.73	0.63	0.49	0.71	0.73
r2_a	0.30	0.04	0.45	0.49	0.30	0.05	0.46	0.49

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: based on the ELCA panel survey 2010-2013-2016. The standard errors (in parentheses) are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as agricultural problems of the household (except drought or other weather-related problems). It also includes controls for the dependency ratio in 2010, the age of the household head, a dummy for whether or not the household head is a woman, a dummy for whether or not the household has a credit in that year, a dummy at the community level for whether or not the access to the cabecera (center of the town) is reachable and in good shape, and the minutes to reach the cabecera for the community. High-temp is a dummy equal to one for the municipalities with average temperature higher than 27 Celsius degrees, and zero for the other municipalities. Sample restricted to rural households producing uniquely crops (excludes livestock producers or those producing livestock and crops).

5 Adaptation responses to drought impacts

I start by using the three waves of the ELCA to verify if drought measures constructed with the SPI affect the agricultural outcomes. I argue that the SPI drought measures can be used as an alternative way to capture the impact of climate variability, in addition to the ones considered already in the literature (see section 4.2 and section 4.4). The SPI drought measures also allow me to determine better extreme climate events and facilitates the interpretation. First, I study the reaction by households after 2013 to droughts in 2010 (*short-term* and *medium-term adaptation*); and second, the reaction of the households after 2016 to *consecutive droughts* in 2010 and 2013. Categorizing the effects in this way should allow to disentangle how the households react in the short-term and in the medium-term to shocks happening in 2010. For the medium-term effects, as Burke and Emerick (2016) mention, with panel data the effects found in the short-term could be underestimated, as rural households could adapt more to weather shocks (assuming that they can). To some extent, the results of *short-term* and *medium-term adaptation* and *adaptation following consecutive droughts* could also be compared to the results of weather and climate of section 4.2, respectively.

Figure 5 of Appendix 3C shows the timeline of the three waves of the ELCA 2010-2013-2016 and the ENSO events. As observed, there was neither El Niño nor La Niña around 2013, while El Niño phenomena occurred between July 2009 and March 2010 and before and during 2016 (November 2014 to May 2016). The event in 2010 could have affected the agricultural outcomes in 2010 (the baseline); in an attempt to rule out this possibility, I show later on that the socioeconomic control variables and the outcome variables were balanced with respect to the drought in 2010. In addition, Appendix 3A and 3B give evidence of a moderate drought in 2010 and an extreme drought in 2016, using the SPI measure. Also, Table 12 of Appendix 3A shows the different measures of SPI and drought by year of the survey.

5.1 Identification strategy using the DID approach and the SPI measure of droughts

The analysis aims to capture rural households' changes of their agricultural practice and in their labor market participation in the short-term and medium-term. I proceed by 1) using the three years 2010, 2013 and 2016, to see if the agricultural outcomes in 2013-2016 were affected by the drought in 2010 (*short-term* and *medium-term adaptation*); and 2) comparing years 2010, 2013 and 2016, to see if the agricultural outcomes in 2016 were affected differently for those who suffered a drought in 2010 and also in 2013 (*consecutive droughts adaptation*). Appendix 3E studies the effects of SPI on gross agricultural productivity (in value terms) and the additional outcomes of this section and it shows the impact from the SPI. As the SPI takes continuous values, I prefer to construct dummy drought measures using the indices. This allows to determine better when a drought event happened and to capture easily the effects of droughts on agricultural outcomes in a DID framework. Using a dummy of drought also allows to make an easier interpretation of the impact of SPI. In this sense, the drought in 2010 determines the treatment and control groups (drought-no drought) in all the specifications. Table 12 in Appendix 3A describes the measures of droughts by year of the survey, which were constructed using the SPI. In the municipalities, for 18% of the households of the sample there was a drought in 2010 if I use the SPI at 12 months ("Drought 2010 (<=-1) (SPI12)"). Using the SPI at 6 months indicates a drought for 62% of the households of the sample ("Drought 2010 (<=-1) (SPI6)"). The equation to estimate for the rural household h is then:

$$\begin{aligned}\mathbf{Y}_{h,m,r,t} = \nu + \beta_{\mathbf{1}} \times \mathbf{D_{2010}}_m \times A_t + \beta_2 \times D_{2010_m} + \beta_3 \times A_t \\ + \theta \times X_{h,m,r,t} + \delta_r + \delta_t + \delta_m + \delta_h + \varepsilon_{h,m,r,t}\end{aligned} \tag{11}$$

$\mathbf{Y}_{h,m,r,t}$ agriculture outcomes for rural household h (or agricultural unit), of municipality m, region r in year t (2010-2013-2016);

$\mathbf{D2010}_{m,h}$ treatment dummy for drought in municipality m of household h in year 2010; and 0 otherwise;

A_t is a 'post-treatment' dummy;

$X_{h,m,r,t}$ vector of controls for household characteristics;

δ_r, δ_t, δ_m, δ_h dummies by *region*, by *year*, by *municipality* and by *household*.

Following Abadie et al. (2017), the standard errors are clustered at the municipality level m to account for the correlation in treatment within municipality. The estimations use the inverse weights of 2010, as recommended by the ELCA team. The coefficient of interest is β_1. The identification assumption relies on the fact that rural households in treatment and control groups (affected versus not affected by drought in 2010) were similar in 2010 - the parallel trends assumption. This assumption is tested in the results section. Additionally, I test if the control variables are balanced in the same treatment and control groups. Furthermore, I include *year* and *municipalities* fixed effects to avoid any omitted variable bias in this aspect.

5.2 Effects of drought on agricultural productivity in the short and medium term

The DID uses the drought shock in 2010 to determine treatment and control groups (drought in 2010 versus no drought in 2010). I use the variable "Dummy 1 or more months drought($<=-1$)(SPI12)" to define a moderate drought in 2010 in the main specification (see Table 2 for the drought definition).

Table 16 in Appendix 3F shows the socioeconomic control variables in 2010 for the groups of drought 2010 versus no drought in 2010, aggregated by municipality. Although I find that all the control variables are balanced, they are included in the estimations. Interestingly, the variables of the percentage of crops facing problems in the parcels of the household are balanced as well as the household structure between the two groups of drought versus no drought in 2010. Also, there is no statistical difference in the variables of wealth and the access to the town center.

Table 17 in Appendix 3F presents the balance of the outcome variables for the group of drought versus no drought in 2010, aggregated by municipality. There is no statistical difference between the groups affected by drought in 2010 compared to the one without a drought. Also, it is compelling to find that the variables of land use, of gross agricultural productivity (in value terms) and investment, among others, are similar on average in both groups in 2010, giving evidence of the validity of the parallel trends assumption.

Table 8 summarizes the main findings of the DID, comparing outcomes in survey year 2010, 2013 and 2016.[22] I find evidence that the drought measures can affect different channels. In panel a), having a drought in 2010[23] increases the land size planted in crops in 2013 and the area dedicated to livestock along the different measures, with the results statistically significant for crops but not for livestock. The variable captures only the effect on the total area used for livestock, but not gross agricultural productivity (in value terms) or total production of livestock. For crops, the drought in 2010 increases the land used by 11.5%-14.4% and the coefficients are statistically significant at the 5% and 1% level. This goes in line with the findings of Aragón et al. (2021) and Costinot et al. (2016) where rural households respond to droughts by planting and using more land, as well as the findings of the theoretical framework proposed in section 3. The more planted area is also in line with a higher productivity in terms of the value of the total production, particularly for drought measures using the SPI at 6 months. This result is similar to the findings in section 4.2, also by crop type. The gross agricultural productivity (in value terms) of vegetables and fruits are not affected by droughts. Cereals, and to a lesser extent, coffee seem to benefit from droughts (except for coffee production during extreme droughts). However, the results depend on the high versus low-temperature municipalities as discussed in section 4.2. Also here, the interpretation of these results should be taken with caution as the variables of gross agricultural productivity use a restricted sample of only crop producers.

[22] Although the measures of adaptation could have started before 2010, the ELCA panel survey starts in 2010 and it makes it difficult to check exactly if rural households implemented similar strategies before. However, Figure 3 shows no evidence of extreme droughts during the three or four years previous to 2010, with very few municipalities affected by moderate droughts in the three years before 2010. As such, the drought measure is constructed based on the SPI index, which is the anomaly with respect to this long-term mean.

[23] The dummies for drought in 2010 during the agricultural growing season perform worse than those defined in the calendar year and were all the time zero. Also, the extreme drought in 2010 using the SPI 12 months give only zeros, which makes it impossible to use them in the estimations of the tables.

Table 8: DID for 2010-2013-2016 using Drought in 2010 on main agricultural outcomes

a) Production

	Land (Ha) ln		Value prod. total (Millions Col. Pesos/Ha) ln				
	Crops	Livestock	Total	Vegetables	Fruits	Cereals	Coffee
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Drought 2010 ($<= -1$) (SPI12)xPost(2013)	0.057	0.056	-0.190	-0.263	0.215	-0.385	0.138
	(0.037)	(0.095)	(0.192)	(0.209)	(0.168)	(0.359)	(0.127)
Drought 2010 ($<= -1$) (SPI6)xPost(2013)	0.109**	0.068	0.386***	-0.182	0.248	0.181	0.166**
	(0.044)	(0.083)	(0.112)	(0.315)	(0.198)	(0.305)	(0.072)
Drought 2010 ($<= -2$) (SPI6)xPost(2013)	0.135***	-0.064	-0.122	0.164	-0.084	0.340***	-0.341***
	(0.031)	(0.044)	(0.108)	(0.103)	(0.083)	(0.105)	(0.093)
N	7902	7902	1770	1770	1770	1770	1770
r2	0.73	0.78	0.62	0.62	0.48	0.70	0.72
r2_a	0.56	0.64	0.29	0.29	0.04	0.45	0.48

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

b) Employment and Investment

	HH Head or partner work			Land Water (ha) ln			Land INV(ha) ln
	Employed	Agro.	Off-farm	Any	Own	Ext.	ANY no house
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Drought 2010 ($<= -1$) (SPI12)xPost(2013)	0.110	0.132	-0.011	0.182*	-0.031	0.223**	-0.124
	(0.066)	(0.089)	(0.077)	(0.102)	(0.046)	(0.091)	(0.134)
Drought 2010 ($<= -1$) (SPI6)xPost(2013)	0.171***	0.301***	0.031	0.068	-0.046	0.125	-0.186**
	(0.049)	(0.032)	(0.073)	(0.089)	(0.054)	(0.080)	(0.075)
Drought 2010 ($<= -2$) (SPI6)xPost(2013)	0.288***	0.333***	-0.033	0.106*	-0.227***	0.362***	-0.142**
	(0.036)	(0.059)	(0.031)	(0.057)	(0.038)	(0.055)	(0.056)
N	7902	7902	7902	7902	7902	7902	7902
r2	0.66	0.63	0.49	0.76	0.71	0.61	0.55
r2_a	0.44	0.40	0.17	0.61	0.52	0.36	0.26

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: based on the ELCA panel survey 2010-2013-2016. The standard errors (in parentheses) are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as agricultural problems of the household (except drought or other weather-related problems). It also includes controls for the dependency ratio in 2010, the age of the household head, a dummy for whether or not the household head is a woman, a dummy for whether or not the household has a credit in that year, a dummy at the community level for whether or not the access to the cabecera (center of the town) is reachable and in good shape, and the minutes to reach the cabecera for the community. Each row corresponds to the interaction of post-treatment and Drought in 2010 using the SPI on the outcome variable in the column. Each row is part of different estimations. The N, r2 and r2_a in each column corresponds to the estimations of the drought measure in the first row but the explanatory power of the other estimations was almost the same when using the other ones. In columns 3)-7) of Panel a), sample restricted to rural households producing uniquely crops (excludes livestock producers or those producing livestock and crops).

5.3 Effects of consecutive droughts on agricultural productivity

In Table 9, I compare the waves 2010, 2013 and 2016 to see how rural households react to a drought in 2010 and again in 2013. I change the variable of drought used in the previous DID to represent cumulative droughts, a dummy for having experienced a drought in 2010 and also in 2013.[24] In panel a) of Table 9, consecutive drought in 2010 and 2013 increases the total land dedicated to livestock by 15.3%, and to crops by 10.1%. There is an increase in the total gross agricultural productivity by 67.7%, statistically significant at the 1% level. The value of the total production of fruits and cereals increases by 104.2% and 29.7% respectively (columns 5 and 6 in panel a), while gross agricultural productivity of vegetables decrease by 46.7%. With respect to perennial crops, there is an increase in the productivity of fruits after droughts, but no change in the value of coffee production. For annual crops, vegetables show a reduction in the gross agricultural productivity after droughts, while cereals tend to benefit more. Similar to section 4.2 for annual crops, vegetables are more affected while cereals tend to benefit from droughts and weather variation.

[24] The drought variables using the agricultural growing season and the extreme droughts were always zero, which prevents me from using them in the estimations.

Table 9: DID for 2010-2013-2016 using the cumulative Drought 2010 and 2013 on main agricultural outcomes

a) Production

	Land (Ha) ln		Value prod. total (Millions Col. Pesos/Ha) ln				
	Crops	Livestock	Total	Vegetables	Fruits	Cereals	Coffee
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Drought 2010&2013 ($<= -1$) (SPI12)xPost(2016)	0.015	0.142***	0.517***	-0.383***	0.714***	0.260*	-0.076
	(0.042)	(0.037)	(0.100)	(0.086)	(0.058)	(0.130)	(0.065)
Drought 2010&2013 ($<= -1$) (SPI6)xPost(2016)	0.096*	0.027	0.120	0.157	-0.035	0.124	-0.146
	(0.052)	(0.059)	(0.141)	(0.170)	(0.112)	(0.140)	(0.155)
N	7902	7902	1770	1770	1770	1770	1770
r2	0.73	0.78	0.62	0.62	0.49	0.70	0.72
r2_a	0.56	0.64	0.29	0.29	0.05	0.44	0.48

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

b) Employment and Investment

	HH Head or partner work			Land Water (ha) ln			Land INV(ha) ln
	Employed	Agro.	Off-farm	Any	Own	Ext.	ANY no house
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Drought 2010&2013 ($<= -1$) (SPI12)xPost(2016)	0.070	0.018	0.007	-0.075*	-0.204***	-0.018	0.171***
	(0.041)	(0.067)	(0.033)	(0.039)	(0.046)	(0.029)	(0.046)
Drought 2010&2013 ($<= -1$) (SPI6)xPost(2016)	0.099**	0.174**	0.020	0.027	0.034	0.022	0.006
	(0.035)	(0.065)	(0.041)	(0.065)	(0.080)	(0.030)	(0.102)
N	7902	7902	7902	7902	7902	7902	7902
r2	0.66	0.63	0.49	0.76	0.71	0.61	0.55
r2_a	0.44	0.40	0.17	0.61	0.52	0.36	0.26

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: based on the ELCA panel survey 2010-2013-2016. The standard errors (in parentheses) are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as agricultural problems of the household (except drought or other weather-related problems). It also includes controls for the dependency ratio in 2010, the age of the household head, a dummy for whether or not the household head is a woman, a dummy for whether or not the household has a credit in that year, a dummy at the community level for whether or not the access to the cabecera (center of the town) is reachable and in good shape, and the minutes to reach the cabecera for the community. Each row corresponds to the interaction of post-treatment and Drought in 2010-13 using the SPI on the outcome variable in the column. Each row is part of different estimations. The N, r2 and r2_a in each column corresponds to the estimations of the drought measure in the first row but the explanatory power of the other estimations were almost the same when using the other ones. In columns 3)-7) of Panel a), sample restricted to rural households producing uniquely crops (excludes livestock producers or those producing livestock and crops).

5.4 How do households adapt?

5.4.1 Labor Market

In terms of the labor market, panel b) of Table 8 shows that the drought in 2010 increases the probability of the household head or partner being employed by 17.1 to 28.8 percentage points and the probability of doing agricultural work by 30.1 to 33.3 percentage points, but there is no effect in terms of off-farm work. This could be associated to the use of more hectares of land used by the rural household. As the rural household expands the use of land for crops and for livestock, household members might need to work more on the farm.

Panel b) of Table 9 also shows some results indicating adaptation in the labor market after consecutive droughts. There is an increase in the probability of being employed and doing agricultural work by 9.9 and by 14.4 percentage points respectively (column 1 and column 2), statistically significant at the 5% level. This could indicate that after two consecutive droughts, rural households might still follow similar strategies to the ones found previously in the short-term and medium-term in section 5.2. They increase the total land area dedicated to crops, keep working more on the farm, and using some perennial crops such as fruits. The increase in land devoted to fruits could be explained by the fact that perennial crops tend to be a more stable source of income rather than annual crops. Following consecutive droughts, there are smaller increases in land and on-farm labor, which indicates a different response, and may also be linked to the fact that the drought in 2013 was not as severe as the one in 2010 (see Figure 3).

5.4.2 Water Use

In terms of access to water (short-term and medium-term), the drought in 2010 increased the land with any water in 2013 by 10.6%-20%, particularly from external sources by 25%-43.6% (panel b) of Table 8). In the short-term and medium-term, rural households might try to look for additional sources of water when facing a drought shock and they depend less on own sources, which is consistent with the decrease observed in own water in column 5).

In addition, Panel b) of Table 9 shows the results for consecutive droughts on water access. There is a reduction of land with access to any water (own and external sources), statistically significant at the 10% level (columns 4 of panel b)), driven by the reduction in the land with access to own sources. This is similar to the result found in the *short-term* and *medium-term adaptation*, so droughts affect the chances to use own sources of water by the rural household. External water sources may also be more difficult to come by following consecutive droughts, as the sources of water of the rural households start to be depleted. This is an interesting difference between adaptation after one drought only and consecutive droughts.

5.4.3 Investment

Regarding investment (short-term and medium-term) in panel b) of Table 8, the drought in 2010 reduces the investments in the land plot (excluding housing), which could be seen as a way to smooth consumption for the household and postpone investments in the short-term and medium-term. For the consecutive droughts, I observe an increase in the hectares of land with investments (excluding housing) for rural households facing a consecutive drought (in 2010 and 2013). This corresponds to an increase by 18.6% of investments of this type in 2016. A potential explanation could be that as droughts become more frequent, rural households might want to make investments in the farm to reduce the impact of potential future droughts. I explore on which particular items the rural households focus more by analysing the type of investments (irrigation, structures, etc.).

While there was a reduction of investment excluding housing as *short-term* and *medium-term adaptation* in Table 8, an increase was observed following *consecutive droughts* in Table 9. Panel a) of Table 10 shows that the reduction of 20.4% (second line of column 2) of any investment excluding housing is explained by the reductions in investments, mainly on structures and then on other items. The reduction by 15.3% in the third line of column 2) is explained by the investments in fruits, wood and commercial items, but the item of structures shows an increase. After consecutive droughts, there is an increase in the investment excluding housing, that appears to be driven mainly by the investments in fruits, a perennial crop. Interestingly, there is a reduction on the investments in housing after consecutive droughts. There is also a slight increase in the investment in irrigation of around 3% following droughts in the short-term and medium-term but a reduction of the same size after consecutive droughts. To summarize, the initial reduction in investment is observed mainly through reductions in investment in fruit crops, commercial items and structures for the farm; this could be interpreted as a consumption smoothing strategy for the household to reduce the impact of droughts. The increase after consecutive droughts is explained by more investments to produce fruits and a reduction on housing investments. Relating to the theoretical model of section 3, as temperature increases (higher values of climate) or for consecutive droughts, the production of some crops can benefit by increasing the use of adaptive input, up to an optimal point after which it is no longer profitable.

Table 10: DID for Drought in 2010 by type on investment

a) Investment 1

	Land INV(ha) ln				
	Any (1)	Any no house (2)	Irrigation (3)	Structures (4)	Conservation (5)
Drought 2010 ($<= -1$) (SPI12)xPost(2013)	-0.120	-0.124	-0.008	-0.082	0.042
	(0.145)	(0.134)	(0.014)	(0.053)	(0.030)
Drought 2010 ($<= -1$) (SPI6)xPost(2013)	-0.187**	-0.186**	0.028**	-0.152***	-0.023
	(0.076)	(0.075)	(0.013)	(0.043)	(0.031)
Drought 2010 ($<= -2$) (SPI6)xPost(2013)	-0.128**	-0.142**	0.021*	0.126**	0.038**
	(0.057)	(0.056)	(0.012)	(0.046)	(0.018)
Drought 2010&2013 ($<= -1$) (SPI12)xPost(2016)	0.053	0.171***	-0.030**	-0.004	0.021
	(0.061)	(0.046)	(0.011)	(0.036)	(0.018)
Drought 2010&2013 ($<= -1$) (SPI6)xPost(2016)	-0.061	0.006	0.001	-0.020	0.009
	(0.121)	(0.102)	(0.021)	(0.082)	-0.025
N	7902	7902	7902	7902	7902
r2	0.58	0.55	0.42	0.49	0.47
r2_a	0.31	0.26	0.04	0.17	0.13

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

b) Investment 2

	Land INV(ha) ln				
	Fruits (1)	Wood (2)	Commer. (3)	House (4)	Others (5)
Drought 2010 ($<= -1$) (SPI12)xPost(2013)	0.065	-0.026	-0.115	-0.007	-0.023
	(0.108)	(0.016)	(0.071)	(0.045)	(0.028)
Drought 2010 ($<= -1$) (SPI6)xPost(2013)	0.005	-0.006	0.005	-0.029	-0.052**
	(0.033)	(0.009)	(0.031)	(0.044)	(0.021)
Drought 2010 ($<= -2$) (SPI6)xPost(2013)	-0.134***	-0.034***	-0.286***	0.033	-0.011
	(0.019)	(0.006)	(0.025)	(0.028)	(0.016)
Drought 2010&2013 ($<= -1$) (SPI12)xPost(2016)	0.158***	0.019***	0.010	-0.141***	0.022**
	(0.012)	(0.006)	(0.009)	(0.034)	(0.008)
Drought 2010&2013 ($<= -1$) (SPI6)xPost(2016)	0.035**	0.008	0.005	-0.097**	-0.013
	(0.015)	(0.011)	(0.019)	(0.045)	(0.019)
N	7902	7902	7902	7902	7902
r2	0.51	0.42	0.42	0.50	0.45
r2_a	0.20	0.05	0.05	0.17	0.10

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: ELCA panel survey 2010-2013-2016. Standard errors (parentheses) clustered at the municipality level m. Using inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as the same controls used in previous estimations (see section 4.2). Each row corresponds to the interaction of post-treatment and Drought in 2010 using the SPI on the outcome variable in the column. Each row is part of different estimations. N, r2 and r2_a in each column from the first drought measure estimations.

5.4.4 Land use

In order to explore deeper the type of land uses of the rural households, Table 11 shows the estimations by the different categories of land use following droughts and consecutive droughts used in the DID. Panel a) shows that the increase observed previously of the land used for crops is mainly driven by permanent and to a lesser extent by transitional crops, while mixed crops present a reduction in the land used following droughts. Interestingly, the total area of land increases after a consecutive drought in column 1) of panel a). A potential explanation of this is that rural households might have bought additional plots of land or perhaps by deforesting nearby areas. However, this is an aspect that should be explored in more detail in future research.

Panel b) of Table 11 shows that after droughts, there is a reduction of land used for pastures and land left fallow. When facing droughts, the rural households re-allocate land by reducing the type of land less exploited and assigning it to production of crops and for livestock. This trade-off appears in the theoretical framework of section 3, where the rural household can transfer the land left fallow into the production of the different crops that she produces. In fact, the results of the theoretical framework show that the rural households adapt to extreme climate by incorporating the land left fallow and allocating it to the production of the different crops that they produce.

Table 11: DID for Drought in 2010 by type of land use

a) Land use 1

	Land (Ha) ln				
	Total (1)	Crops (2)	Perm. (3)	Transit. (4)	Mixed (5)
Drought 2010 ($<= -1$) (SPI12)xPost(2013)	0.065	0.057	0.119	0.047	-0.111
	(0.051)	(0.037)	(0.092)	(0.033)	(0.096)
Drought 2010 ($<= -1$) (SPI6)xPost(2013)	0.053	0.109**	0.041	0.072**	0.008
	(0.049)	(0.044)	(0.062)	(0.029)	(0.045)
Drought 2010 ($<= -2$) (SPI6)xPost(2013)	-0.038	0.135***	0.252***	-0.053**	-0.078**
	(0.027)	(0.031)	(0.038)	(0.023)	(0.028)
Drought 2010&2013 ($<= -1$) (SPI12)xPost(2016)	0.162***	0.015	0.097	-0.035	-0.042
	(0.034)	(0.042)	(0.058)	(0.029)	(0.032)
Drought 2010&2013 ($<= -1$) (SPI6)xPost(2016)	0.093*	0.096*	0.131	0.007	-0.030
	(0.049)	(0.052)	(0.078)	(0.037)	(0.061)
N	7902	7902	7902	7902	7902
r2	0.86	0.73	0.63	0.61	0.50
r2_a	0.77	0.56	0.39	0.35	0.17

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

b) Land use 2

	Land (Ha) ln				
	Livestock (1)	Pasture (2)	Forest (3)	Others (4)	No used (5)
Drought 2010 ($<= -1$) (SPI12)xPost(2013)	0.056	-0.073	0.032	0.017	0.005
	(0.095)	(0.068)	(0.035)	(0.016)	(0.071)
Drought 2010 ($<= -1$) (SPI6)xPost(2013)	0.068	-0.013	0.026	-0.029*	-0.077
	(0.083)	(0.086)	(0.023)	(0.016)	(0.055)
Drought 2010 ($<= -2$) (SPI6)xPost(2013)	-0.064	0.080	0.016	0.026*	-0.342***
	(0.044)	(0.046)	(0.017)	(0.012)	(0.038)
Drought 2010&2013 ($<= -1$) (SPI12)xPost(2016)	0.142***	-0.078***	0.053***	0.095***	0.028
	(0.037)	(0.023)	(0.016)	(0.008)	(0.024)
Drought 2010&2013 ($<= -1$) (SPI6)xPost(2016)	0.027	0.013	0.033	-0.011	-0.009
	(0.059)	(0.044)	(0.020)	(0.014)	(0.034)
N	7902	7902	7902	7902	7902
r2	0.78	0.44	0.60	0.47	0.59
r2_a	0.64	0.08	0.35	0.12	0.32

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: ELCA panel survey 2010-2013-2016. Standard errors (parentheses) clustered at the municipality level m. Using inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as the same controls used in previous estimations (see section 4.2). Each row corresponds to the interaction of post-treatment and Drought in 2010 using the SPI on the outcome variable in the column. Each row is part of different estimations. N, r2 and r2_a in each column from the first drought measure estimations.

5.5 Heterogeneous effects and alternative strategies

5.5.1 Access to credit

Table 19 in Appendix 3G shows the results interacting the drought measures with the control variable of having access to credit (the *short-term* and *medium-term adaptation*). It shows that moderate droughts increase the land dedicated to crops and livestock for those with credit compared to those without it (the interaction term of columns 1 and 2 of panel a), but extreme droughts change the behaviour of the households. For those without credit, an extreme drought increases the hectares of land dedicated to crops but reduces the ones for livestock. Those with credit reduce the land dedicated to crops after an extreme drought, compared to households without a credit (the interaction term), but the net effect is an increase in the land used for crops and a reduction of livestock (the sum of both coefficients). Regarding the value of total production, there are statistically significant reductions for rural households with credit. The net effect after an extreme drought for households with a credit is a decrease in the value of the total production. Also note that the households without credit access benefit from droughts and present increases in the gross agricultural productivity of of cereals and coffee, which could be due to higher production in yields or higher prices or both. Unfortunately, the way that the variables of value of the crops production are constructed does not allow me to disentangle exactly which effect dominates. On the contrary, for those with credit access, the extreme droughts only increased the productivity of vegetables while reducing the productivity of coffee compared to those without credit.

For the work variables, in both cases (having access to credit or not) I observe an increase the probability of the household head or partner to be employed and work in the farm, but once the droughts are extreme, those with access to credit tend to reduce labor participation in the farm or in off-farm activities with respect to household without credit access. Being exposed to an extreme drought in 2010 increases the probability of doing on-farm work for those without credit access by 42.3 percentage points. However, extreme drought reduces the probability of doing on-farm work by 10.4 percentage points for household with credit access with respect to those without it. Both effects are statistically significant at the 1% and 5% level. The net effect is still positive for those with credit. Being exposed to an extreme drought increases the probability of doing on-farm work by 31.9 percentage points for the households with credit access. In conclusion, there seems to be some significant differences depending on having access or not to credit, when households face extreme events. Having access to credit might reduce the labor participation, as these households have extra sources of income. It could be that those without credit might not have another choice than working, in their own farms or doing off-farm work.

Another important mechanism relates to the variables for land with access to water. On the one hand, being exposed to a drought and having a credit increases the hectares of land with access to water (any and external) compared to those without credit. In line with the findings for moderate droughts, the interaction in the table shows an increase in the hectares of land for those with credit, compared to those without it. The net effect of droughts for households with credit, column 4 and 6 of panel b) in Table 19, is positive across the water sources (any or external). In this sense, having a credit could facilitate households getting access to external sources of water for their farms. On the other hand, only for extreme droughts there is a reduction in the access to water for households without a credit. When households face extreme droughts, there is a reduction by 26% to 36% in the hectares of land with access to water across all the sources (any, own or external) for those without credit. In terms of investment excluding housing, column 7 of panel b), droughts have a negative impact for those without credit. It is only for extreme droughts, having a credit increases the chances of making investments (excluding housing) for the households exposed to droughts, compared to those without credit. However, the net impact for those with credit is close to zero (the sum of the two coefficients of column 7 of panel b) in Table 19).

5.5.2 Migration as an alternative adaptation strategy

Finally, I explore an alternative way in which rural households can cope with droughts. As has been shown in the literature, household can respond to droughts on the extensive margin through migration (see Cattaneo et al. (2019)). I develop this by constructing two different measures: 1) "Migrating outside Municipality" for cases when the household moved outside of the initial municipality of 2010. This accounts for 5% of the ELCA sample in Appendix 3C and those were excluded in all the previous estimations as explained in the data section 2. And 2) "Moving inside Municipality" for cases when the coping mechanism is through movements to another community inside the same initial municipality. Compared to migration outside of the municipality, these movements are not very far and should be considered as re-location inside the same initial municipality. As they respond to different channels, they are analyzed separated by using the variable "Migrating outside Municipality" and are mutually excluded. These movements inside the municipality account for 11.2% of the ELCA sample of table 13 in Appendix 3C and were included in all the previous estimations.

Table 18 in Appendix 3G shows the results of the estimations for type of movement. The first three rows correspond to the estimations for the drought measures used in the *short-term* and *medium-term adaptation* analysis, while the next two rows are for the drought measures used in the *consecutive droughts adaptation* analysis. Column 1) of the table indicates a reduction in the probability of migrating following the drought in 2010 between 3 to 11 percentage points, statistically significant at the 10% and 1% level, respectively. However, it is important to take into account that the estimations of column 1) do not control for household fixed effects as they remove all the variability explained by the variability in the explanatory variables (estimated coefficients close to zero in all the variables). Results of column 1) are thus not totally comparable with the estimations in previous sections. However, column 2) of Table 18 uses the same controls and fixed effects and are comparable to the results of previous sections. It shows an increase in the probability of moving (re-locating) to another community inside the same municipality by 4.9 to 11.9 percentage points following a moderate drought in 2010 (not for extreme drought), which is statistically significant at conventional levels. The behaviour is similar for the measures of moderate droughts in the analysis of *short-term* and *medium-term adaptation* and in the *consecutive droughts adaptation* analysis. Interestingly, extreme drought in 2010 reduced the probability of re-locating to another community inside the municipality. Moderate droughts might encourage households to move to other areas inside the same municipality, perhaps looking for job options or other alternative ways to get income. But for extreme droughts, it is harder to find sources of income in the municipality. This corresponds to the findings of the theoretical framework according to which the rural households reduce the production of the crops and the use of adaptive input as climate becomes too extreme. However, it is difficult to assert that the rural households in the sample try to migrate to other municipalities as the estimations of column 1) are not totally comparable.

6 Conclusion

This article analyses the effects of weather factors on gross agricultural productivity for a country in development - Colombia - as the literature on agricultural adaptation has mainly focused on developed countries such as U.S. (see Deschênes and Greenstone (2007) and Schlenker and Roberts (2009)). It combines the Colombian panel survey (ELCA) conducted in 2010, 2013 and 2016 with weather information from satellite images to explore how rural households adapt. I start by using similar identification frameworks as the ones already explored in the literature, in order to have a comparison. Then, I propose an alternative way to measure the impact of climate variability on agriculture, by constructing a measure of droughts using the SPI in a DID framework. I divide the DID analysis in two, to see how rural households adapt in the short-term and the medium-term and then, with respect to consecutive droughts.

I separate the effect of climate from yearly weather deviations for the Colombian rural households following Kelly et al. (2005), Deschênes and Kolstad (2011), and in particular Bento et al. (2020). First, the long-run mean of rainfall has a positive effect on gross agricultural productivity and while temperature deviations affect positively gross agricultural productivity, there is no effect from the long-run temperature mean. Also, the analysis of the marginal effects show that the higher temperature affects positively gross agricultural productivity in low-temperature municipalities but negatively in high-temperature municipalities. This shows the potential winners and losers from climate trends and weather shocks and gives evidence of adaptation of rural households in high-temperature municipalities. With respect to the marginal effects by crop, cereals and coffee benefit from higher temperature (long-run and deviations), mostly in low-temperature municipalities; vegetables are mostly affected negatively by the increasing temperature trends; fruits are negatively affected by temperature shocks and climate in low-temperature municipalities while positively affected in high-temperature municipalities; gross productivity of coffee seems to be only affected negatively by temperature shocks in high-temperature municipalities.

Regarding nonlinear effects, the GDD-HDD measures explain less the gross agricultural productivity of the rural households studied, compared to the climate and weather deviation variables. With respect to the marginal effects by crop, the HDD affect negatively the gross agricultural productivity of cereals and coffee in high-temperature municipalities, while they benefit low-temperature municipalities. On the contrary, HDD increase the gross agricultural productivity of vegetables and fruits of high-temperature municipalities while decreasing it in low-temperature municipalities.

Finally, section 5 studies if those affected by previous droughts adapt better to those not affected by those shocks. When facing droughts, as *short-term* and *medium-term adaptation*, the rural households re-allocate land by reducing the type of land left fallow and assigning it to production of crops and for livestock. This captures some of the trade-offs proposed in the theoretical model of section 3. It also goes in line with higher values of the total production, particularly for cereals and coffee. Following consecutive droughts (in 2010 and in 2013), rural households also expand the land area dedicated to crops and livestock, with an increase in the gross agricultural productivity of cereals and fruits, but with a negative effect on vegetables. Using more land available in the farm leads the household head or partner to do more agricultural work in the short-term and medium-term. This is similar to Aragón et al. (2021) who find that high-temperatures reduced gross agricultural productivity, and that rural households attenuate the effect on output by increasing the planted area and by mixing crops.

Across the analysis, the marginal effect on perennial crops (fruits and coffee) depends on the high versus low-temperature municipalities and the type of crop. In low-temperature municipalities, higher temperature benefits coffee while it reduces the gross agricultural productivity of fruits; in high-temperature municipalities the marginal effect is the opposite and benefits fruits while reducing the gross agricultural productivity of coffee. With respect to the marginal effects on annual crops, the gross agricultural productivity of vegetables is more affected while cereals tend to benefit from droughts and weather variation. The analysis of the climate-yearly weather deviations and the DID gave qualitatively similar findings, with a positive effect from temperature weather shocks and droughts (short-term and medium-term) on gross agricultural productivity.

In the short-term and medium-term after consecutive droughts, rural households smooth consumption by reducing non-housing investments and increasing the hectares of land with investments (excluding housing). As droughts become more frequent, rural households make investments in the farm to reduce the impact of potential future droughts. Rural households increase the land used, work more in the plots and postpone investments, but as droughts start to be more frequent, it might become more difficult to implement those measures of adaptation. Additionally, the drought in 2010 decreased the access to own water while external access to water increased in the short-term and medium-term. However, when facing consecutive droughts, it becomes more difficult to get access to any water (own and external sources).

A future research agenda is to check the behavior of the farmers who experienced consecutive droughts also in later waves of the ELCA panel (when they become available). Also, explore more in detail the effect of prices and effect of volume in the gross agricultural productivity analyzed here, as well as analyse the potential channels playing a role in the low-temperature and high-temperature municipalities. This deserves attention and it has not been extensively explored in low and middle income countries. Finally, additional heterogeneous effects can be further explored with respect to commercial versus subsistence rural households. Regarding policy implications of the responses to climate change in agriculture, policymakers should take into account the winners and losers of extreme heat, and probably focus more on high-temperature areas. Adaptation to extreme temperature in areas with already high temperature can be more difficult as rural households have fewer possibilities to implement measures against droughts. While low-temperature areas could benefit from higher temperature, some crops might also benefit and have the possibility of being produced there. Food security policies might have to consider these aspects too, switching the production from some crops to others, moving the production of specific crops from some areas to others, or providing safety nets in the most affected high-temperature areas.

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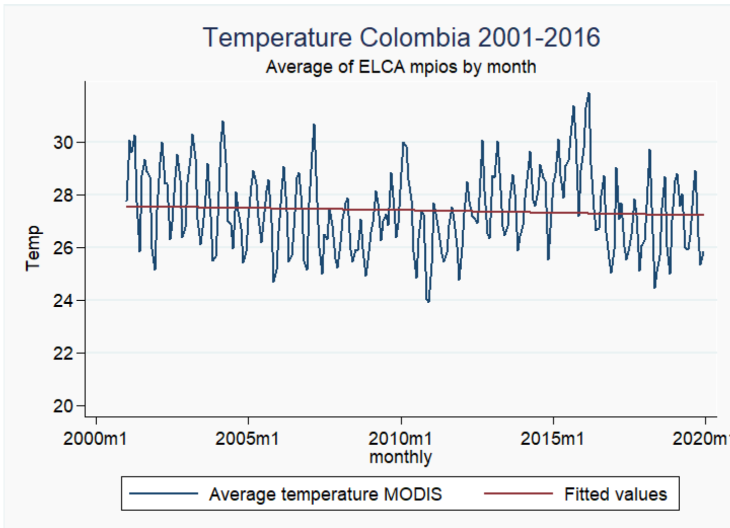
Appendices

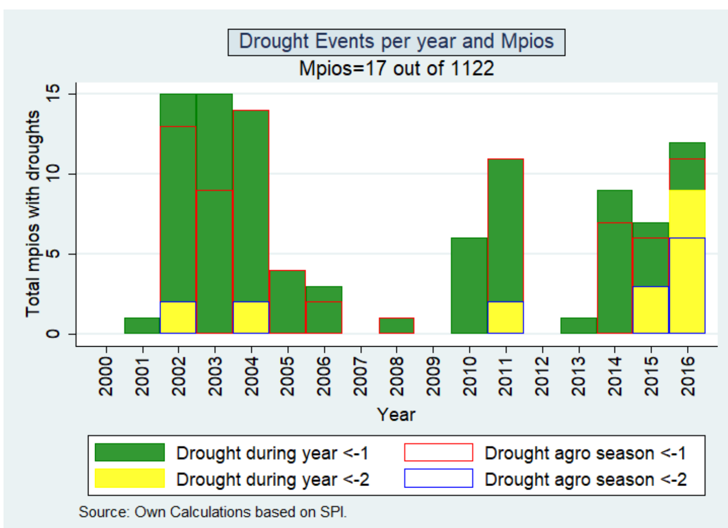
3A Average temperature - municipalities of the sample

Figure 2: Average Temperature Colombia - ELCA municipalities



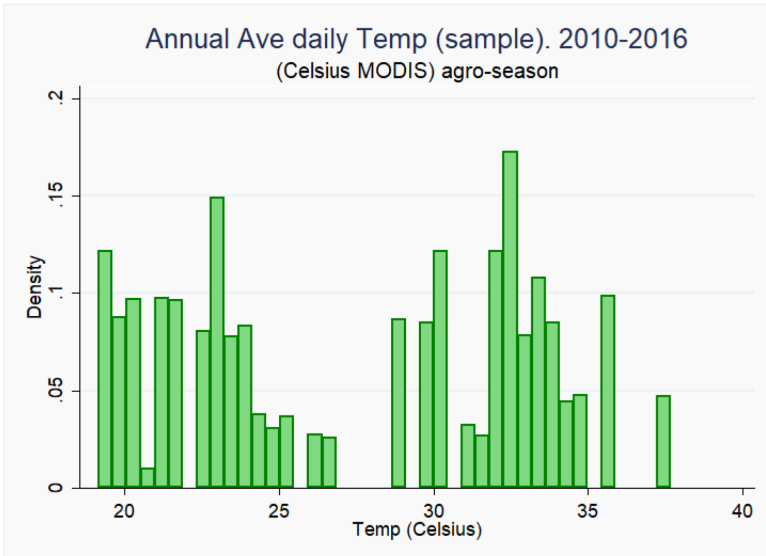
Source: Based on MODIS Land Surface Temperature data imputed to each municipality. Satellite images MOD11A1.006 at 1km of resolution.

Figure 3: Droughts by year in the ELCA municipalities



Notes: SPI refers to the number of standard deviations by which observed anomaly deviates from long-term mean. The figure uses a monthly scale of 12 and corresponds to the number of months over which water deficits accumulate.

Figure 4: Histogram Temperature Agricultural Growing Season



Source: Based on MODIS Land Surface Temperature data imputed to each municipality. Satellite images MOD11A1.006 at 1km of resolution.

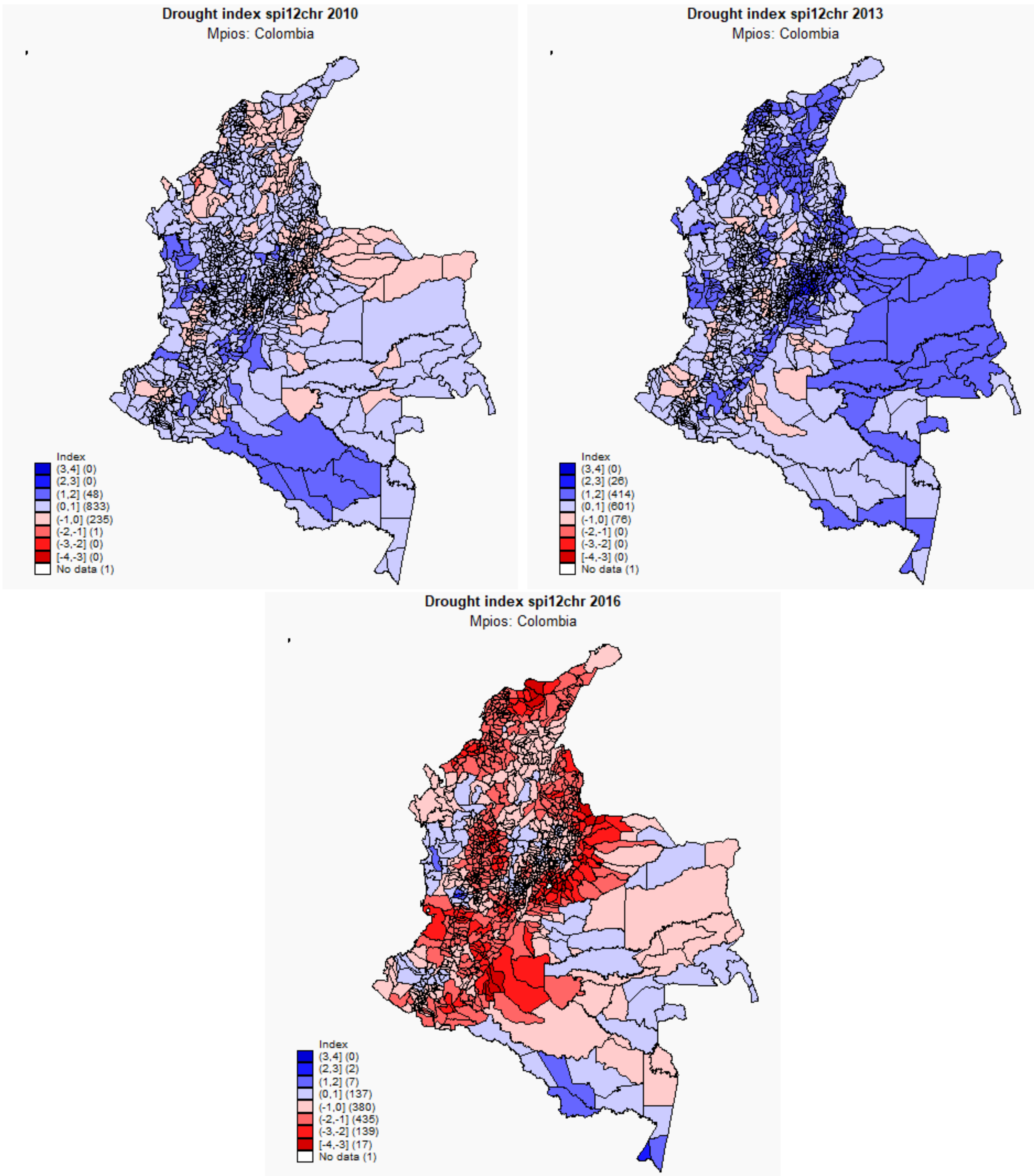
Table 12: SPI variables by ELCA year - Average

	2010 mean	2013 mean	2016 mean
SPI Index 12 months CHIRPS(opposite)	-0.77	-1.03	1.31
SPI Index 12 months CHIRPS(opposite)-agro season	-1.23	-1.37	1.14
Dummy 1 or more months drought(<=-1)(SPI12)	0.18	0.03	0.79
Dummy 1 or more months drought(<=-1)(SPI12)-agro season	0.00	0.00	0.75
Dummy 1 or more months drought(<=-2)(SPI12)	0.00	0.00	0.68
Dummy 1 or more months drought(<=-2)(SPI12)-agro season	0.00	0.00	0.47
Drought 2010 (<=-1) (SPI12)	0.18	0.18	0.17
Drought 2010-13 (<=-1) (SPI12)	0.03	0.03	0.03
SPI Index 6 months CHIRPS(opposite)	-0.17	-0.44	1.21
SPI Index 6 months CHIRPS(opposite)-agro season	-0.78	-1.04	1.12
Dummy 1 or more months drought(<=-1)(SPI6)	0.62	0.56	0.79
Dummy 1 or more months drought(<=-1)(SPI6)-agro season	0.00	0.05	0.77
Dummy 1 or more months drought(<=-2)(SPI6)	0.01	0.07	0.73
Dummy 1 or more months drought(<=-2)(SPI6)-agro season	0.00	0.00	0.60
Drought 2010 (<=-1) (SPI6)	0.62	0.61	0.60
Drought 2010-13 (<=-1) (SPI6)	0.55	0.56	0.54

Source: based on the ELCA panel survey 2010-2013-2016 and weather data, using expansion factors for 2010 as recommended by the ELCA team.

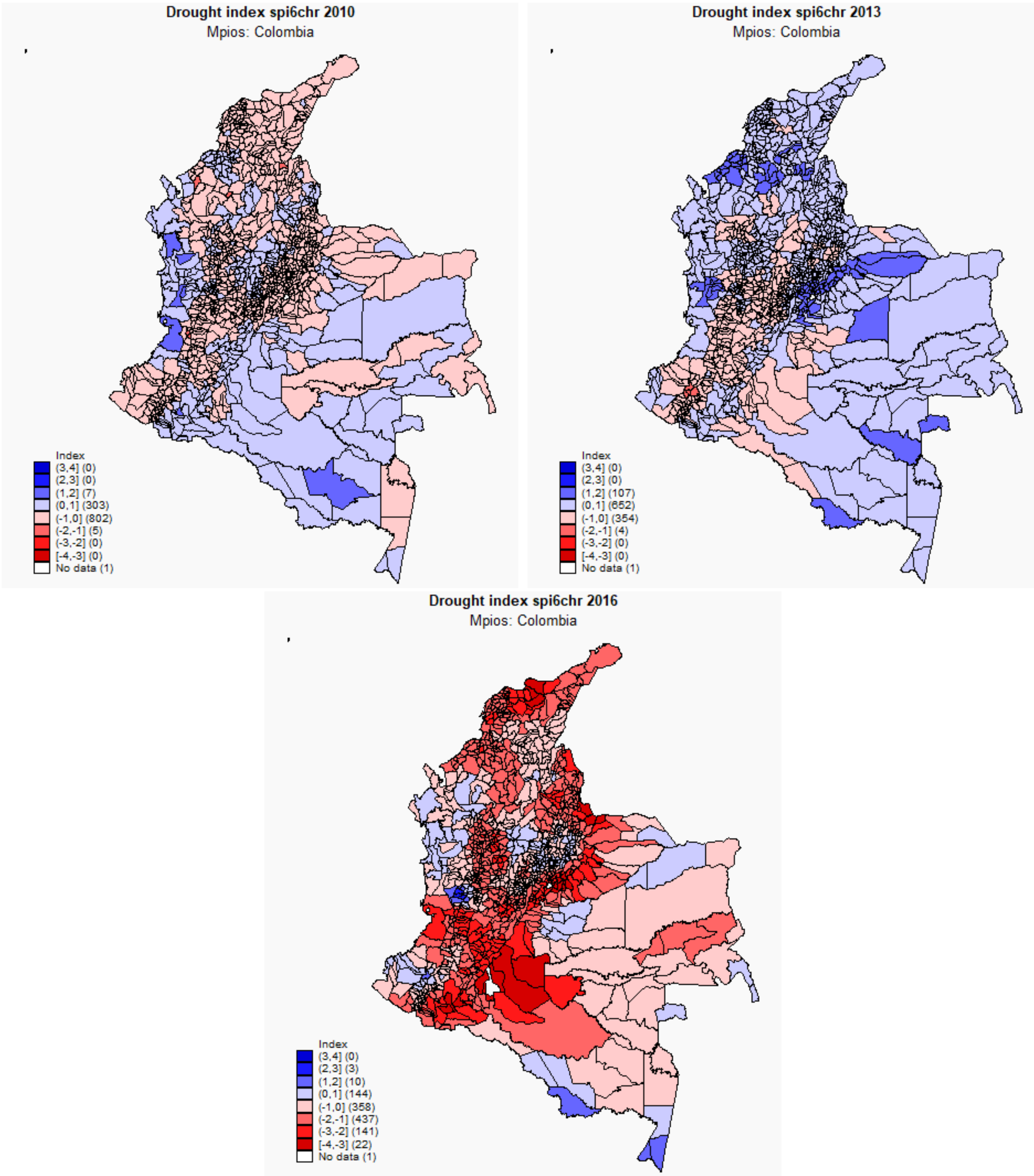
3B Maps of SPI drought measures by municipality

Scale=12 months



Notes: SPI number of standard deviations by which observed anomaly deviates from long-term mean. Monthly scale (12-6) as number of months over which water deficits accumulate. Calculated based on CHIRPS data.

Scale=6 months



Notes: SPI number of standard deviations by which observed anomaly deviates from long-term mean. Monthly scale (12-6) as number of months over which water deficits accumulate. Calculated based on CHIRPS data.

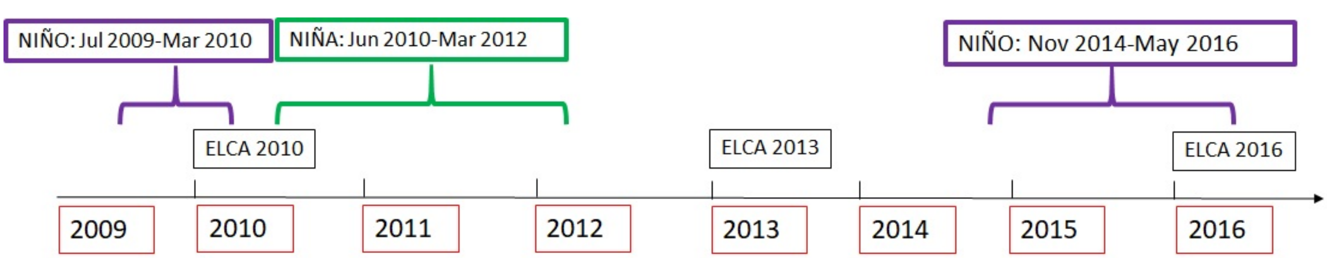
3C ELCA sample

Table 13: ELCA sample by municipality and year

Municipalities	2010	2013	2016	Total
	Observ.	Observ.	Observ.	Observ.
Saboya	435	428	385	1248
Cerete	318	312	293	923
Chinu	180	177	164	521
Cienaga de Oro	288	287	274	849
Sahagun	300	291	277	868
Simijaca	181	175	140	496
Susa	206	201	179	586
Tocaima	155	153	128	436
Circasia	217	212	158	587
Cordoba	76	71	57	204
Filandia	193	178	148	519
Belen de Umbria	557	543	450	1550
Puente Nacional	325	318	290	933
Sampues	130	127	109	366
Natagaima	187	185	163	535
Ortega	502	492	441	1435
Purificacion	261	257	230	748
Total	4511	4407	3886	12804

Source: created based on the ELCA

Figure 5: Time-line of ELCA surveys and El Niño phenomenon.



Source: created based on the ELCA and El Niño periods from the NOAA.

3D Test of climate and weather deviations with temperature squared

Table 14: Climate and Yearly weather deviations

	Value prod. total (Millions Col. Pesos/Ha) ln					
	MEAN TEMPERATURE			MAXIMUM TEMPERATURE		
	AGRO YEAR			AGRO YEAR		
	HIGH TEMP.	TEMP. SQUARED	BOTH	HIGH TEMP.	TEMP. SQUARED	BOTH
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Trend 30 years (MEAN) (AGRO YEAR)	4.054**	5.236***	4.972**	4.358***	5.042***	4.547***
	(1.798)	(1.581)	(1.764)	(1.446)	(1.239)	(1.452)
Rainfall Shock (MEAN) (AGRO YEAR)	0.250**	0.265**	0.276***	0.285***	0.309***	0.282***
	(0.094)	(0.099)	(0.087)	(0.086)	(0.091)	(0.087)
Temperature Trend 15 years (MEAN) (AGRO YEAR)	2.208***	4.558***	0.000			
	(0.645)	(1.248)	(.)			
Temperature Shock (MEAN) (AGRO YEAR)	0.091	0.060	0.000			
	(0.083)	(0.071)	(.)			
High-Temp=1 × Temperature Trend 15 years (MEAN) (AGRO YEAR)	-1.202		2.185			
	(0.811)		(1.492)			
High-Temp=1 × Temperature Shock (MEAN) (AGRO YEAR)	-0.204***		-0.150			
	(0.061)		(0.103)			
Temperature Trend 15 years (MAX) (AGRO YEAR)				1.652***	2.607	0.000
				(0.520)	(1.513)	(.)
Temperature Shock (MAX) (AGRO YEAR)				0.104**	0.059	0.000
				(0.036)	(0.036)	(.)
High-Temp=1 × Temperature Trend 15 years (MAX) (AGRO YEAR)				-0.695		0.932
				(0.619)		(1.089)
High-Temp=1 × Temperature Shock (MAX) (AGRO YEAR)				-0.169***		-0.158
				(0.057)		(0.109)
Temperature Trend 15 years squared (MEAN) (AGRO YEAR)		-0.057**	-0.144**			
		(0.021)	(0.051)			
Temperature Shock squared (MEAN) (AGRO YEAR)		-0.089**	-0.021			
		(0.034)	(0.055)			
Temperature Trend 15 years squared (MAX) (AGRO YEAR)					-0.025	-0.080*
					(0.023)	(0.038)
Temperature Shock squared (MAX) (AGRO YEAR)					-0.039**	0.001
					(0.017)	(0.027)
Observations	1770	1770	1770	1770	1770	1770
r2	0.63	0.63	0.63	0.63	0.63	0.63
r2_a	0.30	0.30	0.30	0.30	0.30	0.30

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: based on the ELCA panel survey 2010-2013-2016. The standard errors (in parentheses) are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as agricultural problems of the household (except drought or other weather-related problems). It also includes controls for the dependency ratio in 2010, the age of the household head, a dummy for whether or not the household head is a woman, a dummy for whether or not the household has a credit in that year, a dummy at the community level for whether or not the access to the cabecera (center of the town) is reachable and in good shape, and the minutes to reach the cabecera for the community. High-temp is a dummy equal to one for the municipalities with average temperature higher than 27 Celsius degrees, and zero for the other municipalities. Sample restricted to rural households producing uniquely crops (excludes livestock producers or those producing livestock and crops).

3E Identification strategy and results using the SPI

I estimate the next equation at the level of the rural household h as:

$$\mathbf{Y}_{h,m,r,t} = \eta + \delta \times \mathbf{SPI}_{m,t} + \gamma_x \times X_{h,m,r,t} + \tau_r + \tau_t + \tau_m + \tau_h + \epsilon_{h,m,r,t} \tag{12}$$

$\mathbf{Y}_{h,m,r,t}$ agriculture outcomes for rural household h (or agricultural unit), of municipality m, region r in year t;

$\mathbf{SPI}_{m,t}$ represents the Standard Precipitation Index;

$X_{h,m,r,t}$ vector of controls for household and community characteristics, as in equation 9;

τ_r, τ_t, τ_m, τ_h dummies by *region*, by *year*, by *municipality* and by *household*.

The standard errors are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010. The coefficients of interest are δ.

Table 15 shows the results of the effect of SPI on gross agricultural productivity, to compare with section 4.2 and section 4.4, including other agricultural outcomes. The "SPI 12 months (opposite)" captures the cumulative water deficit over twelve months during the calendar year (February of the previous year to January of the year) or agricultural growing season (February of the previous year to August of the previous year) (see section 2). The opposite of the measure is the SPI multiplied by minus one, so higher values correspond to droughts. I also consider the SPI for six months.

Panel a) of Table 15 shows no effect of the SPI on the total land used in hectares, or land used for crops but it reduced the land used for livestock, with no effect on the total value of gross agricultural productivity (in value terms). By crops, the SPI affected negatively the gross agricultural productivity (in value terms) of fruits, coffee, and to a lesser extent, vegetables. Additionally, the negative impact on livestock is larger from the SPI at twelve months rather than six months, as the SPI 12 months captures more serious droughts. An increase in one unit of the SPI (values larger than one define droughts and values larger than two an extreme drought) reduces the value of the gross agricultural productivity of fruits by 13.9%-16.9%, (statistically significant at the 10% level). Panel b) of Table 15 measures adaptation in different forms, either in the labor market, or by investments. A one unit increase in the SPI indices reduce the probability of doing agricultural work by 6.1 to 7.6 percentage points for the household at the 10% significance level, without affecting the other labor market outcomes. The SPI increases the land plots with access to own sources of water by 4.4%-6.4%, but not to external water. Once households face drought problems, they might try to find their own sources of water for the land and depend less on external sources, that could be more affected by droughts. Additionally, there are increases of investments (excluding housing) of the rural household on the plots by 9.3%-12.1%.

Table 15: Impact of SPI on main agricultural outcomes

a) Production

	Land (Ha) ln		Value prod. total (Millions Col. Pesos/Ha) ln				
	Crops (1)	Livestock (2)	Total (3)	Vegetables (4)	Fruits (5)	Cereals (6)	Coffee (7)
SPI 12 months (opposite)	-0.014	-0.076**	-0.104	-0.080	-0.094	0.102	-0.095*
	(0.022)	(0.027)	(0.076)	(0.057)	(0.055)	(0.090)	(0.048)
SPI 12 months (opposite)-agro season	-0.007	-0.100**	-0.099	-0.049	-0.169*	0.141	-0.094*
	(0.029)	(0.036)	(0.078)	(0.059)	(0.081)	(0.094)	(0.048)
SPI 6 months (opposite)	-0.013	-0.043*	-0.107	-0.113*	-0.018	0.062	-0.088*
	(0.014)	(0.024)	(0.069)	(0.063)	(0.035)	(0.085)	(0.047)
SPI 6 months (opposite)-agro season	-0.024	-0.057	-0.128	-0.028	-0.139*	0.101	-0.115**
	(0.022)	(0.039)	(0.092)	(0.081)	(0.073)	(0.116)	(0.049)
N	7902	7902	1770	1770	1770	1770	1770
r2	0.73	0.78	0.62	0.62	0.49	0.70	0.72
r2_a	0.56	0.64	0.29	0.29	0.04	0.45	0.49

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

b) Employment and Investment

	HH Head or partner work			Land Water (ha) ln			Land INV(ha) ln
	Employed (1)	Agro. (2)	Off-farm (3)	Any (4)	Own (5)	Ext. (6)	ANY no house (7)
SPI 12 months (opposite)	-0.025	-0.076*	0.033	0.024	0.044**	-0.012	0.093**
	(0.030)	(0.041)	(0.025)	(0.032)	(0.020)	(0.028)	(0.037)
SPI 12 months (opposite)-agro season	-0.014	-0.068	0.049	0.038	0.064**	-0.007	0.121**
	(0.038)	(0.050)	(0.035)	(0.057)	(0.023)	(0.051)	(0.049)
SPI 6 months (opposite)	-0.025	-0.061*	0.015	0.010	0.023	-0.014	0.054
	(0.021)	(0.031)	(0.018)	(0.017)	(0.017)	(0.019)	(0.044)
SPI 6 months (opposite)-agro season	-0.022	-0.074	0.025	0.027	0.031	-0.000	0.063
	(0.040)	(0.060)	(0.028)	(0.032)	(0.031)	(0.034)	(0.060)
N	7902	7902	7902	7902	7902	7902	7902
r2	0.66	0.64	0.49	0.76	0.71	0.61	0.55
r2_a	0.44	0.40	0.17	0.61	0.53	0.36	0.27

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: based on the ELCA panel survey 2010-2013. The standard errors (in parentheses) are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as agricultural problems of the household (except drought or other weather-related problems). It also includes controls for the dependency ratio in 2010, the age of the household head, a dummy for whether or not the household head is a woman, a dummy for whether or not the household has a credit in that year, a dummy at the community level for whether or not the access to the cabecera (center of the town) is reachable and in good shape, and the minutes to reach the cabecera for the community. High-temp is a dummy equal to one for the municipalities with average temperature higher than 27 Celsius degrees, and zero for the other municipalities. Each row corresponds to the coefficient estimated of the effect of the SPI index on the outcome variable in the column and are part of different estimations. The N, r2 and r2_a in each column corresponds to the estimations of the SPI in the first row but the explanatory power of the other estimations were almost the same when using the SPI agro season. In columns 3)-7) of Panel a), sample restricted to rural households producing uniquely crops (excludes livestock producers or those producing livestock and crops).

3F Balance tables Drought vs No Drought 2010

Table 16: Socioeconomic variables 2010 - Balance tables

	Sample: Drought-No drought 2010 as T vs C			
	(1)	(2)	(3)	(4)
Variable	No Drought	Drought	Diff	N
Dependency ratio (<=14 + >=65)/(15-64) Per. 2010	82.710	78.270	6.784	17
	(12.323)	(12.985)	(0.000)	
Age HH head	46.752	47.323	-4.045	17
	(2.894)	(2.528)	(0.000)	
Dummy women HH head	0.186	0.184	0.007	17
	(0.076)	(0.084)	(0.000)	
Percentage crops (DROUGHT problem)	0.234	0.358	0.271	17
	(0.187)	(0.241)	(0.000)	
Percentage crops (PEST problem)	0.282	0.284	-0.006	17
	(0.086)	(0.088)	(0.000)	
Percentage crops (BRUSH problem)	0.075	0.045	0.014	17
	(0.042)	(0.027)	(0.000)	
Percentage crops (RAIN problem)	0.041	0.034	-0.034	17
	(0.025)	(0.023)	(0.000)	
Percentage crops (SEEDS problem)	0.011	0.013	-0.004	17
	(0.008)	(0.013)	(0.000)	
Percentage crops (VANDALISM problem)	0.010	0.003	-0.004	17
	(0.013)	(0.003)	(0.000)	
Percentage crops (OTHER problem)	0.069	0.029	-0.012	17
	(0.107)	(0.023)	(0.000)	
Percentage crops (NONE problem)	0.506	0.462	-0.067	17
	(0.188)	(0.189)	(0.000)	
Land (ha) (OWNED)	2.337	1.831	0.712	17
	(1.330)	(0.600)	(0.000)	
Land (ha) (OWNED WITH TITLE)	1.830	1.256	0.702	17
	(1.051)	(0.384)	(0.000)	
PCA 1: HH WEALTH	0.177	0.190	0.003	17
	(0.078)	(0.051)	(0.000)	
PCA 1: HH (LIVESTOCK ASSETS)	0.063	-0.089	0.322	17
	(0.441)	(0.458)	(0.000)	
PCA 1: HH (AGR. ASSETS)	-0.186	-0.135	0.108	17
	(0.113)	(0.102)	(0.000)	
Dummy HH has credit	0.502	0.445	0.090	17
	(0.075)	(0.120)	(0.000)	
Dummy access cabecera is ok (community)	0.283	0.518	-0.378	17
	(0.305)	(0.177)	(0.000)	
Minutes to reach cabecera (community)	44.384	40.517	5.430	17
	(27.041)	(12.831)	(0.000)	
Observations	11	6	17	

Source: uses ELCA panel survey only for 2010. Standard errors (in parentheses) clustered at the municipality level m to account for the correlation in treatment within municipality. The estimations use the inverse weights of 2010 as recommended in the documentation of the ELCA survey. It controls for *region*, *year* and *municipality* fixed effects. Treatment and control are determined based on whether there was a drought in 2010 in the municipality of the household. It uses the variable "Dummy 1 or more months drought($<= -1$)(SPI12)" to define a drought in 2010. * p<0.10 ** p<0.05 *** p<0.01

Table 17: Agricultural variables in 2010 - Drought vs No Drought in 2010

	Sample: Drought-No drought 2010 as T vs C			
	(1)	(2)	(3)	(4)
Variable	No Drought	Drought	Diff	N
Agro sale (Millions Col. Pesos/Ha) ln	0.343	0.488	-0.341	17
	(0.192)	(0.234)	(0.000)	
Total Agro costs (Millions Col. Pesos/Ha) ln	0.425	0.484	-0.203	17
	(0.154)	(0.145)	(0.000)	
Percentage crops (YEARLY)	0.758	0.379	-0.219	17
	(0.210)	(0.086)	(0.000)	
Percentage crops (SEMIANNUAL)	0.132	0.392	0.261	17
	(0.121)	(0.193)	(0.000)	
Percentage crops (QUARTERLY)	0.037	0.146	-0.037	17
	(0.038)	(0.070)	(0.000)	
Percentage crops (MONTHLY)	0.034	0.066	-0.004	17
	(0.051)	(0.062)	(0.000)	
Percentage crops (BIMONTHLY-OTHER)	0.039	0.017	-0.000	17
	(0.054)	(0.012)	(0.000)	
Land size HH (Ha) ln	0.974	0.935	0.382	17
	(0.269)	(0.254)	(0.000)	
Total Area planted (Ha) (perman.+trans.+mixed) ln	0.380	0.441	0.313	17
	(0.114)	(0.192)	(0.000)	
Land PERMANENT crops (Ha) ln	0.178	0.200	0.145	17
	(0.122)	(0.160)	(0.000)	
Land TRANSITIONAL crops (Ha) ln	0.204	0.122	0.023	17
	(0.138)	(0.073)	(0.000)	
Land MIXED crops (Ha) ln	0.092	0.267	0.170	17
	(0.091)	(0.205)	(0.000)	
Land LIVESTOCK (Ha) ln	0.307	0.152	-0.056	17
	(0.246)	(0.103)	(0.000)	
Land PASTURE (Ha) ln	0.183	0.160	0.096	17
	(0.119)	(0.102)	(0.000)	
Land FOREST (Ha) ln	0.059	0.059	0.038	17
	(0.086)	(0.022)	(0.000)	
Land OTHER USES (Ha) ln	0.081	0.045	0.006	17
	(0.028)	(0.029)	(0.000)	
Land NO USED (Ha) ln	0.070	0.153	0.114	17
	(0.029)	(0.107)	(0.000)	
vr prodtot (Millions Col. Pesos/Ha of crops) ln	1.579	1.617	-0.582	17
	(0.504)	(0.554)	(0.000)	
vr prodtot-vegetable (Millions Col. Pesos/Ha of crops) ln	0.309	0.544	-0.527	17
	(0.361)	(0.387)	(0.000)	

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Variable	(1) No Drought	(2) Drought	(3) Diff	(4) N
vr prodtot-fruit (Millions Col. Pesos/Ha of crops) ln	0.248	0.179	0.144	17
	(0.229)	(0.125)	(0.000)	
vr prodtot-cereal (Millions Col. Pesos/Ha of crops) ln	1.053	0.824	-0.258	17
	(0.658)	(0.756)	(0.000)	
vr prodtot-coffee (Millions Col. Pesos/Ha of crops) ln	0.149	0.327	0.000	17
	(0.280)	(0.388)	(0.000)	
Tropical Livestock Units (FAO reference) ln	0.392	0.347	0.089	17
	(0.266)	(0.105)	(0.000)	
HH head-partner employed	0.362	0.347	0.036	17
	(0.110)	(0.185)	(0.000)	
HH head-partner look for job	0.242	0.234	0.135	17
	(0.109)	(0.098)	(0.000)	
HH head-partner agro work	0.207	0.254	0.069	17
	(0.106)	(0.186)	(0.000)	
HH head-partner no agro work	0.238	0.208	0.039	17
	(0.067)	(0.065)	(0.000)	
HH head-partner Ave. wage (Millions Col. Pesos) ln	-1.291	-1.091	-0.145	17
	(0.348)	(0.304)	(0.000)	
HH head-partner Ave. hours worked month	44.097	48.029	5.581	17
	(6.394)	(5.347)	(0.000)	
Land (ha) (ANY WATER) ln	0.617	0.497	0.019	17
	(0.281)	(0.270)	(0.000)	
Land (ha) (OWN WATER) ln	0.449	0.380	0.081	17
	(0.204)	(0.228)	(0.000)	
Land (ha) (EXTERNAL WATER) ln	0.206	0.147	-0.063	17
	(0.217)	(0.096)	(0.000)	
Land (ha) ANY INVEST ln	0.299	0.365	0.065	17
	(0.191)	(0.238)	(0.000)	
Land (ha) IRRIGATION INVEST ln	0.009	0.005	-0.009	17
	(0.012)	(0.007)	(0.000)	
Land (ha) STRUCTURES INVEST ln	0.051	0.067	0.010	17
	(0.052)	(0.083)	(0.000)	
Land (ha) CONSERVATION INVEST ln	0.052	0.019	-0.012	17
	(0.057)	(0.021)	(0.000)	
Land (ha) FRUITS INVEST ln	0.026	0.084	0.077	17
	(0.028)	(0.089)	(0.000)	
Land (ha) WOOD INVEST ln	0.010	0.039	0.000	17
	(0.009)	(0.041)	(0.000)	
Land (ha) COMMERC. INVEST ln	0.006	0.115	-0.004	17
	(0.009)	(0.125)	(0.000)	
Land (ha) HOUSING INVEST ln	0.117	0.047	-0.004	17
	(0.158)	(0.016)	(0.000)	

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Variable	(1) No Drought	(2) Drought	(3) Diff	(4) N
Land (ha) OTHER INVEST ln	0.063	0.056	0.008	17
	(0.046)	(0.026)	(0.000)	
Land (ha) ANY NO HOUSING INVEST ln	0.199	0.331	0.063	17
	(0.115)	(0.243)	(0.000)	
Dummy after moving to another comm inside mpio 2010	0.000	0.000	0.000	17
	(0.000)	(0.000)	(0.000)	
Observations	11	6	17	

Source: based on the ELCA panel survey 2010. The standard errors (in parentheses) are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010 as recommended in the documentation of the ELCA survey. It controls for *region*, *year* and *municipality* fixed effects. Treatment and control are determined based on whether there was a drought in 2010 in the municipality of the household. The statistics correspond to year 2010. It uses the variable "Dummy 1 or more months drought($<= -1$)(SPI12)" to define a drought in 2010. * p<0.10 ** p<0.05 *** p<0.01.

3G Effects on migration and heterogeneity with credit

Table 18: DID for 2010-2013-2016 for type of movement in the municipality

	Type of movement	
	Migrating outside Municipality (1)	Moving inside Municipality (2)
Drought 2010 ($<=-1$) (SPI12)xPost(2013)	-0.036	0.050
	(0.025)	(0.049)
Drought 2010 ($<=-1$) (SPI6)xPost(2013)	-0.027*	0.059**
	(0.013)	(0.025)
Drought 2010 ($<=-2$) (SPI6)xPost(2013)	-0.111***	-0.057***
	(0.009)	(0.017)
Drought 2010&2013 ($<=-1$) (SPI12)xPost(2016)	-0.001	0.119***
	(0.010)	(0.017)
Drought 2010&2013 ($<=-1$) (SPI6)xPost(2016)	-0.003	0.049*
	(0.007)	(0.023)
FE for Rural Household	No	Yes
N	8845	7902
r2	0.06	0.66
r2_a	0.06	0.44

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: based on the ELCA panel survey 2010-2013-2016. The standard errors (in parentheses) are clustered at the municipality level m to account for the correlation in treatment within municipality and the estimations use the inverse weights of 2010. Includes *region*, *year* and *municipality* fixed effects as well as agricultural problems of the household (except drought or other weather-related problems). The fixed effects for rural household are not included in the estimations of migration (column 1) as they washed out all the variability of the explanatory variables. It also includes controls for the dependency ratio in 2010, the age of the household head, a dummy for whether or not the household head is a woman, a dummy for whether or not the household has a credit in that year, a dummy at the community level for whether or not the access to the cabecera (center of the town) is reachable and in good shape, and the minutes to reach the cabecera for the community. Each row corresponds to the interaction of post-treatment and Drought using the SPI on the outcome variable in the column. Each row is part of different estimations. The N, r2 and r2_a in each column corresponds to the estimations of the drought measure in the first row but the explanatory power of the other estimations were almost the same when using the other ones.

Table 19: DID for Drought in 2010 on main agricultural outcomes - Heterogeneity having credit

a) Production

	Land (Ha) ln		Value prod. total (Millions Col. Pesos/Ha) ln				
	Crops (1)	Livestock (2)	Total (3)	Vegetables (4)	Fruits (5)	Cereals (6)	Coffee (7)
Drought 2010 (<=-1) (SPI12)xPost(2013)	-0.032	-0.004	0.148	-0.018	0.213	-0.308	0.177*
	(0.052)	(0.106)	(0.151)	(0.263)	(0.200)	(0.358)	(0.099)
Drought 2010 (<=-1) (SPI12)xPost(2013)xCredit	0.188**	0.124	-0.759**	-0.540*	0.022	-0.180	-0.090
	(0.069)	(0.076)	(0.263)	(0.285)	(0.133)	(0.254)	(0.130)
Drought 2010 (<=-1) (SPI6)xPost(2013)	0.021	-0.009	0.583	0.205	0.264	0.338*	0.156**
	(0.048)	(0.100)	(0.583)	(0.591)	(0.260)	(0.181)	(0.057)
Drought 2010 (<=-1) (SPI6)xPost(2013)xCredit	0.164***	0.143*	-0.390	-0.845	-0.014	-0.281	0.020
	(0.046)	(0.074)	(1.018)	(0.700)	(0.145)	(0.786)	(0.057)
Drought 2010 (<=-2) (SPI6)xPost(2013)	0.229***	-0.133***	0.071	-0.524***	-0.148**	0.431***	0.016
	(0.032)	(0.044)	(0.153)	(0.126)	(0.054)	(0.130)	(0.106)
Drought 2010 (<=-2) (SPI6)xPost(2013)xCredit	-0.121**	0.078	-0.256	1.051***	0.083	-0.125	-0.514***
	(0.055)	(0.046)	(0.150)	(0.165)	(0.104)	(0.128)	(0.065)
N	7902	7902	1770	1770	1770	1770	1770
r2	0.73	0.78	0.62	0.62	0.49	0.71	0.72
r2_a	0.56	0.64	0.29	0.29	0.04	0.45	0.48

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

b) Employment and Investment

	HH Head or partner work			Land Water (ha) ln			Land INV(ha) ln
	Employed (1)	Agro. (2)	Off-farm (3)	Any (4)	Own (5)	Ext. (6)	ANY no house (7)
Drought 2010 (<=-1) (SPI12)xPost(2013)	0.052	0.073	-0.046	0.015	-0.104	0.110	-0.198**
	(0.058)	(0.072)	(0.074)	(0.090)	(0.065)	(0.086)	(0.080)
Drought 2010 (<=-1) (SPI12)xPost(2013)xCredit	0.120	0.123*	0.062	0.354***	0.150	0.246**	0.161
	(0.078)	(0.059)	(0.109)	(0.081)	(0.091)	(0.100)	(0.189)
Drought 2010 (<=-1) (SPI6)xPost(2013)	0.125**	0.221***	0.050	-0.018	-0.058	0.027	-0.200**
	(0.053)	(0.044)	(0.105)	(0.078)	(0.077)	(0.080)	(0.094)
Drought 2010 (<=-1) (SPI6)xPost(2013)xCredit	0.090*	0.154***	-0.036	0.159**	0.024	0.182**	0.029
	(0.048)	(0.041)	(0.087)	(0.066)	(0.070)	(0.078)	(0.158)
Drought 2010 (<=-2) (SPI6)xPost(2013)	0.242***	0.423***	0.110**	-0.377***	-0.235***	-0.381***	-0.554***
	(0.043)	(0.058)	(0.038)	(0.068)	(0.076)	(0.048)	(0.071)
Drought 2010 (<=-2) (SPI6)xPost(2013)xCredit	0.071	-0.104**	-0.150***	0.654***	0.055	0.937***	0.506***
	(0.045)	(0.043)	(0.030)	(0.082)	(0.080)	(0.076)	(0.067)
N	7902	7902	7902	7902	7902	7902	7902
r2	0.66	0.63	0.49	0.76	0.71	0.61	0.55
r2_a	0.44	0.40	0.17	0.61	0.52	0.37	0.26

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: ELCA panel survey 2010-2013-2016. Standard errors (parentheses) clustered at the municipality level m. Using inverse weights of 2010. Includes *region*, *year*, *municipality* and *household* fixed effects as well as the same controls used in previous estimations (see section 4.2). Each row corresponds to the interaction of post-treatment and Drought in 2010 using the SPI on the outcome variable in the column. Each row is part of different estimations. N, r2 and r2_a in each column from the first drought measure estimations. In columns 3)-7) of Panel a), sample restricted to rural households producing uniquely crops (excludes livestock producers or those producing livestock and crops).