Within Growing Season Weather Variability and Land Allocation Decisions: Evidence from Maize Farmers in Ethiopia*

Musa Hasen Ahmed[1], Wondimagegn Mesfin Tesfaye[2], and Franziska Gassmann[1]

[1]UNU-MERIT, Maastricht University, Netherlands

[2]World Bank Groups, Ethiopia

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Abstract: We investigate if and how farmers adjust their land allocation decisions in response to within-growing season weather variability using novel crop-specific data collected over seven consecutive years. By focusing on maize-producing smallholder farmers in Ethiopia, we show that farmers respond quickly to growing season weather variability by adjusting their land allocation decisions. In addition to quantifying a substantial adaptation margin that has not been documented before, our findings also reveal the presence of a weather variability-induced expansion of maize production into areas that are less suitable for maize cultivation.

Keywords: Weather variability, Adaptation, Land allocation, Crop substitution

JEL Classification: Q1, Q15, Q24, Q54, C33

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1 Background and Motivation

As climate models project warmer and more variable futures, studies revealing its socio-economic impacts, including the adverse effects on the agricultural sector under different scenarios, have been accumulating (Chen and Gong, 2021; Lobell et al., 2008; Hsiang et al., 2017; Costinot et al., 2016; Schlenker and Roberts, 2009; Chen et al., 2016). This calls for improving farmers' adaptive capacity and a better understanding of their adaptation techniques. Particularly, understanding how farmers respond to shocks that occur close to the planting season provides valuable information to design policies that enhance adaptive capacity and prevent long-lasting welfare losses (Jagnani et al., 2021; Ramsey et al., 2020).

This being the case, the great bulk of existing studies concentrates on farmers' responses to climate knowledge acquired over the long term. Since the majority of farm management decisions are made based on weather expectations before the actual events are realized, and because such subjective predictions are heavily influenced by prior weather experience, investigating the role of climate knowledge gained over time provides valuable inputs for policy formulations. However, both economics and psychology literature (e.g., Ji and Cobourn (2021); Camerer and Loewenstein (2011)) argue that recent realizations of an event can have a disproportionately larger influence on expectations. As a result, understanding how farmers react to short-term weather variability is essential to thoroughly understand the nexus between weather variability and farmers' adaptation strategies.

A few recent empirical studies have looked at farmers' responses to short-term weather variability. Jagnani et al. (2021) show that Kenyan farmers adjust their input use decisions in response to temperature variations that happened during the initial cropping cycle. Relatedly, Cui and Xie (2022) show farmers in China adjust their planting dates based on weather conditions realized eight weeks before the actual planting period. We aim to contribute to this growing area of research by providing the first causal estimate on the impacts of initial planting season weather patternson land allocation decisions.

Specifically, by disaggregating the climate variables into initial planting and planting stages of the crop growing cycles, we analyze to what extent smallholder farmers in Ethiopia adjust land allocation decisions in response to plausibly exogenous temperature variation realized before the actual planting time.

Ethiopia provides an appealing setting for this research. Weather variability is a recurring phenomenon in the country, and rain-fed agricultural activities constitute the single most important source of income for virtually all households residing in rural areas of the country. As a result, rural livelihoods in the country are highly vulnerable to weather fluctuations. The availability of one of the world's largest yearly detailed agricultural surveys also presents a unique opportunity. Specifically, we use Ethiopia's Annual Agricultural Sample Survey that covers entire farming communities of the country.

In the literature, numerous studies investigate the role of weather variability on land allocation decisions. Among them, He and Chen (2022), Morton et al. (2006), Zaveri et al. (2020), Li et al. (2013), Mu et al. (2018), Zaveri et al. (2020) and Lungarska and Chakir (2018) explain how the share of cropland, forest, and grazing land vary due to weather variability. Though these studies provide pertinent information regarding the role of weather patterns on land allocation decisions, they defined land-use decisions broadly by aggregating land covered by all crop types as a single variable. However, since each crop has its unique optimal heat and moisture requirement, the impacts of weather variability might be disproportionately stronger for some crops and might encourage farmers to reallocate resources to crops that suit better current weather conditions (Arora et al., 2020).

Among crop-specific studies, Cui (2020) discover that growing season climate change, measured by historical data over the past 30 years, significantly affects land allocation decisions of maize farmers of the United States. However, Cui (2020) reflects farmers' reactions to long-term climate change rather than weather variability that occurred around the planting seasons. Miao et al. (2015) demonstrate how excessive rainfall during planting season discourages farmers in the United States from growing maize. Other studies like Seo and Mendelsohn (2008), Kurukulasuriya and Mendelsohn (2008), and Moniruzzaman (2015) explore the relationship between crop choice and climatic variables by relying on cross-sectional data. However, results from cross-sectional analyses are vulnerable to omitted variable bias and do not permit establishing a causal link between weather variability and agricultural outcomes (Blanc and Schlenker, 2017).[1]

We contribute to the literature in the following aspects. First, we provide a causal estimate of the impact of temperature variation realized before the actual planting time on land allocation decisions by focusing on maize-producing smallholder farmers in Ethiopia. We combine village-level panel data from more than 36,000 farmers gathered over seven years with high-resolution weather data to obtain accurate weather variability indicators that are comparable across time and space. Second, we investigate the role of the natural endowment on farmers' adaptation decisions. Geographical factors like environmental suitability for a given crop could have a differential impact on farmers' adaptation strategies. For example, if maize is the best crop for a specific region, producers may choose to use modern technology such as drought-resistant varieties rather than abandon the crop during unfavorable weather conditions. Drier conditions during the planting seasons might also lead to the expansion of drought-tolerant crops such as maize into less suitable areas. On the other hand, areas that are more suitable for maize production may not have additional land that has to be converted into maize production if they have already allocated their land for maize production. We examine if farmers' response to within-growing season weather variability depends on the suitability of the fields for maize production using the FAO-GAEZ suitability database that reports the productivity potential of a given area for different crops.

To causally identify the impacts of the initial growing season weather variability, our

[1]In addition to studies that investigate the role of weather variability on land allocation decisions, some studies have also looked at the role of the price (e.g.: Haile et al. (2014, 2016); Hendricks et al. (2014)), access to insurance (e.g.: Wu (1999); Yu et al. (2018)), competition with other enterprises (e.g.: Wang et al. (2020); Li et al. (2019); Gardebroek et al. (2017); Motamed et al. (2016)) and access to irrigation water (Manning et al. (2017); Taraz (2017)).

identification strategy makes use of an exogenous year-to-year weather variation within rural villages. Our identification is plausible because farm households are not expected to precisely predict weather conditions for the upcoming growing season across time and space (Deschênes and Greenstone, 2007; Burke and Emerick, 2016).

Our results show that farmers adjust their land allocation decisions due to within growing season weather variability. More specifically, we document that after absorbing the effects of village level fixed effects as well as time-varying region level characteristic along with other factors, a 1°C in the pre-planting season increases the size of land allocated to maize production by 14.8 percent. To the best of our knowledge, this adaptation margin of adjustment to initial growing season weather variability has not been documented before. We show that a portion of the increase in the size of land allocated to maize production is achieved by replacing other crops. We also present suggestive evidence that shows the presence of weather variability-induced expansion of maize production into areas that are less suitable for maize production. To guarantee the robustness of our findings, we run them through a variety of tests. We confirm that the findings are not confounded by the previous year's growing season weather conditions or own price. We also employed a spatial panel data model to account for geographical and temporal effects.

The remaining sections of the paper are organized as follows. Section two discusses the socioeconomic importance of maize in Ethiopia and the mechanisms through which weather variability affects maize production and farmers' resource allocation decisions. A detailed description of the sources and types of data used in the analysis are presented in section three. The fourth section discusses the methodological strategy employed in the study. The fifth section presents and discusses the findings of the study, and the final section concludes.

2 Profile of Maize in Ethiopia

Maize is one of the dominant crops in Ethiopia both in terms of production volume and the number of farmers engaged in cultivating it. Recent figures from the Central

Statistics Agency of Ethiopia (CSA) show that out of 15.05 million cereal-farming households in the country, 10.57 million grow maize on 2.1 million hectares of land. The crop accounts for one-third of the overall grain production in the country (Central Statistical Agency of Ethiopia, 2019, 2018). Estimates also show that smallholder farmers in the country allocate at least half of their farmland to maize production in major growing areas (Ertiro et al., 2019). As shown in figure 1, maize is produced in wider regions of the country. Its adaptability, the growing demand for strove, and ability to give more calories and food per cultivated land[2] are some of the reasons that have contributed to its popularity in the country (Abate et al., 2015).

FAOSTAT shows that maize production in the country increased five-folds between 1993 and 2018. The country has relatively good productivity records compared with the averages of Africa in general and Eastern Africa in particular (Figure 2). However, the productivity gap between Ethiopia and the global average or other country groups is very high. Low levels of technology adoption, poor access to input and financial markets, and frequent weather variability are among the main factors for such low productivity levels (Marenya et al., 2020; Kassie et al., 2018; Croppenstedt et al., 2003).

Though maize is considered a suitable crop for warmer conditions, several studies show that the crop is also sensitive to water shortage and heat stress (Srivastava et al., 2018; Schlenker and Roberts, 2009; Lobell et al., 2011). Lobell et al. (2011), for instance, shows that a one degree Celsius of warming in Africa will result in a significant yield loss for 65 percent of maize-growing areas in the continent, even under optimal rain-fed conditions.[3]

The effects of weather variability on maize productivity depend on timing and intensity. For instance, Seyoum et al. (2017) show that drought that occurred in the early stages

[2]The daily per capita fat, calories, and Protein contribution of maize in the Ethiopian diet have already reached 1.31g, 398kcal, and 9.2g, respectively FAOSTAT (2020)

[3]Surprisingly, Deschênes and Greenstone (2007) found that short-run weather variability has no significant impact on both agricultural yield and farm profit in the United States. However, Fisher et al. (2012) revealed that this unexpected finding is primarily due to data management and estimating errors, and after correcting these flaws, they discovered a negative relationship between climatic variability and agriculture using the same dataset.

reduces yield by up to 80%, whereas the yield reduction associated with droughts that began after the flowering period is about 10%. This is partly associated with the fact that high temperatures during the early stages affect kernel development by limiting the number and size of endosperm cells. Likewise, adverse weather conditions during the seedling and vegetative stages can also affect maize growth by limiting growth rate, delaying canopy closure, and reducing soil shading (Commuri and Jones, 2001; Engelen-Eigles et al., 2000).

3 Data

The study compiles datasets from different sources: The Annual Agricultural Sample Survey of the Central Statistics Agency of Ethiopia (CSA), the Land Suitability Index from the FAO-GAEZ database, and weather data from various sources.

The study uses Ethiopia's Annual Agricultural Sample Survey (AgSS) as the main source for the outcome and control variables, which is an annual agricultural sample survey that covers over 36,000 private farm holders, making it one of the world's largest annual agricultural surveys (Mann et al., 2019). The AgSS data collection process involves a stratified two-stage sampling technique. In the first stage, around 2000 enumeration areas (EAs) are selected using sampling probability proportional to the number of farm households obtained from the most recent Population and Housing Census Frame that exists in the country. This stage is followed by the selection of about 20 agricultural households from each sample EA using random sampling. Starting from 2010, CSA has adjusted its sample selection process. Accordingly, the same EAs are used in each consecutive survey year, but households are re-sampled every year. Using this opportunity, a panel dataset is constructed by aggregating values at the EA level. This created a balanced panel sample comprising 1,815 EAs over the period 2010-16.[4] Figure 1 depicts the location of the study villages. Figure 3 depicts the location of the study villages (EAs).

[4]Detailed sampling procedure can be found on the agency's website at http://www.statsethiopia.gov.et/

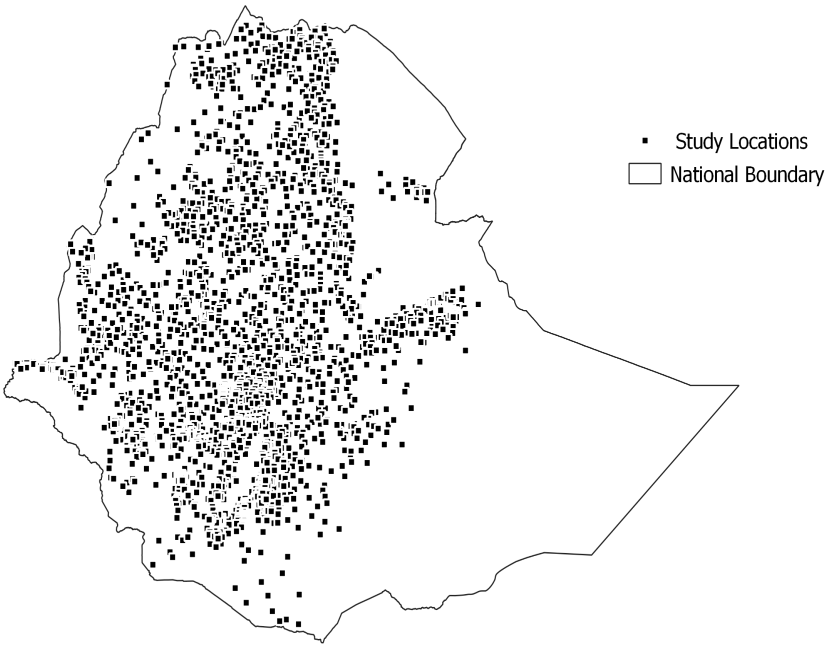

Figure 1: Location of the sampled areas
Note: The survey covers all parts of the country except some parts of Afar and Somali regional states, which are located in the northeast and southeast of the country. Households in the excluded area are pastoralists and they do not have a sedentary way of life.

The main variables of interest for this study is temperature. Daily temperature data is obtained from the ERA-Interim Reanalysis archive.[5] The data set has a 0.25x0.25 degree resolution. From the the daily temperature observations, aggregate weather indicators are constructed for two stages of the crop growth cycle for each survey period. The two stages are (1) the planting and fertilizer application period, which covers 60 days after the beginning of the planting date, and (2) the initial planting stages (or pre-planting period), which accounts for the land preparation period and covers 60 days before the planting days.[6] The two stages are constructed based on the crop-planting calendar accessed from the Nelson Institute for Environmental Studies of the University of Wisconsin-Madison (Sacks et al., 2010).

[5]Meteorological data can also be accessed from the Ethiopian Meteorological Service. However, the number of missing observations or values reported as zero on days when no records are made creates a significant empirical problem(Colmer, 2019). In particular, since the construction of our weather variables requires daily records, a complete list of observations is essential.

[6]The stages are constructed following earlier studies like Jagnani et al. (2021).

To investigate the role of land suitability for maize production on farmers' responses to weather variability, we utilize the FAO-GAEZ dataset.[7] FAO-GAEZ calculates the suitability of a given field for a particular crop by predicting the maximum attainable yields using agronomic models and three main inputs. These inputs are (1) crop attributes (mainly estimated through field experiments), (2) physical attributes (including soil characteristics, elevation, and land gradient), and (3) assumptions about the level of modern inputs utilization. We use the maize suitability index constructed for rain-fed farming with the assumption of low inputs utilization. Figure 2 presents the index extracted for Ethiopia. By taking the national average production potential as a threshold, we categorize EAs into two groups: suitable and less suitable EAs. Table A1 provides the descriptive statistics for the potential yields along with other working variables.

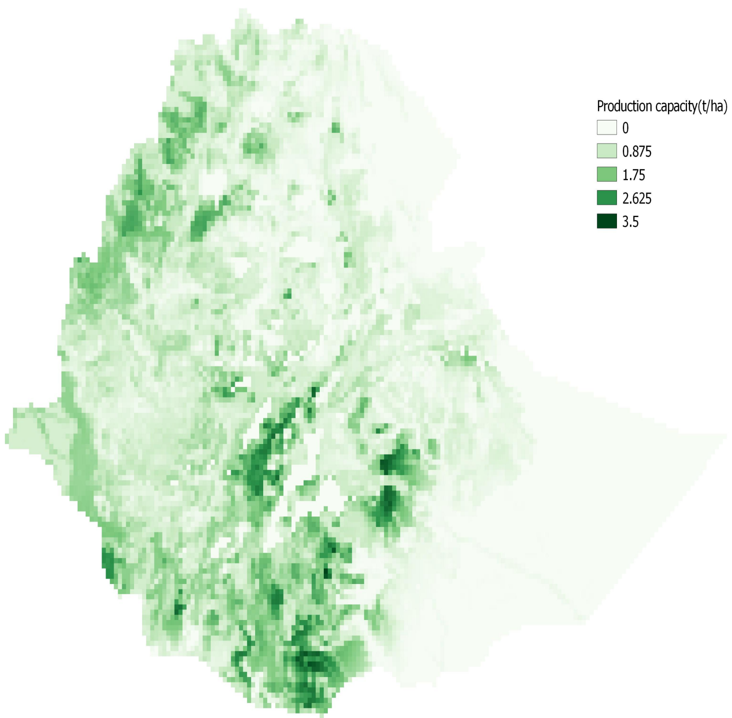

Figure 2: Maize production capacity: *Source FAO/IIASA*

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[7] The FAO-GAEZ is also used by Bustos et al. (2016); Nunn and Qian (2011) and Costinot et al. (2016).

4 Estimation Strategy

The following panel fixed effects estimation is used to causally identify how temperature variation realized prior to normal planting time influences actual agricultural land allocation decisions:

$$Y_{rdvt} = \beta_i[Temp]^{pp}_{rdvt} + \gamma_i[Temp]^{pt}_{rdvt} + \theta X_{rdvt} + \alpha_v + \varphi_{rt} + \varepsilon_{rdvt} \tag{1}$$

Y_{rdvt} is the dependent variable that represents the size of cultivated land covered by maize (in hectare) in a given region r, district d, village v, and time t. $Temp$ stands for average daily temperature in a given season measured in °C (We also use alternative definitions as a robustness exercise). The superscript pp and pt represent pre-planting (initial) and planting seasons, respectively. β is our parameters of interest. α_v controls for village fixed effects and φ_{rt} accounts for unobservables that vary across regions over time and are expected to absorb the effects of any shock that is explicit to a given region in any given year. X stands for EA-level time-varying controls (e.g., EA level averages of the ages of the household heads, family size, access to credit, level of irrigation utilization, and oxen size). Rainfall conditions around the planting period are undoubtedly among the most crucial factors expected to influence farmers' resource allocation decisions in countries like Ethiopia, where the vast majority of farmers do not have access to irrigation. Hence, we control rainfall using data accessed from the Climate Hazards Group InfraRed Precipitation Station (CHIRPS) (Funk et al., 2015). The dataset has 0.25x0.25 degree resolution. We follow the recommendations of related studies (e.g., Fishman (2016); Kassie et al. (2014) and Lobell and Asseng (2017)) and used Wet Days Frequency to control both the amount and distribution of rainfall.

We also investigate whether the effect of weather variability on land allocated for maize is realized through substitution with other crops. This is done by examining the effects of within-growing season weather variability on land allocated to maize relative to another crop. This helps to understand how weather variability affects the comparative advantage of maize compared with other crops (Cui, 2020). The regression equation used to address this objective is given in equation 2.

$$(\frac{L_M}{L_M + L_O})_{rdvt} = \; = \beta_i [Temp]^{pp}_{rdvt} + \gamma_i [Temp]^{pt}_{rdvt} + \theta X_{rdvt} + \alpha_v + \varphi_{rt} + \varepsilon_{rdvt} \qquad (2)$$

where L_M and L_O stand for the size of land allocated for maize and a specific alternative crop, respectively. We focus on major crops (e.g., barley, teff, wheat, etc. as shown in Table A1 and 6). All remaining variables and other terms follow equation 3.

In estimating the above equations, there could be spatial interactions across neighboring locations of the study area, and failing to account for such interactions may lead to biased and inconsistent estimates (LeSage, 1997; Fisher et al., 2012).[8] For instance, the land allocation decisions of neighboring EAs (our dependent variable) could spatially be correlated since they might share similar geographic attributes (like soil fertility status) and input and output markets.[9] Similarly, the extrapolation techniques used to generate gridded and reanalyzed climate data can create a spatial correlation between the climate variables (our independent variables) (Auffhammer et al., 2013). Studies also show that rainfall at a given location could be correlated with rainfall received in the neighboring areas (Maccini and Yang, 2009). Spatial correlation might also arise due to spatial correlation of the error terms due to confounding variables in omitted climatic measures (Auffhammer and Schlenker, 2014).

In principle, the empirical model has to control for spatial interactions from all three sources (dependent and independent variables and error terms) to produce unbiased and consistent estimates. However, the problem of over-fitting makes it difficult to use models that can effectively control the interactions from the three sources in applied research (Elhorst et al., 2014). Studies such as Elhorst et al. (2014); Harari and Ferrara (2018), and Mamo et al. (2019) argue that the parameters of the spatial model can be identified without facing the problem of over-fitting by controlling for spatial correlation in the independent and dependent variable using the Spatial Durbin Model

[8]The possible sources of interactions are interactions in one or a combination of the dependent variables, regressors, or error terms across locations (Anselin, 2001).

[9]This fact is empirically verified by Miao et al. (2015).

(SDM) and by accounting for spatial dependence in the error term through clustering the standard errors. Hence, as a robustness check, we use Stata's *xsmle* package produced by Belotti et al. (2017) to estimate the impacts of temperature variation on land allocation decision using the Spatial Durbin Model.

5 Results and Discussion

5.1 The effects of growing season weather variability on the size of land allocated for maize production

Table 1 presents the estimated effects of average temperature realized during eight weeks before the planting season. As seen in column 1, temperature in the initial growing season have a significant impact on farmers' land allocation decisions. More specifically, it shows that after absorbing the effects of EA fixed effects as well as time-varying region level characteristic along with other factors, a 1°C in the pre-planting period increases the size of land allocated to maize production by 14.8 percent. Related studies like He and Chen (2022) and Miao et al. (2015) show that farmers modify their land allocation decisions based on the planting season weather conditions. As a result, we re-estimate the impacts by adding the average daily temperature of the growing season as an additional regressor to see if the estimated effect of the pre-planting weather condition is absorbing the effects of growing season weather conditions. As shown in column B of the table, the effects of pre-planting season temperature remain statistically significant affect controlling the growing season average temperature.

The relation between higher temperature levels and maize production could be because of the nature of the crop. Maize is considered a drought-tolerant crop. Warming temperatures are expected to boost staple crop production, including maize, by facilitating photosynthetic processes (Jagnani et al., 2021). Furthermore, as shown in Figures 3 and 4, the average daily temperatures in the study area throughout the study period were mostly within the range over which maize yields generally increased as temperatures rose (Lobell et al., 2011). Studies like Seo and Mendelsohn (2008)

Table 1: Estimated Impacts of Average Temperature on Maize Land Allocation

VARIABLES	Maize land (log)	Maize land (log)
Temp Pre-Planting	0.148***	0.140***
	(0.037)	(0.041)
Temp Planting		-0.031
		(0.038)
Rainfall control	Yes	Yes
Other control	Yes	Yes
Region year fixed effects	Yes	Yes
EA fixed effect	Yes	Yes
Observations	12,705	12,705
R-squared	0.864	0.865

Note: The table presents the effects of within growing season weather conditions (captured by average daily temperature) on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop. Temp: average daily temperature; EA-level controls included in the analysis are the age of the household head, family size, number of oxen owned, and access to credit, extension service, and irrigation. we use Wet Days Frequency to control both the amount and distribution of rainfall in both seasons. Standard errors clustered at district level in parentheses; *** p<0.01.

and Wang et al. (2010) also show that farmers tend to grow maize as temperatures get warm.

The other reason for this relationship might be linked with the recent progress made in improving the accessibility of drought-tolerant maize varieties in the country. For instance, as of 2016, about 9000 tons of certified drought-resistant maize variety, known as BH661[10] was distributed in the country and the seed had covered 18 percent of maize land in the country (Ertiro et al., 2019).

5.2 Robustness checks

5.2.1 Incorporating additional controls

In this subsection, we examine the robustness of the results presented in Table 1 by incorporating past weather variables and own price.

Because most farm management decisions are made based on expectations about fu-

[10]The cultivation of the BH661 variety for commercial farming is officially approved by the National Variety Release Standing Committee in 2011.

ture weather conditions, past weather conditions substantially influence farmers' decisions. Studies like Ji and Cobourn (2021) show that land allocation decisions of farm households are affected by the lagged weather condition. Hence, a robustness check is conducted to check whether the results could be confounded by the previous year's growing season weather conditions. Column (1) of Table 2 provides the result estimated by including one year lagged planting season weather patterns.

Table 2: Robustness of the Result: Additional Controls

	(1)	(2)	(3)
VARIABLES	Maize land (log)	Maize land (log)	Maize land (log)
Temp Pre-Planting	0.192***	0.126***	0.141***
	(0.042)	(0.041)	(0.041)
Lagged Temp Planting	Yes	No	No
Lagged average price	No	Yes	No
Future price	No	No	Yes
Other controls	Yes	Yes	Yes
Region year fixed effects	Yes	Yes	Yes
Planting season Temp	Yes	Yes	Yes
Rainfall control	Yes	Yes	Yes
Constant	-10.55***	-3.950***	-2.868***
	(1.315)	(1.008)	(1.014)
Observations	12,705	12,705	12,705
R-squared	0.872	0.865	0.865

Note: the dependent variable is the log value of land under maize crop. Standard errors clustered at district level in parentheses; See notes under Table 1 for additional information such as the list of control variables. *** p<0.01.

In the main results presented in Table 1, the region year interactions are used to control price effects at the regional level. Here, the strength of the results is tested by incorporating own price measured from the nearest market. Among existing studies that estimated the effects of price on land allocation decisions, Chavas and Holt (1990) and Lee and Helmberger (1985) used one-year lagged prices, whereas Lin and Dismukes (2007) relied on future prices. The consistency of the result is tested by incorporating both one-year lagged and future prices. Columns (2) and (3) of Table 2 present the results.[11] As shown in the Table, the results of the main regression equation remains

[11]The average lagged and future prices are calculated at the closest market using monthly food price data obtained from the market monitory survey of the WFP. The price data is accessed from

qualitatively identical in all robustness checking exercises.

5.2.2 Alternative temperature measures

Different temperature metrics may indicate different elements of climate impacts and relying just on average temperatures may overlook other factors Cui and Xie (2022). For example, degree days, which are a measure of cumulative heat, have been used by both agronomic and economic literature (e.g., Lobell et al. (2011); Schlenker and Roberts (2009); Schlenker et al. (2006)) to illustrate the link between temperature and agricultural productivity. Even though we are not directly analyzing the impacts on agricultural productivity, we use degree days as an alternative indicator for a robustness test. GDD is calculated as the intensity of daily exposure to a defined upper and lower temperature ranges at which heat and cold stresses are expected to begin and impede plant growth (Roberts et al., 2013). Related works consider 8°C and 30°C as the lower and upper thresholds in calculating GDD. Table 3 shows the estimated effects of degree days on farmers' land allocation decisions. We show qualitatively identical result with the results of the main regression equation, and the size of the effects is not significantly different. The result shows that each additional degree day equates to a 14% increase in the size of land dedicated to maize farming. We also present additional robustness test results in the appendix (Table A2-A4) that include changing the definitions of our main working variables.

5.2.3 Accounting for spatial interactions

As we discussed in the methodology section of this paper, failing to account for spatial interactions properly can lead to biased estimates. As a result, we use the spatial panel regression model to evaluate the effects of pre-planting season weather conditions on land allocation decisions in our next robustness check. The results are presented in Table 4. As can be seen from the Table, the findings of the main regression equation remain qualitatively unaffected.

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https://dataviz.vam.wfp.org/economic_explorer/prices

Table 3: Robustness of the Result: Alternative Weather Definition

VARIABLES	Maize land (log)
GDD Pre-Planting	0.141***
	(0.040)
GDD Plant	Yes
Rainfall control	Yes
Other control	Yes
Region year fixed effects	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.865

Note: the dependent variable is the log value of land under maize crop. GDD: Degree days computed by considering 8°C and 30°C as the lower and upper thresholds. For comparison, we used daily averages of Degree days; Standard errors clustered at district level in parentheses; See notes under Table 1 for additional information such as the list of control variables. *** $p<0.01$.

Table 4: Robustness of the result: Accounting for the Spatial Interactions

VARIABLES	Maize land (log)
Temp Pre-planting	0.190***
	(0.046)
Temp Planting	Yes
Rainfall control	Yes
Other control	Yes
Region year fixed effects	Yes
EA fixed effect	Yes
Observations	12,705

Note: the dependent variable is the log value of land under maize crop. We use Stata's *xsmle* package produced by Belotti et al. (2017) to obtain the estimates of the above Spatial Durbin Model. Standard errors clustered at district level in parentheses; See notes under Table 1 for additional information such as the list of control variables. *** $p<0.01$.

5.2.4 Falsification test

We used a falsification test to see if the impacts of pre-planting temperature variation on land allocation decisions are masked by time-varying unobservables. We follow Sesmero et al. (2018) and re-estimate our main model by changing the timing of weather data. Accordingly, we re-estimate Table-1 by replacing our pre-planting season temperature with future planting season temperatures (by one wave). If mismatched weather data fails to explain the land allocation decision, it suggests that unobserved factors are unlikely to confound the effect of pre-planting weather conditions reported in our main result. As shown in Table 5, the coefficient of the mismatched weather variable is not statistically significant.

Table 5: Robustness of the Result: Placebo Regression

VARIABLES	Maize land (log)
fTemp Plant	-0.043
	(0.030)
Rainfall control	Yes
Other control	Yes
Region year fixed effects	Yes
EA fixed effect	Yes
Observations	12,705

Note: The table presents the effects of future average temperature (fTemp_plant) on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop. Standard errors clustered at district level in parentheses; See notes under Table 1 for additional information such as the list of control variables.

5.3 Weather variability and crop substitutions

After examining the effects of pre-planting weather conditions on maize growers' land allocation decisions, we fit equation (2) to see if crop substitution effects partially explain the change in the size of maize fields. The findings indicate the presence of crop substitution effects caused by within-growing season weather variability. It shows that higher temperatures during the initial planting period increase the share of land covered by maize relative to other alternative crops such as barley, sorghum, teff and oilseed (Table 6). It is worth emphasizing that if changes in the growing season weather patterns affect both maize and the alternative crops to a similar extent, no effect would be observed.

Among existing studies, Cui (2020) shows that a 0.1°C increase in past temperature increases land allocated to maize and soybean by up to three percent relative to wheat, while the work of Wang et al. (2010) showed that warm temperature encourages maize production but discourages the production of soybeans and vegetables.

Table 6: Effect of Weather Variability on Crop Substitution

VARIABLES	Barley	Sorghum	Teff	Wheat	Pulse	Oilseed
Temp Pre-Planting	0.015**	0.016*	0.017***	0.008	-0.006	0.0193**
	(0.006)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)
Temp Planting	Yes	Yes	Yes	Yes	Yes	Yes
Rainfall control	Yes	Yes	Yes	Yes	Yes	Yes
Other control	Yes	Yes	Yes	Yes	Yes	Yes
Region year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
EA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,705	12,705	12,705	12,705	12,705	12,705
R-squared	0.823	0.744	0.810	0.848	0.838	0.703

Note: The dependent variables are the share of land covered by maize relative to the alternative crops. Standard errors clustered at district level in parentheses; See notes under Table 1 for the list of other control variables. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.4 Heterogeneous effects based on soil suitability

The result of the heterogeneous effects of land suitability on farmers' responsiveness to pre-planting season weather conditions is presented in Table 7. The result shows that adjusting the size of land allocated to maize production due to pre-planting season weather variability is more pronounced in areas that are less suitable for maize production. This could be due to the fact that areas better suited for maize cultivation may not have more land available for conversion to maize production if the land has already been allocated for maize production. Another explanation could be that as a result of drier conditions, farmers may move to the production of drought-tolerant crops like maize, which could lead to the expansion of maize in less suitable areas. However, it is also worth noting that classifying a given area as less suitable for maize production does not imply that maize has lesser comparative advantages in that particular area. It can also imply that the field is less fertile for other types of crops as well.

The study demonstrates the feasibility of expanding maize production into new areas to adapt to changing weather patterns. A recent study by Sloat et al. (2020) shows how rain-fed maize production migrated to areas that were not major produces due to climate change. Similarly, Skarbø and VanderMolen (2016) document the expansion of maize production practices towards higher altitudes due to climate change.

Table 7: Heterogonous Effect Based on Land Suitability

VARIABLES	Maize land (log)	Maize land (log)
Temp Pre-Planting	0.159***	0.149***
	(0.0397)	(0.0433)
Suitable for maize #Temp Pre-Planting	-0.0224	-0.0185
	(0.0415)	(0.0414)
Temp Planting	No	Yes
Rainfall control	Yes	Yes
Other control	Yes	Yes
Region year fixed effects	Yes	Yes
EA fixed effect	Yes	Yes
Constant	-4.072***	-3.207***
	(0.751)	(0.945)
Observations	12,705	12,705
R-squared	0.864	0.865

Note: The dependent variables are the share of land covered by maize relative to the alternative crops. Standard errors clustered at district level in parentheses; See notes under Table 1 for the list of other control variables. *** p<0.01, ** p<0.05, * p<0.1.

6 Conclusion

The recent literature on the impacts of climate change and weather variability on agriculture predominately focuses on estimating the impacts on crop yields, and many of them have documented adverse effects. Another popular research theme within climate economics literature is the study of farmers' adaptation to climate change. This paper contributes to this strand of the literature by examining the effects of within-growing season weather pattern changes on land allocation decisions of farmers by focusing on Ethiopian maize producers.

Our results demonstrate that farmers promptly adjust their land allocation decisions to adapt to within-growing season weather variability. More precisely, we show that initial growing season drier conditions encourage maize production. The results also reveal that the increase in the size of land allocated to maize production is partly achieved through substitution with other crops. We also provide suggestive evidence that shows the presence of weather variability-induced expansion of maize production into areas less suitable for maize production. The findings of the study have several policy implications.

By estimating the effects of within-growing season weather variability on farm households' land allocation decisions, we have documented a notable adaptation margin that has been overlooked in the previous studies. The findings highlight the importance of including short-run responses in climate change research. Hence, the results help to better understand the impacts of climate change and variability on agricultural output and the effectiveness of adaptation investments because neglecting such adaptation margins could lead to biased estimates.

It is also vital to underscore the fact that farm households' decision to expand maize production to confront dryness might be at the cost of crop rotation. Studies show that crop rotations improve farm profit by reducing crop losses due to disease and pests and maintaining soil fertility (Cai et al., 2013). In addition, the expansion of maize into less suitable areas might have implications for farm productivity. As a result, future research may look at the effects of such adaptation strategies on farm productivity and profitability.

Improving the accessibility of micronutrient-rich foods by diversifying farm production has recently drawn attention to achieve food and nutrition security (Sanchez et al., 2020; Poole et al., 2021). Hence, as land reallocation changes the amount of land devoted to a particular crop, it can have an implication on the type and amount of food produced and supplied to the market. Notably, for developing countries like

Ethiopia, where a significant share of food mainly comes from domestic production with little import, weather variability-induced reallocation of land can dictate the types and amount of food that is available and accessible for the population. As a result, the substitution of cash crops by staple crops like maize to withstand weather variability might have implications for farm households' market participation and diet quality. This might underscore the importance of investing in the production and distribution of drought-resistant seeds for high-value crops.

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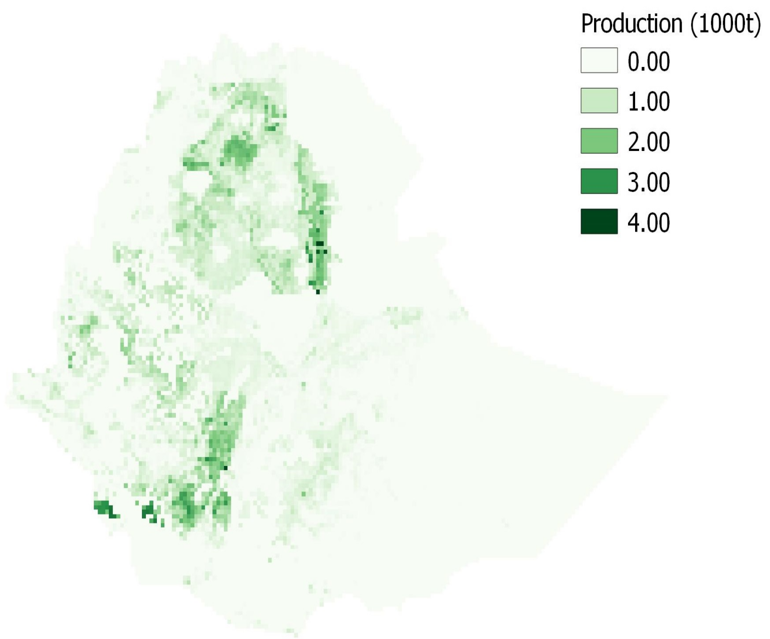

Figure 1: Maize Production areas in Ethiopia: *Source FAO/IIASA*

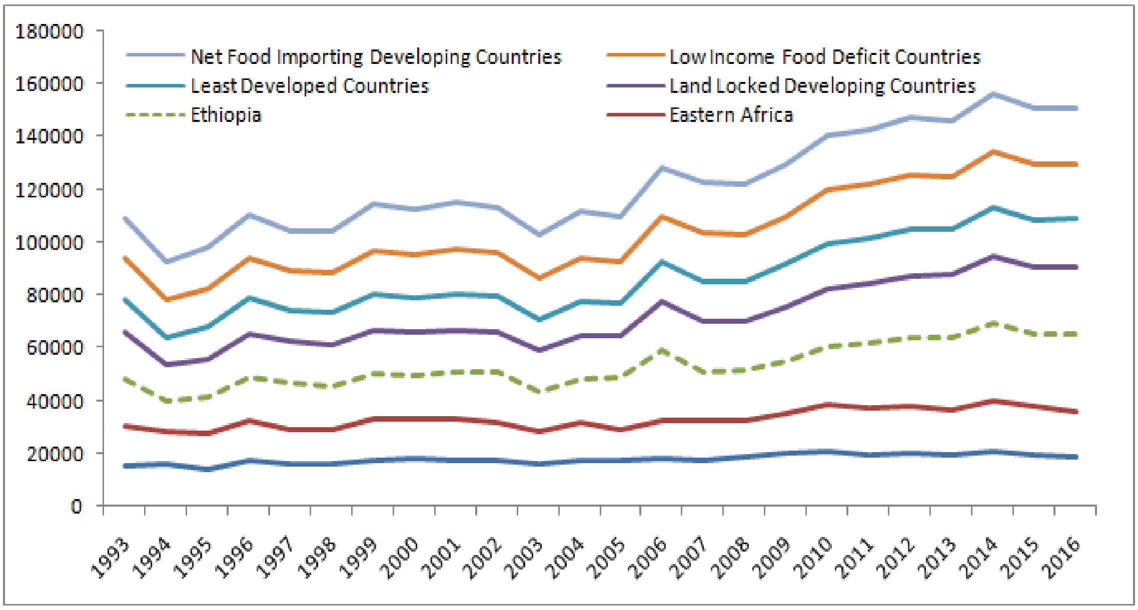

Figure 2: Maize Production in Ethiopia. Harvested production per unit of harvested land measured in hectograms per hectare (hg/ha) on the y-axis. Source FAOSTAT

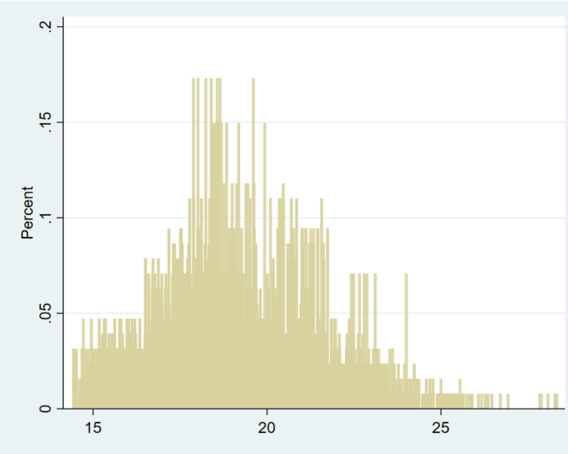

Figure 3: Average daily temperature during pre-planting

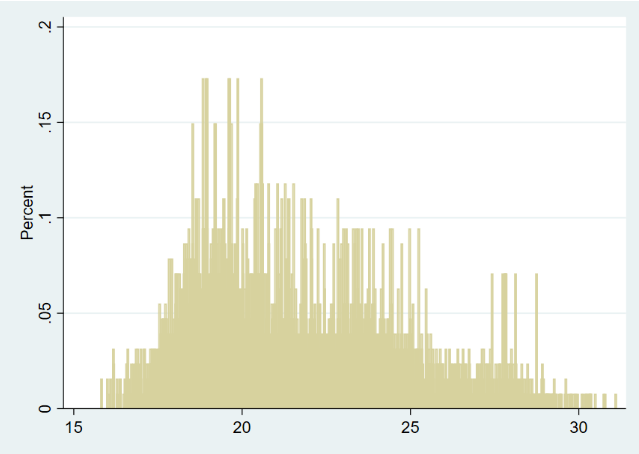

Figure 4: Average daily temperature during planting

Table A1: Summary statistics of working variables

Variables	Mean	Std.Dev.
Sex of the household head (male=1; female=0)	0.805	0.114
Age of the household head	43.392	5.319
Family size	5.192	0.837
Number of oxen owned	0.870	0.688
Access to credit (Yes=1; No=0)	0.181	0.237
Size of cultivated land under agricultural extension(ha)	0.586	0.493
Size of cropped land with access to irrigation(ha)	1.225	7.992
Average temperature during_pp season	18.747	2.071
Wet day frequency during_PP	1.589	2.207
Average temperature during planting season	21.062	2.506
Wet day frequency during planting season	12.198	9.430
Commutative heat degree days during_PP season	637.036	122.706
Commutative heat degree days during planting season	786.270	134.753
Size of cultivated land covered by maize (ha)	6.689	12.984
Size of cultivated land covered barley	3.204	10.364
Size of cultivated land covered sorghum	6.512	15.573
Size of cultivated land covered teff	9.292	20.229
Size of cultivated land covered wheat	4.996	14.058
Size of cultivated land covered pulse	6.265	12.247
Size of cultivated land covered Oil-seed	2.583	9.520

Source: AgSS, 2010-16 and FAO/IIASA. Values are aggregated at EA level

Table A2: Estimated impacts based on alternative weather definition: Number of degree days

VARIABLES	Maize land (log)
Number of days in pre-planting within GDD ranges	0.179***
	(0.0434)
Rainfall control	Yes
Other control	Yes
Region year fixed effects	Yes
EA fixed effect	Yes
Constant	-12.67***
	(2.601)
Observations	12,705
R-squared	0.865

Note: The table presents the effects of temperature using alternative definitions (captured via the number of days above 8°C and below 30°C temperature thresholds) on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop. Standard errors are in parentheses, clustered by district level. Standard errors clustered at district level in parentheses; *** p<0.01.

Table A3: Estimated impacts based on alternative weather definition: change in degree day threshold

VARIABLES	Maize land (log)
GDD Pre-planting	0.141***
	(0.0403)
GDD Plant	Yes
Rainfall control	Yes
Other control	Yes
Region year fixed effects	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.865

Note: The table presents the effects of temperature using alternative definitions (captured via degree days computed using 10°C and 30°C as the lower and upper thresholds in calculating GDD) on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop. Standard errors are in parentheses, clustered by district level. Standard errors clustered at district level in parentheses; *** p<0.01.

Note:

Table A4: Estimated Impacts of Weather Variability on Maize Land Allocation: inverse hyperbolic sine

VARIABLES	Maize land (log)
Temp Pre-Planting	0.0854***
	(0.0234)
Temp Planting	Yes
Rainfall control	Yes
Other control	Yes
Region year fixed effects	Yes
EA fixed effect	Yes
Constant	-1.054**
	(0.483)
Observations	12,705
R-squared	0.882

Note: Note:The table presents the effects of within growing season weather conditions on agricultural land allocation decisions. An inverse hyperbolic sine transformed the dependent variable (the size of land covered by maize) is used. The model includes village fixed effects as well as the interaction between regions dummy and year. Standard errors clustered at district level in parentheses; *** p<0.01, ** p<0.05.