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Early growing season weather variation, expectation formation and agricultural land allocation decisions in Ethiopia

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Abstract
Using unique crop-specific data gathered over 7 years, we study if and how maize-producing farmers in Ethiopia adjust their land allocation decisions in response to pre-planting-season weather variations. We show that farmers adjust their land allocation decisions in response to increased temperatures early in the growing season. In addition to quantifying a substantial adaptation margin that has not been documented before, our study also reveals the presence of a weather variation-induced expansion of maize production into areas that are less suitable for maize cultivation.

KEYWORDS
adaptation, crop substitution, land allocation, weather variation

JEL CLASSIFICATION
O13; Q15; Q54; C33

1 | INTRODUCTION

There are pertinent reasons to be concerned about the effects of climate change on the agriculture sector. As climate predictions show warmer and more variable futures, an increasing number of studies explore the socioeconomic implications of a warmer climate, including the effects on agriculture under different scenarios (Costinot et al., 2016; Hsiang et al., 2017; Jones & Thornton, 2003; Schlenker & Roberts, 2009). Schlenker and Roberts (2009) showed, for example, that even the slowest warming scenario could reduce crop yield by up to 46%. Studies also show that climate change disproportionately hits the poorest segments of the population of developing countries, mainly due to their poor adaptive capacity, high dependence on rain-fed agriculture, and economic fragility (Clay & King, 2019; Cooper et al., 2008; Müller et al., 2011). This calls for improvements in farmers' adaptive capacity and a better understanding of their adaptation techniques. Besides, it is also critical to examine the potential adaptation margins because such information is vital for a more accurate assessment of the expected economic losses due to climate change and weather variation. Particularly, understanding how promptly farmers respond to weather shocks close to the planting season provides valuable information to formulate policies that help to enhance adaptive capacity and avoid long-lasting welfare losses (Jagnani et al., 2021; Ramsey et al., 2020).

Literature shows that farmers in the region use different strategies to manage climate risks (Call et al., 2019; Deressa et al., 2009; Di Falco et al., 2011; Nigussie et al., 2018; Nthambi et al., 2021; Ojo & Baiyegunhi, 2020; Shikuku et al., 2017; Thinda et al., 2020; Waha, 2013). However, the bulk of existing studies concentrates on how farmers adjust their decisions based on 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 realised, and because such subjective predictions are heavily influenced by prior weather experience, investigating the role of climate knowledge gained over time is valuable for policy development. However, both economics and psychology literature (e.g., Camerer & Loewenstein, 2011; Ji & Cobourn, 2021) argue that recent realisations of an event have a disproportionately large influence on human expectations about the likelihood of that event occurring again. For example, Ji and Cobourn (2021) argue that, because farmers over-weight recent weather events in their expectation formation, such events heavily influence their farm management decisions. As a result, understanding how farmers react to short-term weather variations is essential to understand the nexus between weather variations and farmers' adaptation strategies.

A few recent empirical studies have looked at farmers' responses to short-term weather variations. 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 that farmers in China adjust their planting dates based on weather conditions realised eight weeks before the actual planting period.[1] We contribute to this growing area of research by providing a causal estimate of the impacts of initial planting season weather patterns on land allocation decisions using data from a low-income context. Specifically, by disaggregating the climate variables into pre-planting and planting stages of the crop growing cycle, we investigate the extent to which smallholder farmers in Ethiopia adjust land allocation decisions in response to plausibly exogenous weather variations experienced before the actual planting time. Ethiopia provides an appealing setting for this research, where weather variation is high and rain-fed agricultural activities constitute the single most important source of income for virtually all rural households. 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 provides a unique database.

Several studies have investigated the role of weather conditions 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 change with variations in weather. Though these studies provide pertinent information about 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 own specific heat and moisture requirements, weather variation is expected to have disproportionately stronger effects on some crops than

[1]Somehow related to this, recent research by Letta et al. (2022) has demonstrated how food prices respond quickly to drought conditions during the growing season due to anticipated supply shortages before any harvest failure occurs.

others. Such productivity differentials are expected to encourage farmers to reallocate their fields to crops that are better suited to the current weather conditions (Arora et al., 2020). As a result, the probability that a farmer allocates land to a given crop depends on the comparative advantage of that crop (Cui, 2020a; Seo & Mendelsohn, 2008). Hence, if farmers notice warmer temperatures weeks before the planting season, they may prefer to produce crops that withstand such conditions or adopt drought-resistant varieties. For instance, warmer temperatures are expected to boost the productivity of staple crops, such as maize, by hastening photosynthesis (Jagnani et al., 2021). Relatedly, Sesmero et al. (2018) showed that farmers allocate more resources to the production of maize if their expectations about weather conditions become more pessimistic.

Among crop-specific studies, Cui (2020a) demonstrates that growing season climate change, measured by historical data over the past 30 years, significantly affects the land allocation decisions of maize farmers in the United States. However, Cui (2020a) relates farmers' reactions to long-term climate change rather than weather variation that occurs around the planting seasons. Miao et al. (2015) show how excessive rainfall during the planting season discourages farmers in the United States from growing maize, whereas Cui (2020b)—using county-level data from the United States—illustrates how farmers alter harvest decisions by forgoing crops when faced with weather shocks. According to Aragón et al. (2021), Peruvian farmers respond to higher temperatures by increasing the production of tubers. Lesk et al. (2016) show how extreme weather events affect the worldwide area allotted for cereal production. 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 variation and agricultural outcomes (Blanc & Schlenker, 2017).[2]

We contribute to the literature in several ways. First, we provide an estimate of the causal impact of weather variation realised before actual planting on land allocation decisions by focusing on maize-producing farmers in Ethiopia. We combine village-level panel data gathered over 7 years with high-resolution weather data to obtain accurate weather variation 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 abandoning the crop during unfavourable 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. We examine if farmers' response to pre-planting season weather variation 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 identify the impacts of the pre-planting season weather variation on farmers' land allocation decisions, our identification strategy makes use of an exogenous within-season year-to-year weather variation within rural villages. Our identification is plausible because farm households are unlikely to accurately predict the upcoming season's weather conditions across time and place (Burke & Emerick, 2016; Deschênes & Greenstone, 2007).

[2]In addition to studies that investigate the role of weather variability on land allocation decisions, some studies have also looked at the role of 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., Gardebroek et al., 2017; Li et al., 2019; Motamed et al., 2016; Wang et al., 2020) and access to irrigation water (Manning et al., 2017; Taraz, 2017).

The remaining sections of the paper are organised as follows. Section 2 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 is presented in Section 3. The fourth section discusses the methodological strategy employed in the study. The fifth section presents and discusses the findings of the study, and Section 6 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 its cultivation. Recent figures from the Central Statistics Agency of Ethiopia (CSA) show that of 15.05 million cereal-farming households, 10.57 million grow maize on 2.1 million hectares. The crop accounts for one-third of the overall grain production in the country (Central Statistical Agency of Ethiopia, 2018, 2019). 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 A1, online, maize is produced in wide areas of the country. Its adaptability, the growing demand for maize stover, and its yield of food calories per hectare are some of the reasons that have contributed to its popularity (Abate et al., 2015).[3]

FAOSTAT shows that maize production in the country increased five-fold between 1993 and 2018. The country has a relatively good productivity record compared with the averages of Africa in general and Eastern Africa in particular (Figure A2, online). However, the productivity gap between Ethiopia and the global average or other country groups remains high. Low levels of technology adoption, poor access to input and financial markets, and frequent weather variability are among the main reasons for such low productivity levels (Croppenstedt et al., 2003; Kassie et al., 2018; Marenya et al., 2020).

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 (Lobell et al., 2011; Schlenker & Roberts, 2009; Srivastava et al., 2018). The effects of weather variability on maize production depend on timing and intensity. For instance, Seyoum et al. (2017) show that drought in the early growth stages reduces yield by up to 80%, whereas the yield reduction associated with droughts after the flowering period is only 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 & Jones, 2001; Engelen-Eigles et al., 2000).

3 | DATA

Our study is based on data generated from three main 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.

We use Ethiopia's Annual Agricultural Sample Survey (AgSS) as the main source for the outcome and control variables. CSA annually collects the agricultural sample survey that covers over 36,000 private farm holders, focusing on the main cropping season that corresponds to any temporary crop harvested between September and February (locally known as Meher season); 90%

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

of the total cereal output in the country is produced during this season (Asfaw et al., 2018). CSA collects AgSS annually at the end of the Meher cropping season's harvesting period.

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 for the country. This stage is followed by the selection of about 20 agricultural households from each sample EA using random sampling, making AgSS one of the world's largest annual agricultural surveys (Mann et al., 2019).

Starting from 2010, CSA has adjusted its sample selection process. Accordingly, the same EAs are used in each consecutive survey year, but households are resampled every year. Using this base, we construct a panel dataset by aggregating values at the EA level. This creates a balanced panel sample comprising 1815 EAs over the period 2010–16.[4] Figure A3, online, shows the location of the study villages (EAs). Throughout the paper, we use enumeration area and village interchangeably.

Table A1, online, provides the descriptive statistics for the working variables aggregated at the village level. In summary, 80% of households are headed by men. A typical village has household heads that are on average 43 years old with a family size slightly higher than five individuals per household. The average number of oxen owned is 0.87. In terms of access to institutions, 18% have access to credit, while 59% have access to agricultural extension services. Regarding their land allocation decisions, maize takes up 6.7 hectares of land,[5] whereas barley, sorghum, teff, wheat, pulses and oilseed take up 3.2, 6.5, 9.3, 5.0, 6.3 and 2.6 hectares, respectively. The average irrigated agricultural land is 1.2 hectares.

Daily data on rainfall and temperature are sourced from the Climate Hazards Group InfraRed Precipitation Station (Funk et al., 2015) and the ERA-Interim Reanalysis archive, respectively.[6] Both datasets have a 0.25×0.25 degree resolution.[7] From the daily observations, aggregate weather variables are constructed for two stages of the crop growth cycle for each survey period. We construct the crop growth cycle following Jagnani et al. (2021). The two stages are: (a) the planting and fertiliser application period, which covers 60 days after the beginning of the planting date; and (b) the pre-planting period (or initial planting stages), which accounts for the land preparation period and covers 60 days before the planting days. The stages are constructed based on a time-invariant crop-planting calendar accessed from the Nelson Institute for Environmental Studies of the University of Wisconsin-Madison (Sacks et al., 2010). Sacks et al. (2010) provide 0.5-degree resolution gridded maps for the cropping calendar of 19 major crops, including maize.[8] As a result, since we are measuring the weather variables by holding the crop calendar fixed from season to season, our weather variables are unlikely to be affected by endogenous weather-induced changes.

To investigate the role of land suitability for maize production on farmers' responses to weather variation, we utilise the FAO-GAEZ dataset.[9] FAO-GAEZ calculates the suitability of

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

[5]The annual mean values of maize land during the study period are presented in Table A11, online.

[6]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.

[7]We collected data from 15,851 grid cells in total. We present the national and regional boundaries along with 0.25×0.25 gridded lines in Figure A8, online.

[8]Estimation details of the calendar alongside the description of sources and types of data used to construct the calendar can be found in Sacks et al. (2010).

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

a given field for a particular crop by predicting the maximum attainable yields using agronomic models and three main inputs: (a) crop attributes (mainly estimated through field experiments); (b) physical attributes (including soil characteristics, elevation, and land gradient); (c) assumptions about the level of modern inputs utilisation.[10] We use the maize suitability index constructed for rain-fed farming with the assumption of low input utilisation. Figure A4, online, shows the index extracted for Ethiopia. By taking the national average production potential as a threshold, we categorise EAs into two groups: suitable and less suitable EAs. Table A1, online, provides the descriptive statistics for the potential yields along with other working variables.

4 | ESTIMATION STRATEGY

We estimate the following panel fixed effects model of the effect of weather variation prior to planting on land allocations[11]:

$$Y_{rdvt} = \beta_i [Temp]^{pp}_{rdvt} + \omega_i [Rain]^{pp}_{rdvt} + \gamma_i [Temp]^{pt}_{rdvt} + \delta_i [Rain]^{pt}_{rdvt} + \theta X_{rdvt} + \alpha v + \phi_{rt} + \varepsilon_{rdvt} \quad (1)$$

Y_{rdvt} is the dependent variable that represents the area of cultivated land planted to maize (in hectares) in a given region r, district d, village v, and time t. *Temp* stands for our indicators of temperature. We use the average daily temperature in a given season measured in degrees Celsius as our main indicator, following Cui and Xie (2022). We also check alternative definitions as a robustness exercise. *Rain* is our indicator of rainfall conditions. Although rainfall is uncommon in the months leading up to the planting season, 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. We follow the recommendations of related studies (e.g., Fishman, 2016; Kassie et al., 2014 and Lobell & Asseng, 2017) and used Wet Days Frequency to control both the amount and distribution of rainfall. The superscripts *pp* and *pt* represent pre-planting and planting seasons, respectively. B and ω are 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 utilisation and oxen size).

Our identification strategy exploits the random within-season year-to-year variations in local weather conditions. The assumption is that changes in weather conditions experienced by a village are exogenous to unobservable household or village-level characteristics that vary over time (Burke & Emerick, 2016; Deschênes & Greenstone, 2007; Gammans et al., 2017). Our identification is credible since farmers are unlikely to accurately predict upcoming weather conditions across time and location except for specific geographical features like seasonal climatic conditions, which we have controlled by EA, and region-by-year fixed effects. Hence, our identification strategy allows us to construct causal inferences based on the assumption that within-season weather variations are exogenous conditional on village-level attributes, and region-specific time trends.

[10]Detailed information on data sources and types used to calculate the indices, along with assumptions, and an overview of estimation approaches can be accessed at: http://webarchive.iiasa.ac.at/Research/LUC/GAEZv3.0/docs/GAEZ_Model_Documentation.pdf

[11]A simplified theoretical framework that models farmers' land allocation decisions is presented in the Online Appendix.

We also investigate whether the effect of weather variations on land allocated for maize is realised through substitution with other crops. This is done by examining the effects of weather variations on land allocated to maize relative to another crop. This helps to identify how weather variation affects the comparative advantage of maize compared with other crops (Cui, 2020a). The regression equation used to address this objective is given as:

$$\left(\frac{L_M}{L_M+L_o}\right)_{rdvt} = \beta_i\left[Temp\right]^{pp}_{rdvt} + \omega_i[Rain]^{pp}_{rdvt} + \gamma_i\left[Temp\right]^{pt}_{rdvt} + \delta_i[Rain]^{pt}_{rdvt} + \theta X_{rdvt} + \alpha v + \phi_{rt} + \varepsilon_{rdvt} \tag{2}$$

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 Tables A1, online, and 6). All remaining variables and other terms follow Equation (1).

In estimating the above equations, there could be spatial interactions across neighbouring locations of the study area, and failing to account for such interactions may lead to biased and inconsistent estimates (Fisher et al., 2012; LeSage, 1997).[12] For instance, the land allocation decisions of neighbouring EAs (our dependent variable) could be spatially correlated since they might share similar geographic attributes (like soil fertility status) and input and output markets.[13] Similarly, the extrapolation techniques used to generate gridded and reanalysed climate data can create spatial correlations 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 neighbouring areas (Maccini & Yang, 2009). Spatial correlation might also arise due to spatial correlation of the error terms due to confounding variables in omitted climatic measures (Auffhammer & 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 (SDM) and by accounting for spatial dependence in the error term through clustering the standard errors. Hence, as a robustness check, we estimate the impacts of weather variation on land allocation decisions using the Spatial Durbin Model.[14]

5 | RESULTS AND DISCUSSION

5.1 | The effects of pre-planting season weather variation on the size of land allocated for maize production

Table 1 presents the estimated effects of weather variation realised during the pre-planting seasons.[15] As shown in column 1, temperature variation in the pre-planting season has a

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

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

[14]We used *xsmle*, a user-written Stata command designed by Belotti et al. (2017) to fit spatial panel data models.

[15]Figure A7 in the Online Appendix displays detrend size of land allocated to maize production and detrend pre-planting season temperature.

TABLE 1 Estimated impacts of average temperature on maize land allocation

	(1)	(2)
Variables	**Maize land (log)**	**Maize land (log)**
Temperature pre-planting	0.148***	0.140***
	(0.037)	(0.041)
Rainfall pre-planting	−0.003	−0.002
	(0.010)	(0.010)
Planting season weather	No	Yes
Other controls	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 pre-planting season weather conditions on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop; 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 also accounted for the time trend. Planting season weather accounts for temperature and rainfall variations in the planting season. Standard errors clustered at the district level in parentheses; ***$p < 0.01$.

significant impact on farmers' land allocation decisions. More specifically, it shows that after controlling for EA fixed effects as well as time-varying region level characteristics along with other factors, a rise of 1 °C in the pre-planting season increases the size of land allocated to maize production by 14.8%. The results are in line with those of Aragón et al. (2021) and He and Chen (2022), who demonstrated how smallholder farms adapt to high temperatures by changing their land allocation decision. Given the rarity of rainfall during the pre-planting season, the insignificance of rainfall coefficients is unsurprising.[16]

Related studies (e.g., Aragón et al., 2021) show that farmers modify their land allocation decisions based on the planting season temperature conditions. As a result, we re-estimate the impacts by controlling for the planting season weather conditions (both temperature and rainfall variation) 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 2 of Table 1, the effects of pre-planting season temperature remain statistically significant after controlling for the growing season weather conditions.

The magnitude of the effects of pre-planting season temperature on the size of land allocated for maize production is economically sizable. To put this in context, we use our predicted coefficient to compute the extent of the change in total land covered by maize. The 14.0% increase in the size of land allocated to maize production (column 2 of Table 1) translates to an additional 0.94 hectares of maize production at the EA level, based on the sample mean of 6.7 ha. The results should be viewed in light of the fact that the average year-to-year temperature variations within EA during the pre-planting and planting seasons are 0.50 and 0.72 degrees Celsius, respectively, representing 2.7% and 3.4% differences from their averages.

The positive and significant relationship between higher temperature levels during the pre-planting season and the area of land allocated for maize production could be because of the nature of the crop. Warmer temperatures are expected to increase the productivity of staples, including maize, by speeding up photosynthesis (Jagnani et al., 2021). As shown in Figures A5 and A6, online, the average daily temperatures in the study area throughout the study period

[16]The coefficients of pre-planting season rainfall were also insignificant in the related works of Jagnani et al. (2021).

TABLE 2 Robustness of the result: Additional controls

	(1)	(2)	(3)
Variables	**Maize land (log)**	**Maize land (log)**	**Maize land (log)**
Temperature pre-planting	0.192***	0.126***	0.141***
	(0.042)	(0.041)	(0.041)
Rainfall pre-planting	0.010	−0.002	−0.001
	(0.010)	(0.010)	(0.010)
Planting season weather	Yes	Yes	Yes
Lagged planting season weather	Yes	No	No
Lagged average price	No	Yes	No
Future price	No	No	Yes
Other controls	Yes	Yes	Yes
Region by year fixed effect	Yes	Yes	Yes
Observations	12,705	12,705	12,705
R-squared	0.872	0.865	0.865

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

were mostly within the range over which maize yields generally increase as temperatures rise (Lobell et al., 2011). Studies such as Seo and Mendelsohn (2008) and Wang et al. (2010) show that farmers tend to grow maize as temperatures rise. 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[17] was distributed in the country and the seed covered 18% of maize land in the country (Ertiro et al., 2019).

5.2 | Robustness checks

We run a variety of tests to examine the robustness of our main results.

5.2.1 | Incorporating additional controls: past weather variation and own prices

Because most farm management decisions are made based on expectations about future weather conditions, past weather conditions substantially influence farmers' decisions. In line with this, Ji and Cobourn (2021) showed how lagged weather conditions influence land allocation decisions of farm households. Hence, we run a robustness test to see if our results are influenced by the previous year's growing season weather conditions (both temperature and rainfall variation). Column (1) of Table 2 provides the result estimated by including one-year lagged planting season weather patterns.

In the main results presented in Table 1, the region-by-year fixed effect is used to control price effects at the regional level. Here, the strength of the results is tested by incorporating

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

TABLE 3 Robustness of the result: Alternative weather definition

Variables	Maize land (log)
Pre-planting season degree-days	0.141***
	(0.04)
Rainfall pre-planting	−0.005*
	(0.003)
Planting season weather	Yes
Other controls	Yes
Region by year fixed effect	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.865

Notes: The dependent variable is the log value of land under maize crop. 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 the district level are in parentheses. See notes under Table 1 for additional information such as the list of control variables. ***$p < 0.01$.

maize prices 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.[18] As shown in the Table, the results of the main regression equation remain qualitatively identical in these robustness checks.

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 & Xie, 2022). For example, degree-days, which is a measure of cumulative heat, have been used by both agronomic and economic literature (e.g., Lobell et al., 2011; Schlenker et al., 2006; Schlenker & Roberts, 2009) to illustrate the link between temperature and agricultural productivity. Even though we are not directly analysing the impacts on agricultural productivity, we use degree-days as an alternative indicator for a robustness test.

A degree-day is calculated as the intensity of daily exposure to 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 (e.g., Jagnani et al., 2021; Worku et al., 2012) consider 8°C and 30°C as the lower and upper thresholds in calculating degree-days. Table 3 shows the estimated effects of degree-days on farmers' land allocation decisions. We show qualitatively identical results with the results of the main regression equation, though it is notable that pre-planting rainfall now becomes significant at the 10% level.

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

[18]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 ttps://dataviz.vam.wfp.org/economic_explorer/prices

TABLE 4 Robustness of the result: Accounting for the spatial interactions

Variables	Maize land (log)
Temp pre-planting	0.190***
	(0.046)
Rainfall pre-planting	−0.020
	(0.013)
Planting season weather	Yes
Other controls	Yes
Region by year fixed effect	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.865

Notes: The dependent variable is the log of land under maize. 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 the district level are in parentheses. See notes under Table 1 for additional information such as the list of control variables. *** $p < 0.01$.

model to evaluate the effects of pre-planting season weather conditions on land allocation decisions in our next robustness check. As can be seen from Table 4, the findings of the main regression equation remain qualitatively unaffected.

5.2.4 | Falsification test

We used a falsification test to see if the reported impacts of pre-planting temperature variation on land allocation decisions are absorbing the effects of other 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). The future weather condition is unlikely to influence the current year's land allocation decision since farmers do not have access to such information during the decision-making process. If the variable significantly explains the allocation decisions, it suggests that the reported impacts in the main result are due to the effects of other time-varying unobservables. As shown in Table 5, the coefficient of the mismatched weather variable is not statistically significant, implying that unobserved factors are unlikely to confound the effect of pre-planting weather conditions reported in our main result. We also present a consistent result in Table A8, online, using weather conditions during the post-harvesting season as an alternative variable.

5.2.5 | Additional tests

In our main analysis, we consider 60 days before the commencement of the planting season to be an appropriate time to remain in the spirit of Jagnani et al. (2021). We looked at the impacts using 45 and 30 days to see if the result is sensitive to the length of the time spam. As shown in Tables A2, online, the finding remains consistent despite the difference in date.[19] We also rerun

[19]We also looked at the effects over a shorter period and discovered that as the time span gets shorter, the magnitude and statistical significance of the effects decrease, eventually becoming insignificant. This is in line with Sesmero et al. (2018), who highlighted how difficult it is to adjust agricultural input allocation decisions within a very short period of time.

TABLE 5 Placebo regression

Variables	Maize land
Future temperature	−0.043
	(0.030)
Rainfall control	Yes
Planting season weather	Yes
Other controls	Yes
Region by year fixed effect	Yes
EA fixed effect	Yes

Notes: The table presents the effects of the future average temperature on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop. Standard errors clustered at the district level are in parentheses. ***$p < 0.01$.

our main model with a finer set of district-by-year fixed effects to account for any district-specific time-varying features, which might not be controlled by our control variables. Table A3, online, shows the result, which is consistent with our main finding. We also used a simple machine learning technique to calculate the percentage of variation in the dependent variable explained by each independent variable. As indicated in Table A4, online, the most important variable is pre-planting temperature, which accounts for over a quarter of the variation in land allocated for maize production. Lastly, we present additional robustness test results in the Online Appendix (Tables A5–A7), which include changing the definitions of our main working variables.

5.3 | Weather variation 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 areas of maize. The findings indicate the presence of crop substitution effects caused by the pre-planting season temperature variation. It shows that higher temperatures during the pre-planting period increase the share of land covered by maize relative to alternative crops such as barley, sorghum, teff and oilseed (Table 6). It is worth emphasising that if the pre-planting season temperature variations affect both maize and the alternative crops to a similar extent, no effect would have been observed. Among existing studies, Cui (2020a) shows that a 0.1 °C rise in past temperature increases land allocated to maize and soybean by up to 3% relative to wheat, while Wang et al. (2010) showed that warm temperature encourages maize production but discourages the production of soybeans and vegetables.

5.4 | Heterogeneous effects

5.4.1 | 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 A9, online. We find no differences in the effects of pre-planting season temperature variation based on the suitability of the villages for maize production. This means that, regardless of the suitability of villages for maize production, farmers adjust the size of land allocated to maize production due to pre-planting season weather variation. The result demonstrates the feasibility of expanding maize production into new areas to adapt to changing weather patterns. A recent study by Sloat et al. (2020)

TABLE 6 Effect of weather variation on crop substitution

	(2)	(3)	(4)	(5)	(6)	(7)
Variables	**Barley**	**Sorghum**	**Teff**	**Wheat**	**Pulse**	**Oilseed**
Temperature pre-planting	0.0145**	0.0156*	0.0172***	0.008	−0.006	0.0193**
	(0.006)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)
Rainfall pre-planting	0.001	−0.000	−0.002	0.000	0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Planting season weather	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Region by year FE	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	0.81	0.848	0.838	0.703

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

shows how rain-fed maize production migrated to areas that were not previously major producers due to climate change. Similarly, Skarbø and VanderMolen (2016) document the expansion of maize production practices towards higher altitudes due to climate change. However, it is also worth noting that classifying a given area as less suitable for maize production does not imply that maize has a less comparative advantage in that particular area. It can also imply that the field is less fertile for other types of crops as well.

5.4.2 | Based on the temperature level

To see if farmers' responsiveness to pre-planting season weather conditions varies based on the temperature level, we also run our model by including an interaction term of the pre-planting season temperature and a binary variable showing whether the temperature of the EA is above the total average (or median). However, as we present in Table A10, online, we could not find statistically significant effects of the interaction terms. This might be because the average temperature in the studied area during the research period was within the range where maize yield increases as the temperature rises (Figures A5 and A6). As noted by Lobell et al. (2011), Schlenker and Roberts (2009), and others, heat stress reduces maize yield only when temperatures exceed 30°C.

6 | CONCLUSIONS

The recent literature on the impacts of climate change and weather variation 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 pre-planting season weather variation on land allocation decisions of farmers, focusing on Ethiopian maize producers.

We document that, controlling for village-level fixed effects as well as time-varying region-level characteristics along with other factors, a 1°C temperature increase in the pre-planting season increases the area of land allocated to maize production by 14.8%. We show that part of the increase in land allocated to maize is achieved by replacing other crops. We also provide some evidence that weather variation encourages the expansion of maize into less suitable areas. We confirm that these results are not confounded by the previous year's growing season weather conditions or maize price. We also employed a spatial panel data model to account for geographical and temporal effects, which also confirm our main results.

The findings in this paper have the following implications. The results on land allocation adjustments due to the pre-planting season warming contribute to a limited but growing body of work that includes evidence of farmers' response to weather variation by adjusting their input allocation decisions (Jagnani et al., 2021) and planting dates (Cui & Xie, 2022). The findings highlight that focusing only on annual temperatures (ignoring the effects of pre-planting season temperature variation) leaves a significant short-term behavioural response that is important for policy formulation. Similarly, unlike previous studies that looked at how weather variation impacts total cropland (e.g., He & Chen, 2022; Li et al., 2013; Morton et al., 2006 and Zaveri et al., 2020), or land covered by certain food groups (such as Aragón et al., 2021, who focused on land allotted to tuber production), this study focuses on crop level analysis and contributes to the literature by showing how weather variation alters the comparative advantages of crops.

The findings of the study have several policy implications. By estimating the effects of pre-planting season weather variation on farm households' land allocation decisions, we have documented a notable adaptation margin that has been overlooked in previous studies. For instance, the vast majority of studies looking at the impact of rising temperatures on agriculture use field experiments or simulations, overlooking the potential for adaptation (Miao et al., 2015). However, as we have shown above, farmers adjust land allocation decisions in response to weather variations, and ignoring this crucial adaptation margin may lead to an overestimation of actual climate-related losses (Aragón et al., 2021). To put this in perspective, Zhao et al. (2017) and Lesk et al. (2016) showed that each degree Celsius temperature increase reduces worldwide maize yields by 7.4% and 10%, respectively, whereas research conducted in various parts of Ethiopia revealed up to 43% maize yield reduction by the end of the century (Abera et al., 2018; Degife et al., 2021). As a result, accounting for the 14% adaptation margin due to a one degree Celsius temperature increase during the pre-planting season that we have documented might significantly reduce the expected losses.

It is also important to underscore the fact that farm households' decision to expand maize production to cope with increased temperatures 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 achieving food and nutrition security (Poole et al., 2021; Sanchez et al., 2020). Hence, as land allocation changes the amount of land devoted to a particular crop, it can have implications for the type and amount of food produced and supplied to the market. Notably, for developing countries like Ethiopia, where a significant share of food comes from domestic production, weather variation-induced reallocation of land can affect the types and amount of food that is available and accessible to the population. As a result, the substitution of cash crops for staple crops like maize to withstand weather variation 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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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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