Within Growing Season Weather Variability and Adaptation in Agriculture: Evidence from cropping patterns of Ethiopia*

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Abstract:

We examine if and how farmers adjust their land allocation decisions in response to within-growing season weather variability by utilizing a novel crop-specific micro-level data collected over seven consecutive years. Using a spatial panel data model that accounts for spatial and temporal effects, and interactions across neighboring villages, we show that farmers detect within-growing season weather variability and respond promptly by adjusting land allocation decisions. In addition to quantifying a substantial adaptation margin that has not been documented before, our findings also reveal the presence of weather variability-induced expansion of maize production into areas that are less suitable for maize cultivation.

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

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

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1 Background and Motivation

As weather predictions forecast warmer and more variable futures, studies revealing adverse socio-economic effects, including the impacts on agriculture 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). There are compelling reasons to be concerned about the effects on the agriculture sector, as these effects can have far-reaching socioeconomic consequences. More importantly, it disproportionately affects the poorest segments of the population in developing countries mainly due to their dependency on rain-fed agriculture, limited adaptive capacity, and economic fragility (Kurukulasuriya et al., 2006; Clay and King, 2019; Müller et al., 2011; Thornton et al., 2011; Cooper et al., 2008).

This entails boosting farmers' adaptive capacity as well as learning more about how they respond to environmental changes. Particularly, understanding how farmers respond to shocks that happen close to the planting season provides valuable information for the design of policies that helps to enhance adaptive capacity and avoid long-lasting welfare losses (Jagnani et al., 2021; Ramsey et al., 2020). Such information, for instance, enables input suppliers(like seeds and agrochemicals) as well as institutions such as microfinance institutions and agricultural extension to respond quickly.

This being the case, the great bulk of existing works concentrate on farmers' responses to climate knowledge acquired over the long term. Since most farm management decisions are made based on expectations about weather conditions before the realization of the actual weather conditions, and since such subjective expectations are significantly influenced by past weather experience, exploring the role of climate knowledge acquired over time provides important inputs for policy formulations. However, both economics and psychology literature (including Ji and Cobourn (2021); Camerer and Loewenstein (2011)) argue that recent realizations of an event can have a disproportionate influence on farmers' expectations about forthcoming weather conditions. As a result, it is also equally essential to understanding farmers' responses to short-run weather variability.

Few recent empirical works engaged in examining the effects of short-term weather variability. Among them, Jagnani et al. (2021) examine the effects of within-growing season weather variability on farmers of Sub Saharan Africa. They show that Kenyan farmers adjust their chemical and fertilizer use decisions in response to temperature variations that happened during the initial cropping cycle. Relatedly, Cui and Xie (2021) document how farmers adjust their planting dates based on weather conditions realized up to eight weeks before the actual planting period. We aim to contribute to this growing area of research by providing the first causal estimate of the effects of initial planting season weather patterns on 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 maize farmers in Ethiopia adjust land allocation to different crops in response to plausibly exogenous weather pattern changes.

In the literature, numerous studies investigate the role of weather variability on land allocation decisions. Among them, Li et al. (2013); Mu et al. (2018) 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).

A recent crop-specific work by Cui (2020) shows that maize farmers' land allocation decision is significantly influenced by growing season climate change—proxied by the past 30 years' historical data. However, Cui (2020) reflects farmers' response to long-run climate change than weather variability occurred around the planting seasons. Miao et al. (2015) show that planting season weather conditions significantly affect the land allocation decisions of U.S. farmers. 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]

By focusing our attention on maize, we contribute to the literature by examining the impacts of initial growing season weather conditions on land allocation decisions using village-level panel data collected from more than 36,000 farmers. We combine the survey data with high-resolution climate data to identify spatially and temporally comparable weather variability indicators with high precision. Besides, we also investigate the role of 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 instance, if maize is the most suitable crop for a given area, farmers might opt to use new technologies like drought-resistant varieties during unfavorable weather conditions than abandoning the crop. Drier conditions during the planting periods 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

[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)).

production if they have already allocated their land for maize production. Therefore, we examine if farmers' response to 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.

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 the country's rural areas. As a result, the country's rural livelihoods are very vulnerable to weather fluctuations. The availability of one of the world's largest yearly detailed agricultural surveys also presents a unique opportunity.

To causally identify the impacts of the initial growing season weather variation, our identification strategy makes use of an exogenous year-to-year weather variation within rural villages. Our identification is plausible since farm households are unlikely to accurately anticipate upcoming growing season weather conditions (both temperature and rainfall) across time and place (Deschênes and Greenstone, 2007; Burke and Emerick, 2016). We utilize a spatial panel data model that accounts for both spatial and temporal effects.

Our results show that farmers adjust their land allocation decisions to within growing season weather variability. More precisely, after controlling for village level attributes, neighborhood effects, and time-varying regional characteristics, an additional day with a temperature above 22°C in the initial growth period (realized roughly within the eight-week before the beginning of actual planting season) increases the size of land allocated to maize crop by 3.2 percent compared to a day with an average temperature below 18°C. Likewise, one extra wet day during the planting period reduces the size of land allotted for maize by 2.7 percent. Our findings are robust to the inclusion of additional socioeconomic controls or own price. We also confirm that the findings are confounded by the previous year's growing season weather conditions. We also show the consistency of results by changing the definitions of both the outcome and weather variables. To the best of our knowledge, this adaptation margin of adjustment to initial growing season weather variability has not been documented before. We also present suggestive evidence for the presence of weather variability-induced expansion of maize production into areas that are less suitable for maize production.

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

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 wider adaptability, growing demand for strove, and ability to give more calories and food per cultivated land[2] are some of the reasons that

[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)

have contributed to its popularity in the country (Abate et al., 2015).

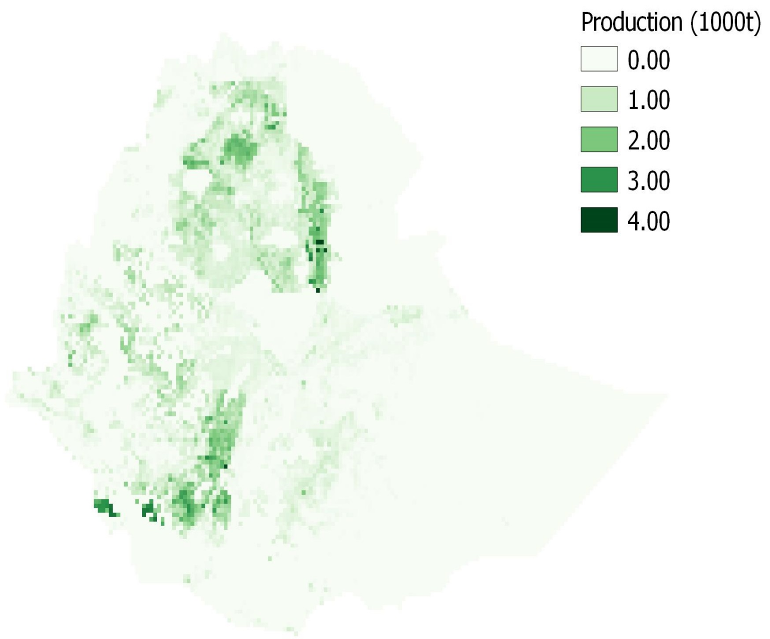

Figure 1: Maize Production areas in Ethiopia: *Source FAO/IIASA*

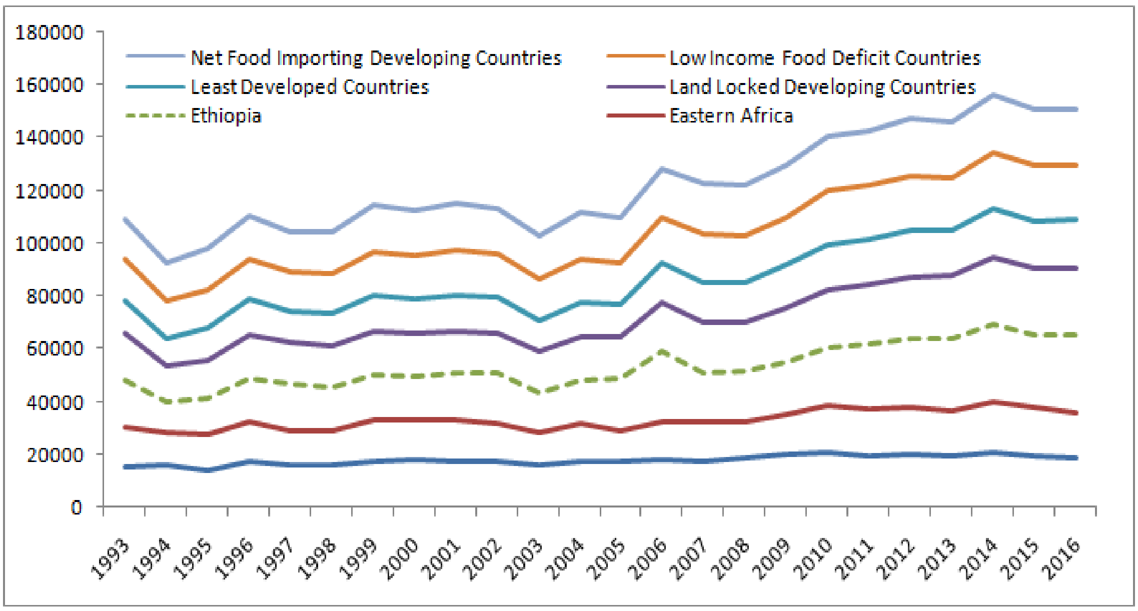

Figure 2: Maize Production in Ethiopia. Harvested production per unit of harvested land measured in hectograms per hectare (hg/ha) on the y-axis. Source FAOSTAT

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 groups where the country belongs 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.

Though maize is considered a suitable crop for warmer conditions, several studies show that the crop is also sensitive to water shortage and heat stresses (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 its timing and intensity. For instance, Seyoum et al. (2017) show that drought that occurred in the early stages 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 (Cairns et al., 2012).

[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.

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 climate data from various sources. The study relies on Ethiopia's Annual Agricultural Sample Survey (AgSS) as the main source for the outcome and control variables. CSA annually undertakes a large agricultural sample survey that covers more than 36,000 private farm holders, which makes it one of the largest annual agricultural surveys in the world (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. However, 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 3 depicts the location of the study villages. Figure 3 depicts the location of the study villages.

The main weather variables of interest for this study are precipitation and temperature. Daily temperature and rainfall data are obtained from the ERA-Interim Reanalysis archive and the Climate Hazards Group InfraRed Precipitation Station (CHIRPS) (Funk et al., 2015).[5] Both datasets have 0.25x0.25 degree resolution. Based on the

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

[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

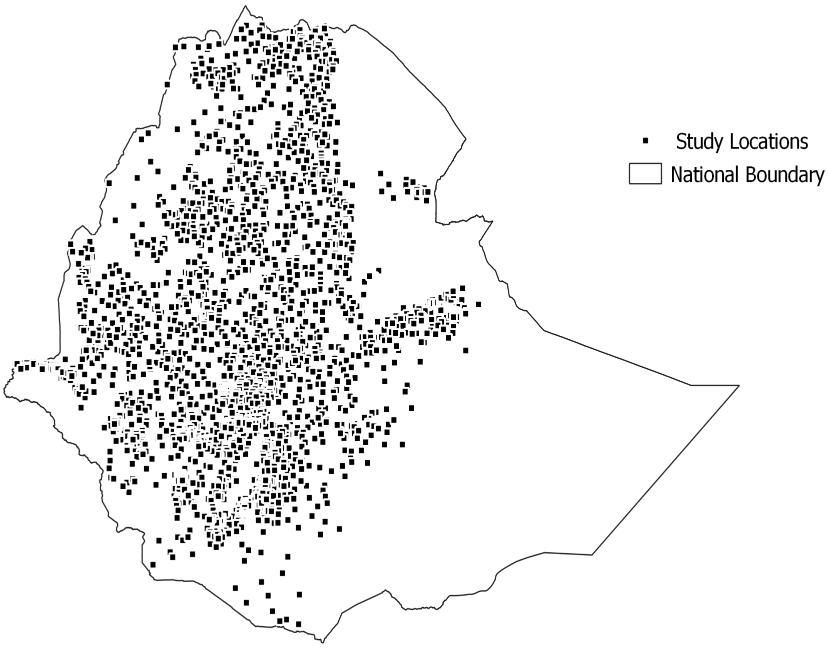

Figure 3: Location of the sampled areas
Note: The survey covers all parts of the country except some parts of Afar and Somali regional states, which are located in the northeast and southeast of the country. Households in the excluded area are pastoralists and they do not have a sedentary way of life.

daily 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 a crop-planting calendar accessed from the Nelson Institute for Environmental Studies of the University of Wisconsin-Madison (Sacks et al., 2010).

Rainfall conditions around the planting period are undoubtedly among the most crucial factors expected to significantly influence farmers' resource allocation decisions

weather variables require daily records, a complete list of observations is essential.

[6]The stages are constructed following existing related works like Jagnani et al. (2021).

in countries like Ethiopia, where the vast majority of farmers do not have access to irrigation. Studies that examined the effects of precipitation on farm performance (such as Fishman (2016); Kassie et al. (2014); Lobell and Asseng (2017)) discuss the importance of controlling both the amount and distribution of rainfall as erratic rainfall distribution can also cause yield reduction even in seasons with sufficient rainfall totals. Hence, Wet Days Frequency (WDF) is used as the indicator for precipitation in this study. WDF is constructed for each season by counting rainy days where the precipitation is above 0.1mm.

The other important weather factor expected to affect farmers' decisions is temperature. Both agronomic and economic literature (e.g. Lobell et al. (2011); Schlenker and Roberts (2009); Schlenker et al. (2006)) recommend the use of cumulative heat exposure, such as Growing Degree Days (GDD) than aggregate averages. GDD 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 consider 8°C and 30°C as the lower and upper thresholds in calculating GDD. However, the minimum daily temperature in the study area during the study period is above 8°C, and temperatures above 30°C are very unusual (see Figures 4 and 5). Given that Ethiopia is located in the Tropics, where there is less variation in the temperature compared to the Temperate region, this is unsurprising. Hence, following Jagnani et al. (2021), temperature bins that count the number of days with an average daily temperature within a given range are constructed for each stage.

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 attain-

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

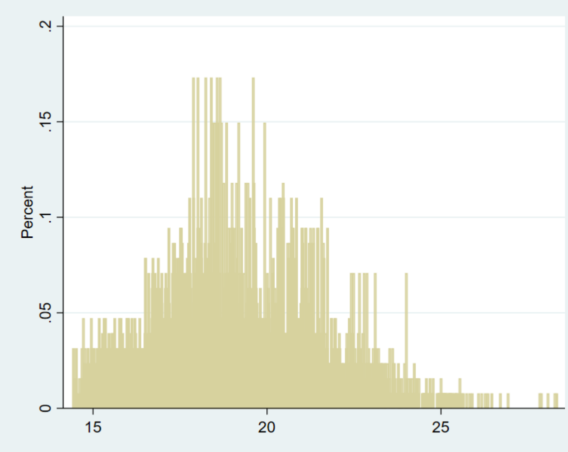

Figure 4: Average daily temperature during pre-planting

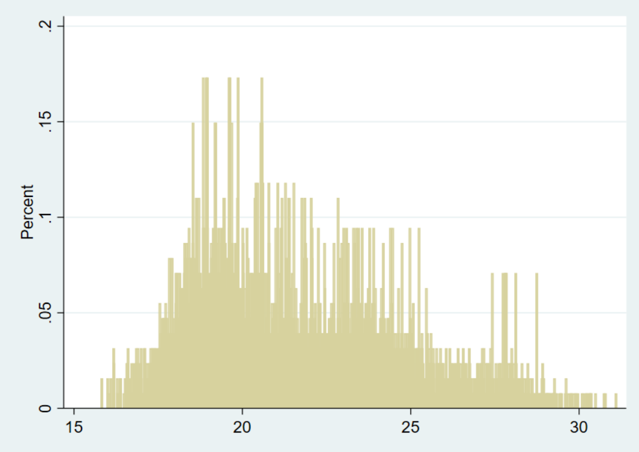

Figure 5: Average daily temperature during planting

able 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 6 presents the index extracted for Ethiopia. By taking national average production potential as a threshold, we categorize EAs into two groups: suitable and less suitable EAs. Table 1 provides the descriptive statistics for the potential yields along with other working variables.

4 Theoretical model for farmers land allocation decision and estimation strategy

Following the work of Cui (2020), farmers' land allocation decisions can be modeled as a profit maximization problem in which a farmer allocates a fixed amount of land between two crops—crops 1 and 2. Assuming the production function (y_k) to be a concave function of the weather conditions (C), farm size (A_k), and other inputs (x),

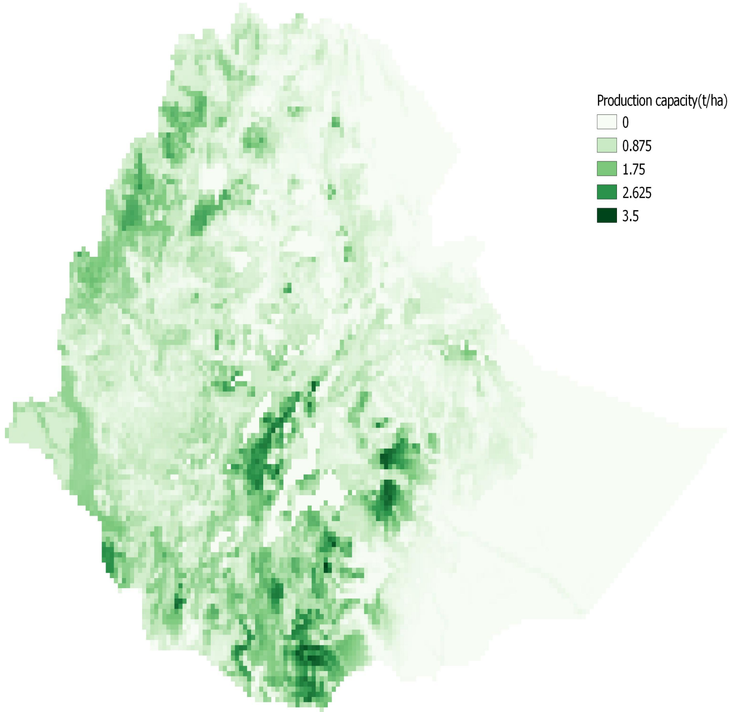

Figure 6: Maize production capacity: *Source FAO/IIASA*

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the maximization problem can be expressed as follows:

$$\underset{A_1 A_2}{max}(p_1 y_1(A_1, C, x) + p_2 y_2(A_2, C, x) - M) \qquad s.t \qquad A_1 + A_2 = 1 \tag{1}$$

M represents a constant marginal cost of land. The farmer is considered to be a price taker (p_1 and p_2), and the total amount of land is scaled to be 1. The marginal effect of weather variability on the optimal size of land allocated to crop 1 can be calculated by optimizing equation (1), as expressed in equations (2):

$$\frac{\partial A_1^*}{\partial C} = \frac{P_1 \frac{\partial^2 y_1}{\partial A_1 \partial C} - P_2 \frac{\partial^2 y_2}{\partial A_2 \partial C}}{P_1 \frac{\partial^2 y_1}{\partial A_1^2} + P_2 \frac{\partial^2 y_2}{\partial A_1^2}} \tag{2}$$

Since the production function is assumed to be concave, the denominator of the above expression is expected to be negative. Thus, the impact of weather variability on

Table 1: Summary statistics of working variables

Variable	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
Size of oxen owned	0.87	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 fields with access to irrigation(ha)	1.225	7.992
Size of cultivated land by maize (ha)	6.689	12.984
Size of cultivated land by barley (ha)	3.204	10.364
Size of cultivated land by sorghum (ha)	6.512	15.573
Size of cultivated land by teff (ha)	9.292	20.229
Size of cultivated land by wheat (ha)	4.996	14.058
Size of cultivated land by Cereals (ha)	31.732	33.255
Size of cultivated land by Pulse (ha)	6.265	12.247
Size of cultivated land by Oilseed (ha)	2.583	9.520
Average potential maize yield (t/ha)	0.783	0.702

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

farmers' land allocation decisions will mainly depend on the relative changes in the marginal values of the land affected by weather variability. If the effect is more severe for crop 1 than crop 2, i.e., $P_1 \frac{\partial^2 y_1}{\partial A_1 \partial C} < P_2 \frac{\partial^2 y_2}{\partial A_2 \partial C} < 0$, then the farmer will increase the size of land allocated to crop 2 by shrinking the size of land allocated to crop 1 compared with the optimal size before the weather change and vice versa.

To empirically estimate the effects of weather variables on agricultural land allocation decisions, the following econometric model is estimated using a fixed effect framework:

$$\begin{aligned} Y_{rdvt} = {} & \beta_2 T(18°\text{C} - 19°\text{C})^{pp}_{rdvt} + \beta_3 T(19°\text{C} - 20°\text{C})^{pp}_{rdvt} + \beta_4 T(20°\text{C} - 21°\text{C})^{pp}_{rdvt} + \\ & \beta_5 T(21°\text{C} - 22°\text{C})^{pp}_{rdvt} + \beta_6 T(> 22°\text{C})^{pp}_{rdvt} + \beta_7 T(18°\text{C} - 19°\text{C})^{pt}_{rvt} + \\ & \beta_8 T(19°\text{C} - 20°\text{C})^{pt}_{rdvt} + \beta_9 T(20°\text{C} - 21°\text{C})^{pt}_{rdvt} + \beta_{10} T(21°\text{C} - 22°\text{C})^{pt}_{rdvt} + \\ & \beta_{11} T(> 22°\text{C})^{pt}_{rdvt} + \beta_{12} WDF^{pp}_{rdvt} + \beta_{13} WDF^{pt}_{rdvt} + \alpha_d + \varphi_{rt} + \varepsilon_{rdvt} \end{aligned} \quad (3)$$

Y_{rdvt} is the dependent variable that represents the size of cultivated land (in hectare) covered by maize measured in a given region r, district d, village v, and time t. WDF stands for wet day frequency, and T(.) denotes the number of days in each season when the average daily temperature falls within the indicated boundaries. The coefficients of the bins will be interpreted in relation to T(<18°C), which is omitted from the regression equation. The superscript *pp* and *pt* represent pre-planting (initial) and planting seasons, respectively. α_d 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.

The above framework is estimated by excluding time-varying controls to avoid bad control scenarios. However, the equation is re-estimated by incorporating community-level time-varying socioeconomic 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) as a robustness check. Interaction terms between weather variables and the suitability class of the EAs are introduced in the above frameworks to explore the heterogeneous effects of potential returns on farmers' responses to climate variability.

We also investigate if 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 4.

$$
\begin{aligned}
(\frac{L_M}{L_M+L_O})_{rvt} = {} & \beta_2 T(18°\mathrm{C}-19°\mathrm{C})^{pp}_{rvt} + \beta_3 T(19°\mathrm{C}-20°\mathrm{C})^{pp}_{rvt} + \beta_4 T(20°\mathrm{C}-21°\mathrm{C})^{pp}_{rvt} + \\
& \beta_5 T(21°\mathrm{C}-22°\mathrm{C})^{pp}_{rvt} + \beta_6 T(>22°\mathrm{C})^{pp}_{rvt} + \beta_7 T(18°\mathrm{C}-19°\mathrm{C})^{pt}_{rvt} + \\
& \beta_8 T(19°\mathrm{C}-20°\mathrm{C})^{pt}_{rvt} + \beta_9 T(20°\mathrm{C}-21°\mathrm{C})^{pt}_{rvt} + \beta_{10} T(21°\mathrm{C}-22°\mathrm{C})^{pt}_{rvt} + \\
& \beta_{11} T(>22°\mathrm{C})^{pt}_{rvt} + \beta_{12} WDF^{pp}_{rvt} + \beta_{13} WDF^{pt}_{rvt} + \alpha_d + \varphi_{pt} + \varepsilon_{rvt}
\end{aligned} \tag{4}
$$

where L_M and L_O stand for the size of land allocated for maize and a specific alternative crop (e.g. barley, teff, wheat, etc. as shown in Table 1 and 3), respectively. 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). In fact, all possible sources of spatial interactions can be traced.[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). Hence, 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.

[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).

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. Equation (5) presents the reduced form of equation (3) in the SDM framework.

$$Y_{rvt} = \rho W Y_{rvt} + \beta_i K^s_{rvt} + \theta_i W K^s_{rvt} + \alpha_d + \varphi_{pt} + \varepsilon_{rvt} \tag{5}$$

Where K stands for the weather variables (temperature bins and WDF) and the superscript s represents the planting periods (either pre-planting or planting season). W denotes the spatial weight matrix that represents the potential interaction between each pair of EAs. WY and WK are spatially lagged dependent (land allocated to maize production) and spatially lagged independent (weather) variables, respectively. All remaining variables and other terms follow equation 3.

We use Stata's xsmle package produced by Belotti et al. (2017) to obtain the estimates of the above spatial fixed effect model. The spatial weights matrix is constructed using the 4-nearest neighbor technique using GeoDa 1.18 software. Since the spatial regression model exploits the dependence structure across units (EAs for our case), the coefficients of spatial models are not the true marginal effects. Hence, the 'effect' option of the xsmle package is used to calculate direct and total marginal effects. In estimating the above equation, standard errors are clustered at the district level.

5 Results and Discussion

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

The estimates of the spatial panel regression model are presented in Table 2. Column (a) provides the estimates of the parameters using a non-spatial regression model for comparison, and the remaining three columns are results of spatial regression. Column (b) gives the coefficients of the parameters, and columns (c) and (d) present the direct and total marginal effects from the spatial regression. As shown in the Table, Rho, the parameter that measures the spatial correlation between neighboring EAs, is statistically significant.

The result shows that initial growing season weather patterns significantly influence farmers' land allocation decisions. Specifically, it shows that drier conditions during the initial planting stage encourage maize cultivation, whereas excess wet days discourage maize production. More precisely, it shows that an additional day above 22°C in the initial period increases the size of land allocated to maize production by 3.2 percent compared to a day with an average temperature below 18°C. Similarly, an extra day with a temperature range of between 21°C and 22°C, 19°C and 20°C, and 18°C and 19°C C leads to a 3.7%, 1.6%, and 1.9% increase in the size of land allocated for maize production compared to a day below 18°C in the initial growth period. Likewise, one extra wet day during the planting period reduces the size of land allocated to maize by 2.7 percent.

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

Table 2: Estimated Impacts of Weather Variability on Maize Land Allocation

Variables	Nonspatial		Spatial	
	(a)	(b)	(c)	(d)
T(18°C-19°C)_PP	0.018***	0.017**	0.018**	0.019***
	(0.005)	(0.008)	(0.008)	(0.006)
T(19°C-20°C)_PP	0.017***	0.019**	0.019***	0.016**
	(0.006)	(0.008)	(0.007)	(0.008)
T(20°C-21°C)_PP	0.002	0.005	0.005	-0.003
	(0.005)	(0.008)	(0.007)	(0.008)
T(21°C-22°C)_PP	0.032***	0.025***	0.025***	0.037***
	(0.006)	(0.008)	(0.007)	(0.01)
T(>22°C)_PP	0.034***	0.030***	0.031***	0.032***
	(0.006)	(0.01)	(0.01)	(0.007)
T(18°C-19°C)_Planting	0.008*	0.005	0.006	0.013*
	(0.004)	(0.006)	(0.006)	(0.007)
T(19°C-20°C)_Planting	0.001	0.004	0.004	-0.001
	(0.005)	(0.009)	(0.009)	(0.006)
T(20°C-21°C)_Planting	0.003	-0.002	-0.001	0.006
	(0.005)	(0.007)	(0.007)	(0.007)
T(21°C-22°C)_Planting	0.006	-0.004	-0.003	0.009
	(0.004)	(0.007)	(0.007)	(0.007)
T(>22°C)_Planting	0.002	-0.005	-0.004	0.006
	(0.005)	(0.008)	(0.008)	(0.006)
wetday_PP	-0.031***	-0.027*	-0.027*	-0.027**
	(0.011)	(0.015)	(0.015)	(0.013)
wetday_Planting	-0.008**	-0.017***	-0.017***	-0.004
	(0.003)	(0.005)	(0.006)	(0.004)
Rho		0.399***		
		(0.037)		
Sigma^2		0.950***		
		(0.051)		
Region # Year	Yes	Yes	Yes	Yes
Time and EA FE	Yes	Yes	Yes	Yes
Observations	12,705	12,705	12,705	12,705
Number of EAs	1,815	1,815	1,815	1,815

Note: the dependent variable is the log value of land under maize crop. Standard errors clustered at district level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Figures 4 and 5, 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 (e. g.: Lobell et al. (2011)). Studies like Seo and Mendelsohn (2008) and Wang et al. (2010) also show that farmers tend to grow maize as temperatures get warm. The inverse relation between excess wet days and maize production is also consistent with the existing literature. Kurukulasuriya and Mendelsohn (2008), for instance, show higher precipitation reduces the probability of maize production in Africa. Similarly, Miao et al. (2015) find out that excess rainfall discourages maize planting and encourages soybean planting in the U.S.

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 tonnes 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 Weather variability and Substitution between Crops

Since the farm equipment used by smallholder farmers to produce different crops in the country are traditional tools and are almost similar, crop-switching costs might not be high. Hence, we examine if crop substitution effects partly explain the change in the size of maize fields due to growing season weather variability by fitting equation (2) in a spatial framework. Table 3 presents the estimates of the total marginal effects.

The findings indicate the presence of crop substitution effects caused by weather variability within the growing season. It shows that higher temperatures during the initial planting period increase the share of land covered by maize relative to cereal, pulses, and oilseeds. For instance, an additional day above 22°C in the initial growth period

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

increases the share of land covered by maize out of the total land covered by cereals by 3.0 percent compared to a day with an average temperature below 18°C. Among the main cereal crops, an extra day above 22°C in the initial growth period increases the share of land covered by maize relative to barley, sorghum, teff, and wheat by three to four percent. Consistent with the result presented in Table 2, excess wet days reduce the relative size of maize with respect to alternative crops considered for this study. 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 have been observed.

Among existing studies, Cui (2020) shows that a 0.1°C increase in past temperature increases land covered by maize and soybean up to three percent relative to wheat, while a centimeter rise in precipitation decreases the relative share of maize and soybean to spring wheat by 2.4%. Similarly, Kurukulasuriya and Mendelsohn (2008) point out that higher precipitation in Africa is linked to a lower likelihood of maize production and a higher likelihood of sorghum production.

5.3 Robustness checks

The robustness of the results presented in Table 2 is tested by incorporating various variables expected to affect farmers' land allocation decisions. The results from the robustness tests are displayed in Table 4. Column (a) is estimated by incorporating additional EA-level socioeconomic controls that include the age of the household head, family size, number of oxen owned, and access to credit, extension service, and irrigation. The definition and descriptive statistics of the variables are presented in Table 1.

Studies like Ji and Cobourn (2021) show that land allocation decisions of farm households might also be affected by the lagged weather condition. Hence, the second

Table 3: Effect of Weather Variability on Crop Substitution

VARIABLES	Barley	Sorghum	Teff	Wheat	Cereals	Pulses	Oilseed
T(18°C-19°C)_PP	0.004***	0.002*	0.003***	0.003***	0.002**	0.002**	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T(19°C-20°C)_PP	0.001	0.001	0.002**	0.000	0.001	0.003***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T(20°C-21°C)_PP	-0.001	-0.002	0.000	-0.001	-0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T(21°C-22°C)_PP	0.005***	0.003*	0.004***	0.004***	0.003***	0.003*	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
T(>22°C)_PP	0.004***	0.003***	0.004***	0.003***	0.003***	0.002**	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T(18°C-19°C)_Planting	0.002	-0.002	-0.002	0.000	0.001	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T(19°C-20°C)_Planting	0.000	-0.001	0.001	-0.001	0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T(20°C-21°C)_Planting	0.001	0.000	-0.001	0.000	0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T(21°C-22°C)_Planting	0.001	-0.001	-0.001	0.001	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T(>22°C)_Planting	0.001	-0.002	-0.001	0.000	0.001	0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
wetday_PP	-0.003	-0.005**	-0.006***	-0.003*	-0.005***	-0.004**	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
wetday_Planting	0.000	-0.003***	-0.001	0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Region X Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and EA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12705	12705	1270	12705	12705	12705	12705
Number of EA	1815	1815	1815	1815	1815	1815	1815

Note: Standard errors clustered at district level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

robustness check is conducted to check whether the results could be confounded by the previous year's growing season weather conditions. Column (b) of Table 4 provides the result estimated by including one year lagged planting season weather patterns.

In the main results presented in Table 2, the interaction of region dummy and year fixed effect is 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 (c) and (d) of Table 4 present the results.[11] As shown in the Table, the results of the main regression equation remain unaffected in all robustness checking exercises. In addition to the aforementioned robustness tests, we also present additional test results that include changing the definitions of our weather variables and the spatial weights matrix (Table A1-A4 in the appendix).

5.4 Heterogeneous effects based on suitability

The result of the heterogeneous effects of land suitability on farmers' responsiveness is presented in Table 5. In general, the result shows that adjusting the size of land allocated to maize production due to within growing season weather variability is more pronounced in areas that are less suitable for maize production. However, it is also important to emphasize the fact that categorizing a given area as less suitable for maize production does not mean that maize has lower comparative advantages in that particular area. It can also imply that the field is less fertile for other types of crops as well.

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

Table 4: Robustness of the result

Variables	(a)	(b)	(c)	(d)
T(18°C-19°C)_PP	0.017**	0.018**	0.016**	0.015**
	(0.007)	(0.008)	(0.008)	(0.008)
T(19°C-20°C)_PP	0.019***	0.021***	0.017**	0.017**
	(0.007)	(0.008)	(0.008)	(0.008)
T(20°C-21°C)_PP	0.005	0.006	0.002	0.002
	(0.008)	(0.008)	(0.008)	(0.008)
T(21°C-22°C)_PP	0.026***	0.025***	0.021***	0.022***
	(0.008)	(0.008)	(0.008)	(0.008)
T(>22°C) _PP	0.032***	0.031***	0.026***	0.027***
	(0.01)	(0.01)	(0.01)	(0.01)
T(18°C-19°C)_Planting	0.005	0.006	0.005	0.005
	(0.007)	(0.007)	(0.006)	(0.006)
T(19°C-20°C)_Planting	0.005	0.003	0.005	0.004
	(0.009)	(0.009)	(0.009)	(0.009)
T(20°C-21°C)_Planting	-0.002	-0.004	-0.002	-0.002
	(0.007)	(0.007)	(0.007)	(0.007)
T(21°C-22°C)_Planting	-0.004	-0.005	-0.004	-0.004
	(0.007)	(0.007)	(0.007)	(0.007)
T(>22°C)	-0.006	-0.003	-0.004	-0.004
	(0.008)	(0.009)	(0.008)	(0.008)
wetday_PP	-0.021	-0.021	-0.025	-0.025*
	(0.015)	(0.015)	(0.015)	(0.015)
wetday_Planting	-0.018***	-0.013**	-0.018***	-0.017***
	(0.005)	(0.006)	(0.005)	(0.005)
Region X Year	Yes	Yes	Yes	Yes
Time and EA FE	Yes	Yes	Yes	Yes
Other controls	Yes	NO	NO	NO
One year lagged growing season weather condition	NO	Yes	NO	NO
One year lagged average price	NO	NO	Yes	NO
future average price	NO	NO	NO	Yes
Rho	0.403***	0.387***	0.398***	0.390***
	-0.035	-0.036	-0.036	-0.036
Sigma^2	0.931***	0.946***	0.948***	0.947***
	-0.05	-0.051	-0.051	-0.051
Observations	12,705	12,705	12,705	12,705
Number of EAs	1,815	1,815	1,815	1,815

Note: Standard errors clustered at district level in parentheses;*** p<0.01, ** p<0.05, * p<0.1

The result illustrates the feasibility of expanding maize production into new areas to adopt changes in the growing season weather patterns. A recent study by Sloat et al. (2020) demonstrates 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.

6 Conclusion and recommendations

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 farmer adaptation to climate change. This paper contributes to this category 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 growing season weather variability. More precisely, we show that initial growing season drier conditions encourage maize production. The results are robust to a set of different robustness tests. The results also reveal that the increase in the size of land allocated to maize production due to growing season dryness is partially achieved through substitution with other crops. Furthermore, we provide suggestive evidence that shows the presence of weather variability-induced expansion of maize production practices into areas that are 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 the land allocation decision of farm households, we have documented a notable adaptation

Table 5: Heterogonous effect based on land suitability

VARIABLES	ln(land under maize)
T(18°C-19°C)_PP	0.012
	(0.008)
Suitable# T(18°C-19°C)_PP	0.005
	(0.007)
T(19°C-20°C)_PP	0.022**
	(0.009)
Suitable# T(19°C-20°C)_PP	-0.008
	(0.009)
T(20°C-21°C)_PP	0.014
	(0.01)
Suitable# T(20°C-21°C)_PP	-0.016*
	(0.008)
T(21°C-22°C)_PP	0.028***
	(0.01)
Suitable# T(21°C-22°C)_PP	-0.009
	(0.009)
T(>22°C)_PP	0.027**
	(0.011)
Suitable# T(>22°C)_PP	0.000
	(0.008)
T(18°C-19°C)_Planting	0.009
	(0.009)
Suitable# T(18°C-19°C)_Planting	-0.006
	(0.009)
T(19°C-20°C)_Planting	0.007
	(0.009)
Suitable# T(19°C-20°C)_Planting	-0.003
	(0.007)
T(20°C-21°C)_Planting	0.006
	(0.008)
Suitable# T(20°C-21°C)_Planting	-0.012
	(0.007)
T(21°C-22°C)_Planting	-0.005
	(0.008)
Suitable# T(21°C-22°C)_Planting	0.003
	(0.008)
T(>22°C)_Planting	-0.006
	(0.009)
Suitable# T(>22°C)_ Planting	0.006
	(0.006)
wetday_PP	-0.031
	(0.019)
Suitable# wetday_PP	0.006
	(0.017)
wetday_Planting	-0.016**
	(0.006)
Suitable# wetday_Planting	-0.002
	(0.005)
Region#Year	Yes
Time and EA FE	Yes
Observations	12,705
Number of EA	1,815

Note: Standard errors clustered at district level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

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 result can contribute to the understanding of the climate change impacts on crop yield since neglecting such margins could lead to biased estimates. This is essential given the projected rise in the frequency and magnitude of weather variations.

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 adaptive methods 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 the significant share of food mainly comes from domestic production with little import from the international market, weather variability induced reallocation of land can dictate the types and amount of food that is available and accessible for the total 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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Table A1: Estimated Impacts of Weather Variability on Maize Land Allocation, alternative weather definition

VARIABLES	Maize land	Maize land	Maize land	Maize land	Maize land
Temperature above 18°C_pp	0.0131***				
	(0.00347)				
Temperature above 18°C_planting	0.00162				
	(0.00291)				
Temperature above19°C_pp		0.00703**			
		(0.00306)			
Temperature above 19°C_planting		0.0023			
		(0.00267)			
Temperature above 20°C_pp			0.00538		
			(0.00335)		
Temperature above 20°C_planting			0.00319		
			(0.00246)		
Temperature above 21°C_pp				0.0148***	
				(0.00373)	
Temperature above 21°C_planting				0.000569	
				(0.00251)	
Temperature above 22°C_pp					0.0143***
					(0.00416
Temperature above 22°C_planting					-0.00199
					(0.00284)
wetday_PP	-0.0337***	-0.0354***	-0.0350***	-0.0316***	-0.0328***
	(0.0108)	(0.0106)	(0.011)	(0.0107)	(0.0108)
wetday_Planting	-0.00948***	-0.0103***	-0.0102***	-0.0110***	-0.0132***
	(0.00302)	(0.00327)	(0.00338)	(0.00311)	(0.00308)
Constant	16.21	5.539	0.714	-9.06	-31.73
	(26.63)	(27.07)	(24.26)	(22.24)	(23.29)

Note: The table presents the effects of temperature using alternative definitions (captured via the number of days above the indicated temperature thresholds) on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop. The model includes village fixed effects as well as the interaction between regions dummy and year. Standard errors are in parentheses, clustered by district level. Standard errors clustered at district level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A2: Estimated Impacts of Weather Variability on Maize Land Allocation, alternative weather definition

VARIABLES	Maize land
T(18°C-19°C)_PP	0.018***
	(0.005)
T(19°C-20°C)_PP	0.015***
	(0.006)
T(20°C-21°C)_PP	-0.001
	(0.005)
T(21°C-22°C)_PP	0.030***
	(0.006)
T(22°C-23°C)_PP	0.044***
	(0.008)
T(>23°C)_PP	0.032***
	(0.007)
T(18°C-19°C)_Planting	0.008*
	(0.004)
T(19°C-20°C)_Planting	0.000
	(0.005)
T(20°C-21°C)_Planting	0.002
	(0.005)
T(21°C-22°C)_Planting	0.001
	(0.004)
T(22°C-23°C)_Planting	0.012**
	(0.006)
T(>23°C)_ Planting	-0.005
	(0.005)
wetday_PP	-0.030***
	(0.011)
wetday_Planting	-0.009***
	(0.003)

Note:The table presents the effects of temperature using alternative definitions (captured via the number of days within the indicated temperature bins) on agricultural land allocation decisions. The model includes village fixed effects as well as the interaction between regions dummy and year. 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, ** p<0.05, * p<0.1

Table A3: Estimated Impacts of Weather Variability on Maize Land Allocation, an alternative spatial weight matrix

VARIABLES	Nearest neighbor -five	Nearest neighbor -six
T(18°C-19°C)_PP	0.016**	0.015*
	(0.008)	(0.008)
T(19°C-20°C)_PP	0.018**	0.018**
	(0.007	(0.007
T(20°C-21°C)_PP	0.005	0.004
	(0.008)	(0.008)
T(21°C-22°C)_PP	0.023***	0.021***
	(0.007)	(0.008)
T(>22°C)_PP	0.029***	0.027***
	(0.01)	(0.01)
T(18°C-19°C)_Planting	0.004	0.004
	(0.007)	(0.007)
T(19°C-20°C)_Planting	0.005	0.005
	(0.009)	(0.009)
T(20°C-21°C)_Planting	-0.003	-0.002
	(0.007)	(0.007)
T(21°C-22°C)_Planting	-0.004	-0.003
	(0.007)	(0.007)
T(>22°C)_Planting	-0.005	-0.002
	(0.009)	(0.008)
wetday_PP	-0.028*	-0.025*
	(0.015)	(0.015)
wetday_Planting	-0.017***	-0.018***
	(0.005)	(0.005)

Note: The table presents the effects of within growing season weather conditions on agricultural land allocation decisions using an alternative spatial weight matrix. The dependent variable is the log value of land under maize crop. The model includes village fixed effects as well as the interaction between regions dummy and year. Standard errors are in parentheses, clustered by district level. Standard errors clustered at district level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

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

VARIABLES	Main
T(18°C-19°C)_PP	0.010***
	(0.003)
T(19°C-20°C)_PP	0.010***
	(0.003)
T(20°C-21°C)_PP	0.004
	(0.004)
T(21°C-22°C)_PP	0.013***
	(0.004)
T(>22°C)_PP	0.017***
	(0.005)
T(18°C-19°C)_Planting	0.007**
	(0.003)
T(19°C-20°C)_Planting	0.005
	(0.003)
T(20°C-21°C)_Planting	0.004
	(0.003)
T(21°C-22°C)_Planting	0.002
	(0.003)
T(>22°C)_Planting	0.002
	(0.004)
wetday_PP	-0.022***
	(0.007)
wetday_Planting	-0.004
	(0.002)

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, * p<0.1