Climate Change and Agriculture: Subsistence Farmers' Response to Extreme Heat*

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Abstract

This paper examines how subsistence farmers respond to extreme heat. Using micro-data from Peruvian households, we find that high temperatures reduce agricultural productivity, increase area planted, and change crop mix. These findings are consistent with farmers using input adjustments as a short-term mechanism to attenuate the effect of extreme heat on output. This response seems to complement other coping strategies, such as selling livestock, but exacerbates the drop in yields, a standard measure of agricultural productivity. Using our estimates, we show that accounting for land adjustments is important to quantify damages associated with climate change.

JEL Classification: O13; O12; Q12; Q15; Q51; Q54

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1 Introduction

A growing body of evidence suggests that extreme temperatures have negative effects on crop yields.[1] Based on these findings, current estimates suggest that climate change will bring dramatic shifts in agriculture: a global warming of 2°C, as in the most optimistic forecasts, would reduce agricultural output by almost 25% (IPCC, 2014). Among those exposed to this shock, the rural poor in developing countries are probably most vulnerable. They are located in tropical areas, where the changes in climate will occur faster and be more intense, and their livelihoods are more dependent on agriculture.

Given these potentially disruptive effects, it is extremely important to understand possible margins of adjustment and the scope for mitigation. Some studies suggest that a possible response to climate change would be the re-allocation of economic activity, in the form of migration, changes in trade patterns or sectoral employment (Colmer, 2018, Costinot et al., 2016, Feng et al., 2012). Other studies, based on farmers' self-stated adaptive strategies, emphasize changes in consumption and savings as potential temporary responses (Di Falco et al., 2011, Gbetibouo et al., 2010, Hisali et al., 2011). Less is known, however, about the potential for productive responses (i.e., changes in input use and agricultural practices), to attenuate the adverse effects of extreme temperatures.[2]

This paper examines how subsistence farmers respond to extreme temperatures. It has two main contributions. First, it examines a population that has been relatively neglected in the literature, despite comprising a large fraction of the rural poor around the world. Second, it documents the role of short-run productive responses, in particular the increase in land use, as a mechanism to mitigate the negative effects of extreme temperatures on agricultural output. To the best of our knowledge, this margin of adjustment has not been documented before. It has, however, significant implications for the quantification of climate change damages, and for understanding the potential long-term effects of weather shocks.

Our empirical analysis combines survey microdata from Peruvian farming households with weather data from satellite imagery. We examine the relationship between temperature and input demands (land and labor), as well as other agricultural outcomes such as total factor productivity, yields, and output. Similar to recent studies of the effect of temperature, we use an approach that exploits within-locality variation in weather.

By focusing on input use, our approach addresses some limitations of existing economic studies of the effect of temperature on agriculture. These studies focus on outcomes such as land prices, profits and yields that can be informative of the costs associated to raising temperatures (as in

[1] See for instance, Burke et al. (2015), Carleton and Hsiang (2016), Chen et al. (2016), Deschenes and Greenstone (2007), Lobell et al. (2011), Schlenker et al. (2005, 2006), Zhang et al. (2017). A review of the biological evidences is available at Wahid et al. (2007).

[2] A recent paper that addresses this questions is Jagnani et al. (forthcoming). Using data from Kenya, they find that farmers increase fertilizer use as a response to increased temperatures early in the growing season. They interpret this finding as a evidence that farmers undertake defensive investments to reduce the adverse impacts of warmer temperatures.

Deschenes and Greenstone (2007) and Schlenker et al. (2006)). Moreover, since profits and yields already include farmers' responses, they can be used to indirectly assess the scope for mitigation and adaptation.[3] These approaches have, however, two important limitations. First, they are not informative of the mitigation and adaptive strategies used by farmers, only of their net effect. Second, because of their reliance on market prices, profits and land values are not very useful in contexts with incomplete agricultural markets or when revenues and costs are difficult to observe, for instance due to self-consumption or the use of household inputs. This limitation is particularly relevant when studying subsistence farmers in less developed countries.

We find that extreme heat *increases* area planted. The magnitude is economically significant: one standard deviation increase in our measure of extreme heat is associated with a 6% increase in land used. Consistent with the additional land being planted with a different crop mix, we find that extreme heat increases the quantity harvested (in absolute and relative terms) of tubers. We also find suggestive evidence of increments in the use of domestic, including child, labor on the farm. The increase in input use occurs despite high temperatures reducing agricultural productivity, and partially offsets the drop in total output. We interpret these findings as evidence that subsistence farmers respond to extreme temperatures by increasing input use within the growing season. This productive adjustment attenuates undesirable drops in output and consumption. Our interpretation is consistent with agricultural household models with incomplete markets (De Janvry et al., 1991, Taylor and Adelman, 2003). In these models, production and consumption decisions are not separable. Thus, at low consumption levels, farmers may resort to more intensive use of non-traded inputs, like land and domestic labor, to offset the impact of negative income or productivity shocks. This margin of adjustment may be particularly relevant for farmers in less developed countries due to the presence of several market imperfections and limited coping mechanisms.

With this interpretation in mind, we also examine several ex-post coping mechanisms previously identified in the literature on consumption smoothing, such as migration, off-farm labor, and disposal of livestock (Bandara et al., 2015, Beegle et al., 2006, Kochar, 1999, Munshi, 2003, Rosenzweig and Wolpin, 1993, Rosenzweig and Stark, 1989). Consistent with previous studies, we find that households reduce their holdings of livestock after a negative weather shock and seem to increase hours working off the farm. Interestingly, the increase in land use as a response to extreme heat occurs even among farmers that resort to other consumption smoothing strategies. This finding suggests that productive responses to extreme temperatures remain important to traditional farmers, even if they have alternative risk-coping instruments at hand.

Our findings have two important implications. First, they suggest a potential dynamic link between weather shocks and long-run outcomes. If the increase in land use comes at the expense of

[3]For instance, Burke and Emerick (2016) find that the effect of extreme heat on crop yields in U.S. has not changed over time. They interpret this finding as evidence of limited long-run adaptation. Similarly, Taraz (2018) examines differences on the effect of temperature on crop yields by baseline climate to assess the scope of adaptation among Indian farmers.

investments (such as fallowing), then this short-term response could affect future land productivity. A similar argument could be made about child labor. While we are unable to examine these implications due to data limitations, future research should explore these links more closely. Second, this farmer response may affect estimations of the damages of climate change on agricultural output. These estimates are usually based on the effect of temperature on crop yields (Deschenes and Greenstone, 2007). This is a correct approach under certain conditions, e.g. if land use is fixed. In that case, changes in crop yields are the same as changes in output. However, if area planted increases with temperature, then using crop yields would overestimate the resulting loss in output. To illustrate this point, we use our results to predict damages of climate change by the end of the century under two standard scenarios (RCP45 and RCP85). Using the effect of temperature on yields, as in the existing literature, suggests output losses of 5-9% under different scenarios. In contrast, taking into account changes in land use, we obtain smaller losses of 0.6 to 1.2%.

The rest of this paper is organized as follows. Section 2 describes the context and the analytic framework. Section 3 discusses the data and the empirical strategy. Section 4 presents our main results and robustness checks. Section 5 examines other other coping mechanisms, while Section 6 discusses the implication of our findings for estimating climate change damages. Section 7 concludes.

2 Background

2.1 Subsistence farming in Peru

Our empirical analysis focuses on subsistence farmers from rural Peru. In 2017, the last year of our study, 24% of the working population was employed in agriculture, but the sector only accounted for 7% of the GDP (INEI, 2018). It is, in other words, a sector of very low productivity, with many characteristics in common with subsistence farming in other developing countries: it is mainly composed by small productive units (i.e., households), with low capital intensity, and low levels of technology adoption (Velazco et al., 2012).

Table 1 presents some key summary statistics of the farmers in our sample and defines the setting for our analysis.[4] Most farmers are poor and depend on agriculture as their main source of livelihood. The incidence of poverty in our sample of farmers is around 50%. For comparison purposes, a similar methodology shows that poverty over the whole of Peru during the period of analysis was 21.6%. The average farm is around 2 hectares, has a low degree of specialization and uses practices akin to traditional, rather than industrial, farming. They rely on domestic labor (including child labor), cultivate a variety of crops instead of monocropping, and leave some land uncultivated. Some of this uncultivated land is reported as fallowing while the rest is covered with grasses, bushed and forests. These last uses are also consistent with sectoral fallowing and crop rotation, but we can not rule out that part of this land is non-agricultural.

[4]Data sources and variable definitions are described in Section 3.1

Figure 1 shows the number of hectares planted by calendar month during years 2014-2017. As one can see, most planting occurs during October-March. These months correspond to spring and summer in the Southern Hemisphere and are considered the main growing season in Peru. However, planting is not a one-off activity as it persists throughout the year. This feature suggests that farmers have some margin to adjust their input use during the agricultural year. Figure 2 shows that planting is usually spread over several months, and not necessarily a one-off event. For instance, around 50% of farmers engaged in planting in two or more months. This last observation suggests that farmers might have flexibility to adjust their decisions during the growing season. We note that the number of months in which farmers decided to plant could be endogenous to weather realizations, an issue we explore below.

Our study concentrates on two climatic regions: the coast and the highlands.[5] These two regions exhibit different climate driven by their proximity to the sea and altitude. The coast is a narrow strip extending from the seashore up to 500 meters above sea level (masl). It has a semi-arid climate, with warm temperatures and little precipitation. The highlands extends from 500 up to almost 7,000 masl, albeit most agriculture stops below 4000 masl. It has a much cooler and wetter climate, with seasonal precipitations in spring and early summer.

These climatic differences are associated with different agricultural practices: coastal farmers are more reliant on irrigation, while agriculture in the highlands is mostly rainfed. Coastal farmers are also less likely to be poor and have a different crop mix, cultivating a larger share of fruits and cereals. While these regional differences do not affect the key results in our analysis (see Section 4.4), they have important implications in terms of the potential effects of greater temperatures due to climate change.

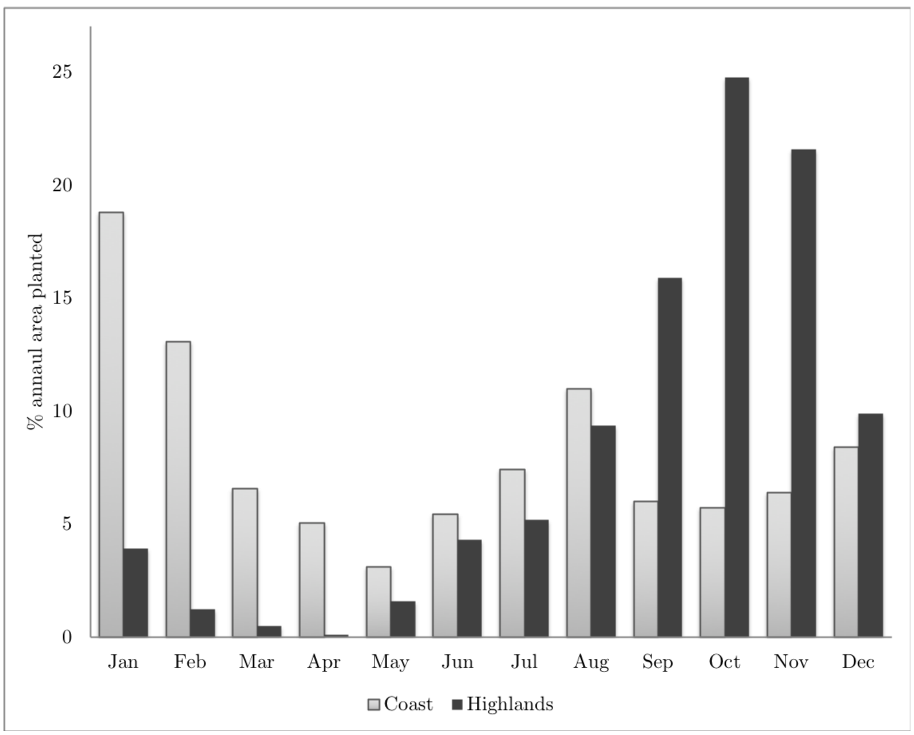
[5]Peru has three main climatic regions: the coast to the west, the Andean highlands, and the Amazon jungle to the east. We do not include observations from the jungle due to small sample size and poor quality of satellite data. We also drop 282 farmers from the coast and highlands reporting land holdings larger than 100 hectares.

Table 1: Summary statistics (ENAHO 2007-2015)

	(1) All	(2) Coast	(3) Highlands
A. Household characteristics			
Poor (%)	51.14	26.55	55.10
Household size	4.34	4.41	4.33
Primary education completed by HH head (%)	50.93	58.48	49.71
Child works (%)	21.82	9.65	23.79
At least 1 HH member has off-farm job (%)	47.54	56.45	46.10
B. Agricultural characteristics			
Value of agric. output (Y)	1049.93	3263.23	693.40
Output per ha. (Y/T)	1048.92	1868.49	917.09
Land used (T), in ha.	1.99	2.41	1.92
No. HH members work on-farm	2.31	2.21	2.33
Hire workers (%)	48.85	57.08	47.52
Uncultivated land (% of land holding)	40.30	11.81	44.89
Irrigated land (% land holding)	36.05	82.00	28.65
Fruits (% total output)	7.41	31.59	3.52
Tubers (% total output)	31.35	5.54	35.50
Cereals (% total output)	31.30	30.43	31.44
Own livestock (%)	77.61	55.95	81.10
Value of livestock	682.11	461.85	717.59
C. Weather during the last growing season			
Average temperature (°C)	22.84	33.07	21.20
Average DD	14.28	22.39	12.97
Average HDD	0.73	2.69	0.41
Share of days with HDD	0.139	0.391	0.097
Precipitation (mm/day)	3.16	0.93	3.51
Observations	53,619	7,439	46,180

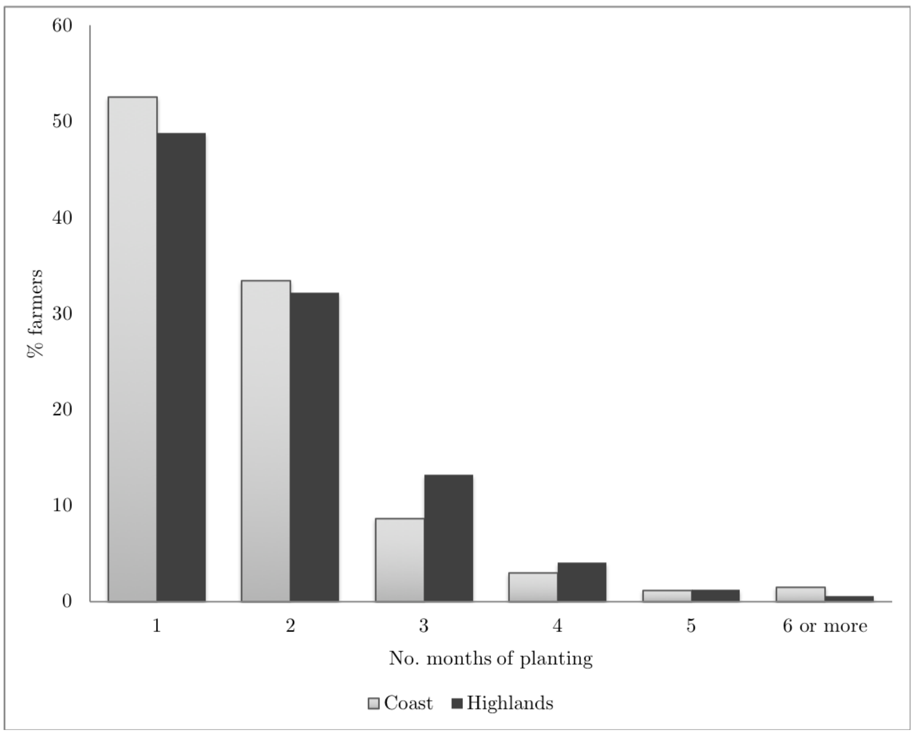
Notes: Output and livestock value measured in 2007 USD. Land is measured in hectares. Temperature is measures in Celsius degrees. HoH= household head. HH= household. DD=degree days. HDD = harmful degree days.

Figure 1: Percentage of annual area planted in a month, by climatic region



Notes: Figure depicts the share of annual area planted in a given month, averaged over farmers in a climatic region. We consider only planting of transitory (annual) crops. *Source:* National Agricultural Survey of Peru, 2014-2017.

Figure 2: Number of months of planting, by climatic region



Notes: Figure depicts the proportion of farmers by the number of months in which they plant transitory crops. *Source:* National Agricultural Survey of Peru, 2014-2017.

2.2 Analytical framework

This section develops a simple framework to examine how subsistence farmers adjust their production decisions as a response to extreme heat. To this end, we follow standard agricultural producer-consumer household models in the development literature (Benjamin, 1992, De Janvry et al., 1991, Taylor and Adelman, 2003) where households make simultaneous, potentially interrelated, consumption and production decisions during the growing season.

Without loss of generality, let us assume an agricultural production function with a single input. We call this input "land" but it can refer to any other variable input such as labor. The household has an endowment of land, T^e. Land can be used for production or "consumed" in non-productive activities (e.g., leisure).[6] Household's utility is $U(c, t)$, where c is consumption of a market good, while t is the amount of land used in non-productive activities. Households obtain income by renting their land and by producing an agricultural good. Production is defined by function $F(A, T)$, where T is the amount of land used in agriculture, and A is farmer's total factor productivity. A is a productivity shifter that captures the idea that farmers using identical inputs can have different levels of output due, for instance, to different farming skills, soil quality, or exposure to weather shocks.[7] Consistent with previous studies on the relation between crop yields and temperature, we assume that extreme heat has a detrimental effect on productivity.[8]

Each growing season, the household maximizes utility by choosing the amount of land allocated to productive and non-productive uses. We consider that land is a variable input. This assumption is driven by the observation that, among subsistence farmers, planting is not a one-off activity, but instead it is spread throughout the year (see Figure 2).[9] Finally, we assume that both the utility and the production functions are increasing and strictly concave.

2.2.1 Household responses to negative productivity shocks

If input markets exist and are well functioning, we can study consumption and production decisions separately (Benjamin, 1992). This separation result is driven by the possibility to trade. Thus, the household's demand and supply of inputs for production and consumption need not be identical to its endowments. The farmer's use of inputs on the farm can then be analyzed by solving the profit maximization problem $\max_{T} \quad \pi = pf(A, T) - rT$, were p and r refers to output and input prices.

[6] The inclusion of land directly in the utility function is a modeling device to create a positive shadow price (i.e., an opportunity cost of using land), and should not be taken literally. Since land cannot be sold or rented out, without this device, the model would predict that farmers will always use all available land. This prediction is inconsistent with the empirical observation that around 40% of land is left uncultivated. An alternative way to generate a non-zero shadow price is to include an intertemporal opportunity cost, for instance by allowing productivity-enhancing fallowing.

[7] In our context, we assume that capital such as irrigation, if used at all, is fixed.

[8] See for example Schlenker and Roberts (2009), Burke and Emerick (2016), Auffhammer et al. (2012), Hsiang (2010), Hsiang (2016), among others.

[9] Note that multi-cropping practices, combined with the availability of uncultivated land, implies that both inputs and outputs are flexible throughout the season, during which A is realized.

The standard solution is the unconditional input demand $T^*(A, p, w)$. In this context, a farmer's response to negative productivity shock, such as extreme heat, is unequivocal: she will *reduce* the amount of land used in her farm.

This prediction can change in the case of incomplete markets. To illustrate this, consider a case in which there are no input markets. In this simplified setting, the farmer's problem becomes:

$$\begin{aligned} \max_{T} \quad & U(c, t) \\ \text{s.t.} \quad & c = pF(A, T) \\ & T + t = T^e. \end{aligned}$$

Solving this problem produces an unconditional demand for land that depends not only on prices and productivity, but also on land endowment, $T(A, p, T^e)$. Moreover, if utility is sufficiently concave (for instance if consumption levels are quite low or farmer has high risk aversion), then $\frac{dT}{dA}$ can be negative.[10]

This result suggests that, in context with imperfect input markets, negative weather shocks, such as extreme heat, could result in an *increase* in input use. This occurs because the farmer uses more inputs to attenuate the fall in agricultural output, and reduce the drop in consumption. This response is akin to coping mechanisms to smooth consumption, such as selling disposable assets. The key distinction is that it involves adjustments in productive decisions. This prediction is relevant because subsistence farmers in rural Peru (and other parts of the developing world) likely face severe imperfections in input markets (Gollin et al., 2013, Restuccia et al., 2008).

This framework also points out to alternative explanations for a positive relation between extreme temperature and input use. For instance, this could occur if extreme temperatures have a negative effect on aggregate supply and raise output prices (p). Similarly, we would observe a positive relation if there are correlated productivity shocks, such as increase in precipitation; or changes in land endowments (for instance, due to sample attrition of small landholders). We address these potential confounders in our identification strategy, and examine the role of prices as an alternative explanation in section 4.4.2.

With this framework in mind, our empirical analysis focuses on examining the effect of extreme heat on input use, as well as on agricultural productivity. There are, however, other possible responses. For instance, recent work on climate change and adaptation has stressed changes in crop mix as a possible response (Burke and Emerick, 2016, Costinot et al., 2016). Similarly, an

[10]Taking total derivatives to first order condition $pU_c F_T = U_t$, we obtain that:

$$\frac{dT}{dA}(F_T^2 U_{cc} + U_c F_{TT} + U_{tt}) + F_T F_A U_{cc} + U_c F_{TA} = 0.$$

Assuming strictly concave utility and production functions, this expression implies that a necessary and sufficient condition for inputs to increase with a negative productivity shock ($\frac{dT}{dA} < 0$) is $-\frac{U_{cc}}{U_c} > \frac{F_{TA}}{F_T F_A}$. Assuming, a Cobb-Douglas technology $f = AT^\alpha$, this condition simplifies to: $-\frac{U_{cc}}{U_c} > 1$.

influential literature highlights how households can smooth consumption by migrating, increasing off-farm work, or selling cattle, among other strategies (see for instance Rosenzweig and Wolpin (1993) or Kochar (1999)). In the empirical section, we also examine these additional potential responses.

3 Methods

3.1 Data

We combine household surveys with satellite imagery to construct a comprehensive dataset containing agricultural, socio-economic, and weather variables. The unit of observation is the household-year. We restrict the sample to households with agricultural activities located in the coast and highlands. Our final dataset consists of around 53,000 observations and spans over the years 2007 to 2015. Table 1 presents some summary statistics for our sample.

3.1.1 Agricultural and socio-economic data

Our main data source is repeated cross-sections of the Peruvian Living Standards Survey (ENAHO), an annual household survey collected by the National Statistics Office (INEI). This survey is collected in a continuous, rolling, basis. This feature guarantees that the sample is evenly distributed over the course of the calendar year.

The survey asks the farmer to report the quantity of crops harvested in the last 12 months, as well as the size and use of parcels planted in that period. We use this information to construct measures of agricultural output and input use. To measure real agricultural output, we construct a Laspeyres index using quantity produced of each crop and baseline local prices.[11] We calculate land used by adding the size of parcels dedicated to seasonal and permanent crops. We distinguish between domestic and hired labor. We measure hired labor using self-reported wage bill paid to external workers in the last 12 months. To measure domestic labor, we use information on household members' employment. In particular, we calculate the number of household members working in agriculture and build an indicator of child labor.[12]

This dataset has three relevant limitations. First, we do not observe the time of planting, only the total land used in the last 12 months. Second, we do not observe which specific crops are cultivated in each parcel.[13] Since most farmers grow several crops and practice inter-cropping, we cannot calculate crop-specific yields. Finally, the information on household employment is available only for the two weeks before the interview. Given that interviews can occur all year round and

[11] As local prices, we use the median price of each crop in a given department (n=24) in 2007.

[12] Child labor is defined as an indicator equal to one if a child living in the household aged 6-14 reports doing any activity to obtain some income. This includes helping in the family farm, selling services or goods, or helping relatives, but excludes household chores.

[13] We only observe total area planted and, separately, total harvests of each crop.

labor use is seasonal, our measures of domestic labor may not reflect actual input use during the whole year. While this measurement error does not affect estimates of the effect of temperature on land use, it can affect estimates of its impact on labor use. In those cases, we address this concern by restricting the sample to farmers interviewed during the main growing season only.

The survey also provides information on socio-demographic characteristics, agricultural practices and farm conditions (such as intercropping, access to irrigation, and use of fertilizers), and geographical coordinates of each primary sampling unit or survey block.[14] In rural areas, this corresponds to a village or cluster of dwellings. We use this geographical information to link the household data to satellite imagery. We complement the household survey with data on soil quality from the Harmonized World Soil Database (Fischer et al., 2008).[15]

3.1.2 Temperature and precipitation

We use satellite imagery to obtain high-resolution measures of local temperature. We prefer to use satellite imagery instead of ground-level measures or gridded products, such as re-analysis datasets, due to the small number of monitoring stations (around 14 in the whole country).[16] We use the MOD11C1 product provided by NASA. This product is constructed using readings taken by the MODIS tool aboard the Terra satellite. These readings are processed to obtain daily measures of daytime temperature on a grid of 0.05×0.05 degrees, equivalent to 5.6 km squares at the Equator, and is already cleaned of low quality readings and processed for consistency.[17]

The satellite data provides estimates of land surface temperature (LST) not of surface air temperature, which is the variable measured by monitoring stations. For that reason, the reader should be careful when comparing the results of this paper to other studies using re-analysis data or station readings. LST is usually higher than air temperature, and this difference tends to increase with the roughness of the terrain. However, both indicators are highly correlated (Mutiibwa et al., 2015).

We complement the data on temperature with information on local precipitation. We use data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) product (Funk et al., 2015). CHIRPS is a re-analysis gridded dataset that combines satellite imagery with monitoring station data. It provides estimates of monthly precipitation with a resolution of 0.05×0.05 degrees.

[14]There are around 3,800 unique coordinate points in our sample. Figure A.1 in the Appendix depicts the location of clusters used in this study.

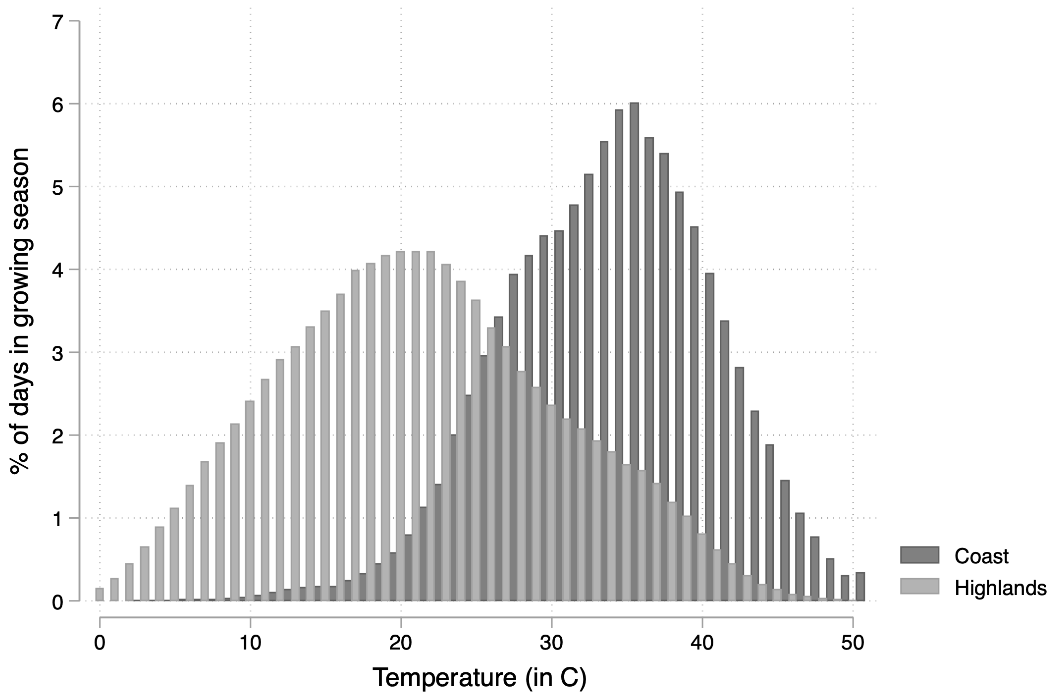
[15]This dataset provides information on several soil characteristics relevant for crop production on a 9 km square grid. The soil qualities include nutrient availability and retention, rooting conditions, oxygen availability, excess salts, toxicity, and workability.

[16]Note that reanalysis datasets use ground-level readings as a main input and thus can be less precise in contexts with a low number of monitoring stations (Auffhammer et al., 2013).

[17]MODIS validation studies comparing remotely sensed land surface temperature estimates and ground, *in situ*, air temperature readings found discrepancies within the 0.1-0.4 ℃ range (Coll et al., 2005, 2009, Wan and Li, 2008).

To link the weather and household data, we attribute to a given household the weather conditions in the cell overlapping its coordinates. Then, we aggregate weather data (which have daily and monthly frequency) to obtain measures of exposure to weather during a given agricultural year. In our baseline specification, we focus on exposure to weather during the last completed growing season. The growing season is the period in which most of planting and crop growth occurs. As shown in Section 2.1, even though planting is a year-round activity, it is particularly concentrated in spring and summer. We use this period as our definition of growing season.[18] Figure 3 shows the distribution of temperatures observed during the last completed growing season for our whole sample.[19]

Figure 3: Distribution of daily average temperature by growing season



Notes: density of daily temperatures during the last completed growing season (i.e., October to March). The unit of observation is farmer-growing season.

[18]We define the growing season as months October to March. In Section 4.4, we check the robustness of our results to alternative ways to aggregate weather over time, such as by climatic season or during last 12 months.

[19]Figure A.3 in the Appendix, shows the average distribution of daily temperatures by growing season, and shows that the distribution is mostly stable over the time of our study.

3.2 Empirical strategy

The empirical analysis aims to study how farmers respond to extreme heat. Based on the discussion in Section 2.2, we focus on productive adjustments, such as changes in input use. To study this response, we estimate reduced-form unconditional factor demands linking input use to weather shocks.

In a standard production model, unconditional factor demands are a function of total factor productivity (TFP), and agricultural prices. In the presence of imperfect input markets, they could also be affected by household endowments.[20] In this context, weather conditions, such as temperature and precipitation, enter into the factor demand through their effects on A.

We approximate the reduced-form factor demand using the following log-linear regression model:

$$\ln y_{ijt} = g(\gamma, \omega_{it}) + \phi Z_i + \rho_j + \psi_t + \epsilon_{ijt}, \tag{1}$$

where the unit of observation is farmer i in district j and growing season t. y is our measure of input use and $g(\gamma, \omega_{it})$ is a non-linear function of temperature and precipitation (ω_{it}). The parameter of interest is γ: the reduced-form estimates of the effect of weather shocks on input use. Note that our specification exploits within-district variation. Thus we cannot estimate the effect of climate, but only of weather shocks. This approach is similar to the panel regressions used in recent studies of the effect of climate on economic outcomes (Dell et al., 2014).

Z_i is a vector of farmer characteristics, ρ_j is a set of district fixed effects, and ψ_t are climatic region-by-growing season fixed effects.[21] These control variables proxy for both determinants of TFP as well as other drivers of input use. Z_i includes possible drivers of TFP such as indicators of soil quality, household head's education, age, and gender, as well as measures of input endowments like land owned and household size, ψ_t controls for common productivity shocks but, to the extent that agricultural markets are national, also for agricultural prices. Similarly, ρ_j accounts for location-specific determinants of productivity, such as climate and soil quality, but can also control for other time-invariant determinants of input use, like proximity to markets.[22]

Similar to previous work, we model the relation between weather and agricultural productivity as a function of cumulative exposure to heat and water.[23] In particular, we construct two measures of cumulative exposure to heat during the growing season (i.e., spring and summer): average degree days (DD) and harmful degree days (HDD).

[20] For instance, in the extreme case of no input markets, input use would be proportional to input endowments. See the discussion in Aragón and Rud (2016).

[21] A district is the smallest administrative jurisdiction in Peru and approximately half the size of the average U.S. county. Our sample includes 1,320 districts out of a total of 1,854.

[22] A potential concern is that the inclusion of fixed effects could absorb a significant amount of weather variance and amplify measurement error (Auffhammer and Schlenker, 2014, Fisher et al., 2012). We examine this issue and find that there is still relatively large weather variation even after including a rich set of fixed effects (see Tables B.2 and B.3 in the Appendix).

[23] See for instance Schlenker and Roberts (2006) and Schlenker et al. (2006).

DD measures the cumulative exposure to temperatures between a lower bound, usually 8℃ up to an upper threshold τ, while HDD captures exposure to temperatures above τ. The inclusion of HDD allows for potentially different, non-linear, effects of extreme heat. Formally, we define the average DD and HDD during the growing season as:

$$DD = \frac{1}{n}\sum_{d=1}^{n}(h_d - 8)\mathbb{1}(8 \leq h_d \leq \tau)$$
$$HDD = \frac{1}{n}\sum_{d=1}^{n}(h_d - \tau_{high}))\mathbb{1}(h_d > \tau),$$

where h_d is the average daytime temperature in day d and n is the total number of days in a growing season with valid temperature data. Note that we do not calculate *total* degree days, but instead the *average* degree days. This re-scaling makes interpretation easier and help us address the issue of missing observations due to satellite swath errors.

A key issue is to define the value of τ. Previous studies in U.S. set this value between 29-32℃ (Deschenes and Greenstone, 2007, Schlenker and Roberts, 2006). These estimates, however, are likely to be crop and context dependent and hence might not be transferable to our case.[24] For that reason, we prefer to use a data-driven approach. To do so, we estimate a flexible version of equation (1) using log of output per hectare as outcome variable and replacing $g(.)$ with a vector of variables measuring the proportion of days in a growing season on which the temperature fell in a given temperature bin.[25] The results, displayed in Figure 4a suggest that point estimates become negative for temperatures above 33 ℃. We use this temperature as our preferred τ in our baseline specification.[26]

We measure exposure to precipitation using the average daily precipitation (PP) during the growing season and its square. With these definitions in mind, we parametrize the function relating weather to productivity $g(\gamma, \omega_{it})$ as:

$$g(\gamma, \omega_{it}) = \gamma_0 DD_{it} + \gamma_1 HDD_{it} + \gamma_2 PP_{it} + \gamma_3 PP_{it}^2.$$

[24] In addition to differences in crop mix and agricultural technology, we use a different measure of temperature (i.e., land surface temperature). These factors make previous estimates not applicable to our case study.

[25] This specification is similar to the one used by Burgess et al. (2017) to study the effect of weather on mortality. Based on the distribution of temperatures in the Peruvian case, we define 11 bins: < 6℃, ≥ 42℃, and nine 4℃-wide bins in between. Our omitted category is the temperature bin 22-25℃.

[26] As a robustness check, we also estimate τ using an iterative regression method similar to those used by Schlenker et al. (2006). We ran 17 regressions with different DD/HDD thresholds ranging from 26℃ to 42℃ and compared their model fit. The results, in Figure A.4 suggests optimal temperatures in the slightly lower 30-32 ℃ range. To ensure that our choice of τ does not drive our main results, in Figures A.5a and A.5b in the Appendix we plot the point estimates of the HDD coefficients for the range of τ mentioned above. Reassuringly, point estimates are of similar size, magnitude, and precision between the 26-35℃ interval.

4 Main results

This section presents our main empirical results on farmers' responses to extreme heat. We start by documenting the relationship between temperature and our main outcomes: land productivity and land use. As a first glance at the data, we use a flexible approach using temperature bins instead of degree days.

The results, shown in Figure 4, suggest that extreme temperatures are associated with reductions in land productivity, but increase in area planted. This negative relationship between productivity and input use is consistent with farmers using more inputs to attenuate the drop in agricultural output. Below, we examine these findings and interpretation in more detail.

4.1 Temperature and agricultural productivity

We use two approaches to examine the relation between temperature and agricultural productivity. First, we follow the existing literature and estimate our baseline specification (1) using yields (i.e., output per unit of land) as our measure of (land) productivity. This specification measures exposure to heat using degree days (DD) and harmful degree days (HDD) averaged over the main growing season (i.e., spring and summer). A limitation of this approach is that yields are a measure of partial productivity that reflect changes in TFP and land used. This is not an issue when land is fixed, but can overestimate the effect of extreme heat on productivity if farmers adjust land.

As a second approach, we estimate a production function. Assuming a Cobb-Douglas specification we modify our baseline specification by using log of output as outcome and controlling for log of input use.[27] This approach allow us to estimate directly the effect of extreme heat on TFP. However, it comes at the cost of imposing parametric assumptions and, potentially, creating an endogeneity problem due to omitted productivity drivers affecting both input use and output. Consistent with the analytical framework proposed in Section 2.2, we address this issue by using endowments, such as household size and owned land, as predictors for input use in an instrumental variable approach.[28]

Table 2 presents our results. The estimates suggest that extreme heat has a negative effect on agricultural productivity.[29] The magnitude of the effect is economically significant: the most

[27]Assuming a Cobb-Douglas production function $Y_{ijt} = A_{ijt}T_{it}^{\alpha}L_{it}^{\beta}$, applying logarithms, and defining $A = \exp(g(\gamma, \omega_{it}) + \phi Z_i + \rho_j + \psi_t + \epsilon_{ijt})$ we obtain the following regression model:

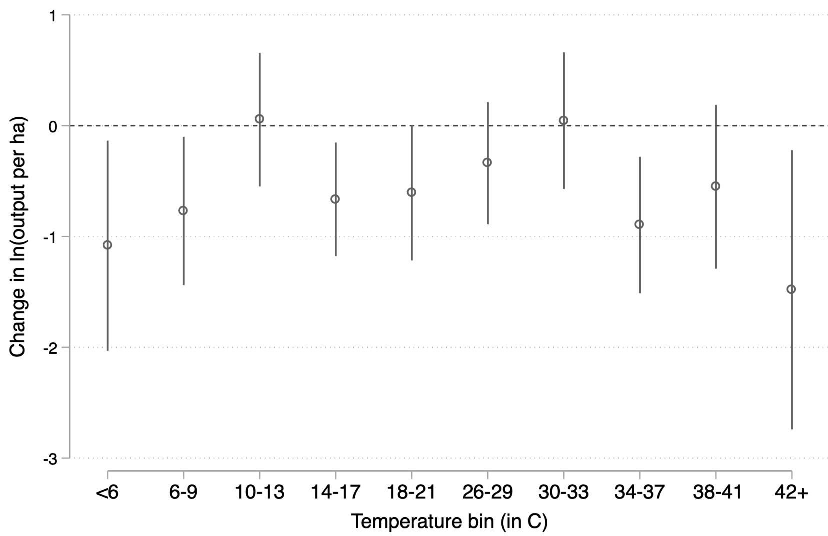
$$\ln Y_{ijt} = \alpha \ln T_{it} + \beta \ln L_{it} + g(\gamma, \omega_{it}) + \phi Z_i + \rho_j + \psi_t + \epsilon_{ijt},$$

where Y is agricultural output, and T and L are quantities of land and labor.

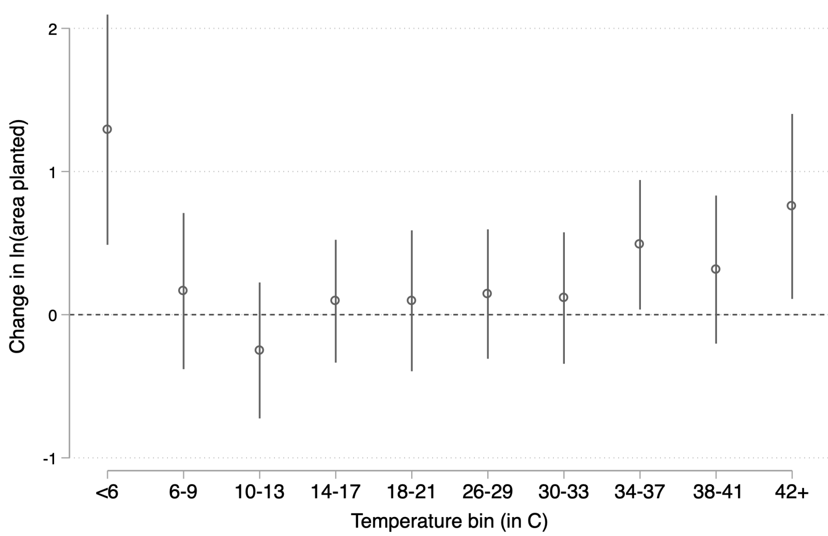
[28]Table B.4 presents first stage estimates. The validity of this IV approach relies on the assumption that any residual correlation between the error term and variable inputs would not carry to endowments. This could be violated, for instance, if there are other unobserved factors that drive both output and inputs endowments, such as political power Goldstein and Udry (2008). Table B.5 in the Appendix provides additional checks of the effect of temperature on productivity controlling by endowments and using a more flexible functional form.

[29]These results are consistent with previous findings of negative effects of high temperatures on yields. See, for instance, Auffhammer et al. (2012), Guiteras (2009), Burgess et al. (2017), Burke et al. (2015), Burke and Emerick

Figure 4: Non-linear relationship between temperature and main outcomes



(a) Effect on ln(output per ha.)



(b) Effect on ln(area planted)

Notes: Figure displays the estimates of the effect of an increase in the percentage of growing-season days in a given temperature bin on ln(output per ha) and ln(area planted). Circles represent points estimates, while lines indicates 95% confidence intervals. Standard errors are clustered at the district level. All specifications include same fixed effects and farmer controls as baseline regressions in column 1 of Tables 2 and 3

(2016), Schlenker and Roberts (2009), Lobell et al. (2011).

conservative estimate suggests that each additional average HDD results in a 7% decrease in agricultural productivity. To put this figure in perspective, note that climate change scenarios discussed in Section 6 envisage that, by the end of this century, the average number of HDD over the growing season could increase between 0.64 and 1.32, while the already warm Coast would experience increments between 3 to 5 HDD.[30]

What happens with total output? Consistent with a negative productivity shock, we find that extreme heat reduces agricultural output (column 4). However, the magnitude of this effect is smaller than for TFP or yields, and we cannot reject the null hypothesis at standard levels of confidence. This finding is suggestive of responses (such as changes in production decisions) that attenuate the effect of the productivity shock on total output.

Table 2: Temperature, agricultural productivity and output

	Y/T	TFP		Y
Dep. Variable:	ln(output/ha)	ln(output)	ln(output)	ln(output)
	(1)	(2)	(3)	(4)
Average DD in growing season	0.020*	0.014*	0.015**	0.011
	(0.011)	(0.007)	(0.007)	(0.009)
Average HDD in growing season	-0.114***	-0.064*	-0.069**	-0.042
	(0.038)	(0.033)	(0.033)	(0.041)
Inputs controls	No	Yes	Yes	No
Method	OLS	OLS	2SLS	OLS
No. obs.	53,493	53,487	53,487	53,619
R-squared	0.335	0.549	0.359	0.348

Notes: Standard errors (in parenthesis) are clustered at the district level. Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and farmer controls such as: household head characteristics (age, age^2, gender, and level of education), indicators of soil quality from Fischer et al. (2008) (nutrient availability, nutrient retention, rooting conditions, oxygen availability, salinity, toxicity and workability) and the share of irrigated land. Input controls: log of area planted, number of household members working in agriculture, and amount spent on hired labor. Instruments for domestic labor and area planted: log of household size and area of land owned. First stage joint significance F-test is 466.7.

[30]Note that our measures of DD and HDD represent the temperatures in an "average" day in the growing season. Thus, an additional HDD represents an average increase of 1 harmful degree (i.e., above 33°C) for all the days in the growing season. Clearly, there are multiple ways to obtain the same average increase. For example, an increase of 1 HDD could occur if the temperature for 50% of the days in the growing season increase from 33°C to 35°C (2 harmful degrees), or if the daily temperature for 25% of days increase from 33°C to 37°C (4 harmful degrees). An increase of 1 HDD is a sizeable change. To put this number in perspective, note that the mean and standard deviation of HDD in our sample are 0.7 and 1.33, respectively.

4.2 Productive responses: changes in input use

We examine changes in input use as a potential margin of adjustment to high temperatures. In our main set of results, we focus on changes in land use, both in terms of area planted and crop mix. Our focus on land stems from its importance as an agricultural input and because, in many contexts, it is subject to severe market imperfections, such as ill-defined property rights. Moreover, we have reasonably good measures of land use, but more limited information on other inputs, such as labor.

Table 3 presents our main results. We find a positive and statistically significant effect of HDD on area planted (column 1). An increase in HHD of 1 degree is associated with an increase of almost 6% in the total area planted. This estimate already controls for endowments, such as the total area of land available, and thus is not simply picking up changes in the size composition of farmers. The increase in land used is sizable and partially explains why, despite its documented negative effects on agricultural productivity, extreme heat has a small and insignificant effect on total output. It also explains why the estimated effect of HDD on yields (Y/T) is larger than on total factor productivity (TFP) (see Table 2).

Columns 2 to 4 examine the effect of extreme heat on crop mix. In our context, farmers practice multi-cropping: the average farmer grows almost six different crops.[31] To study effects on crop mix, we group crops in two categories: tubers (mostly potatoes) and other crops. Tubers are the most important crop among Peruvian subsistence farmers and account for almost 30% of the value of agricultural output and 15% of the area planted.

We find that extreme heat increases the quantity (in absolute and relative terms) of tubers harvested. Coupled with the evidence in the previous section that farmers adjust their land during the growing season, we interpret these findings as suggestive evidence that the additional land is planted with a higher share of tubers. Hence farmers adjust their use of land, both in terms of area planted and crop composition, as a response to extreme heat. These results complement recent studies that examine the role of changes in crop mix as a possible way to increase food security and adapt to climate change (Burke and Emerick, 2016, Colmer, 2018, Harvey et al., 2014).

There are, however, two important caveats. First, we do not observe the area planted with different crops, only the amount harvested. Thus, we are unable to disentangle the effect of extreme heat on planting decisions from different crop sensitivities to temperature. That said, we can rule out that our results are only reflecting less sensitivity of tubers to extreme heat: in that case, we would observe an increase in output share, but a reduction in absolute terms.

Second, our results do not necessarily mean that tubers are more resilient to heat than other crops.[32] Farmers could prefer tubers for several reasons other than heat tolerance. Studies on food

[31] In our sample, fewer than 10% of farmers report growing only one crop. Multi-cropping is a common practice among subsistence farmers across the developing world, and is in stark contrast with the modern agricultural practices of the U.S. and other developed countries, which mostly practice mono-cropping.

[32] There is some evidence that sweet potatoes and cassava are more drought tolerant than other food crops, such

security highlight several advantages of tubers (like potatoes, cassava, and sweet potatoes) over other crops, such as short maturity, sequential harvesting, low water and fertilizer requirements, more reliability, and high nutritional content (Devaux et al., 2014, Motsa et al., 2015, Woolfe, 1992). These features could made them relatively more attractive than other crops, especially in the presence of negative productivity shocks. For instance, Dercon (1996) documents that Tanzanian farmers manage risk by planting less profitable, but more reliable, crops like sweet potatoes. Similarly, in a study of small farmer in Madagascar, Harvey et al. (2014) find that a common coping strategy to productivity shocks is to adjust their diet by replacing rice for tubers.

Table 3: Temperature and land use

	T	ln (output)		Tubers
Dep. Variable:	ln(area planted)	Tubers	Other crops	% output
	(1)	(2)	(3)	(4)
Average DD in growing season	-0.006	-0.197***	0.126***	-0.029***
	(0.009)	(0.028)	(0.016)	(0.003)
Average HDD in growing season	0.055***	0.093**	-0.160***	0.022***
	(0.018)	(0.043)	(0.042)	(0.004)
Endowment controls	Yes	Yes	Yes	Yes
No. obs.	53,493	53,493	53,493	53,493
R-squared	0.443	0.454	0.463	0.525

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2. Endowment controls: log of household size and area of land owned.

Timing Do the effect and responses to extreme heat vary according to the time at which extreme temperatures are experienced? Answering this question is relevant to understand the observed phenomena better and predict impacts more accurately. For instance, effects could vary if crops are more sensitive to extreme heat at some stages of development (sowing, harvesting) than others,

as maize (Braimoh et al., 2018, Motsa et al., 2015). However, the agronomic literature is less clear about the general heat tolerance of a crop. A main reason is that heat tolerance depends on several context-specific factors, such as water availability, pre-conditioning to heat, and developmental stage (Miller et al., 2001, Wahid et al., 2007). For instance, potatoes are more sensitive to heat at earlier stages (seeding) while maize is more susceptible to heat damage at later stages (flowering and grain filling). Damage to potato yields can also be offset by increased soil humidity, but this mechanism does not attenuate the negative effects of heat on maize (Basu and Minhas, 1991, Edreira and Otegui, 2012, Rykaczewska, 2013). There is also a large variation in heat tolerance between different varieties of the same crop. For instance, the heat tolerance of some potato cultivars can be twice as large than that of less resilient varieties (Ahn et al., 2004). Note that in our data, we can only identify crops, not cultivars or varieties.

or if farmers face time-varying constraints to adjust to these shocks (i.e., due to seasonal crop or input suitability). Alternatively, we might be observing a delayed response from farmers to extreme temperatures in previous agricultural seasons, not a response to a contemporaneous shock.

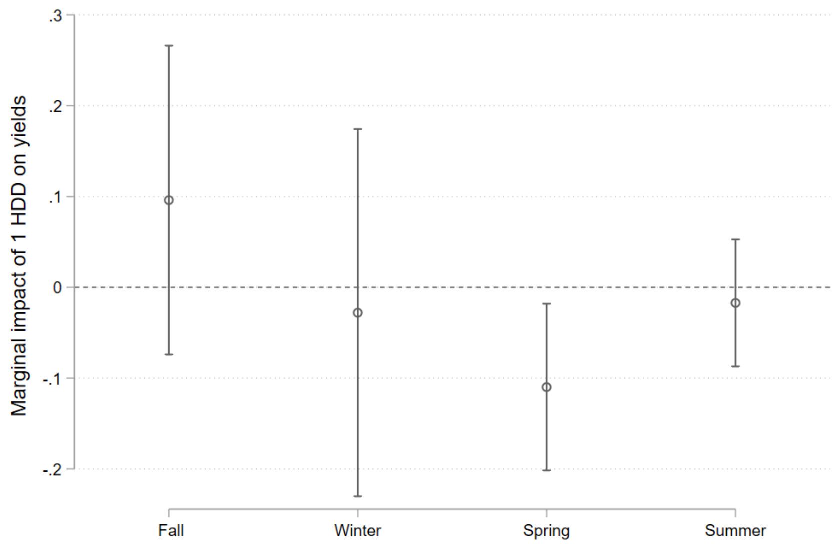
To examine this issue, we first restrict our sample to those farmers interviewed during the fall or winter months (April to September, in the southern hemisphere). As mentioned before, although planting and harvesting are year-round activities, the most important planting period (in terms of area) corresponds to spring and summer, the growing season months. Thus, our sample restriction allows us to focus on those farmers who have already completed most of their annual land use decisions.[33] Then, we construct separate measures of weather for each of the last four seasons (i.e., fall, winter, spring, and summer). Specifically, if a household is interviewed during the fall or winter of year t, we match each observation with the weather outcomes in that location during the fall, winter and spring of year $t-1$ (April to December), and for the summer of year t (January to March). This procedure effectively summarizes the weather conditions over the 12 months previous to the end of the last growing season.

Figure 5 depicts the effect of average HDD in different seasons on our measures of productivity (Y/T) and land used (T). The main observation is that the effect of extreme heat on productivity and land use is driven by shocks that occur during the spring. This timing is consistent with the biological response (and the human reaction) to heat experienced during a sensitive period in the agricultural calendar. Previous studies show that, while plants are vulnerable to high temperatures throughout their life-cycle, the potential harm is highest during the sowing period (Slafer and Rawson, 1994). Moreover, it suggests that the observed changes in land use are a response to productivity shocks within the agricultural season.

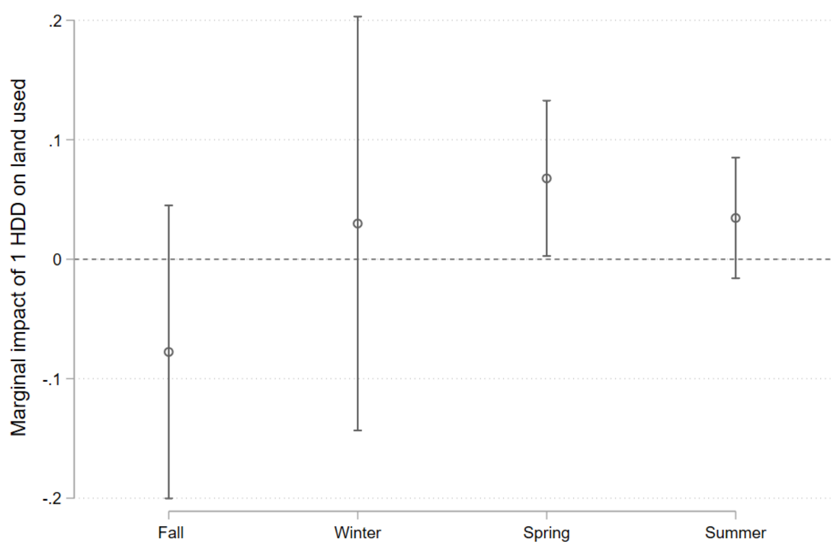
To explore the possibility of within-growing season responses by farmer in area planted, we make use of data from the Peruvian National Agricultural Survey, available for four years, between 2014 and 2017. This is a longitudinal dataset that has farm-level data of monthly planting over a 12-month period. In Figure A.2 and Table B.1 in the Appendix, we show the results of regressing the area planted on a given month on monthly HHD realizations (contemporaneous and lagged values), using farmer fixed effects. Thus, we use within-farmer variation to explore how planting by a farmer responds to temperature shocks during the agricultural season. Results show that farmers increase their planting one and two months after they were exposed to harmful temperatures. These findings support the idea that farmers indeed respond during the growing season to extreme heat, and reduce concerns such that the increase in land is picking up differences in timing of planting across different farmers or locations.

[33] Recall that interviewers ask about the total land used in agriculture over the past 12 months

Figure 5: Effect of exposure to HDD by season



(a) Effect on ln(output per ha.)



(b) Effect on ln(area planted)

Notes: Figure displays the estimates of the effect of HDD in different seasons on ln(yields) and ln(area planted). Circles represent points estimates, while lines indicates 95% confidence intervals. Standard errors are clustered at the district level. All specifications include same fixed effects and farmer controls as baseline regression in Table 2.

4.2.1 Changes in labor use

Finally, we examine the effect of extreme heat on labor. We distinguish two types of labor: domestic and hired. In contrast to land use, we do not have good proxies for labor used during the agricultural season. We only observe the wage bill of hired workers in last 12 months, not actual number of workers. More importantly, we only have information on labor outcomes of household members during the last 2 weeks before the interview, not for the whole agricultural year. Because of these limitations, the results on labor use should be interpreted with caution.

Table 4 presents our findings. Columns 1 to 4 examine the effect on two measures of domestic labor: number of household members working on the farm, and an indicator of child labor. We estimate the effect of HDD using the baseline specification (columns 1 and 2) as well as an alternative specification restricting the sample to farmers interviewed in spring and summer and using average HDD in spring as a measure of exposure to extreme heat. By focusing on households interviewed at the moment when most of the productivity shock occurs, we can partially address the data limitations mentioned above. Column 5 examines the effect on wage bill: our proxy for hired labor.

Similar to the results on land used, we find that HDD has a positive and, in most cases, significant effect on measures of domestic labor. Interestingly, extreme heat seems to increase the likelihood of child labor. This last result is consistent with findings in the literature on child labor showing that poor households may resort to employing children in productive activities when subject to negative income shocks (Bandara et al., 2015, Beegle et al., 2006). In contrast, the coefficient of HHD on hired labor's wage bill is negative, albeit also insignificant. These findings suggest a slight tendency of farms to use more intensively domestic labor as a response to extreme heat.

4.3 Discussion

Our findings are hard to reconcile with predictions from a standard production model. As discussed in Section 2.2, a standard production model would predict a weakly negative relation between HDD and input use, as well as a negative effect on output. The reduction in productivity would drive the negative effect on input use. However, if extreme heat shocks occur after input decisions are sunk (i.e., after planting), there would be no effect of HDD on area planted.[34]

Instead, our findings are consistent with models of subsistence farmers in a context of incomplete markets (De Janvry et al., 1991, Taylor and Adelman, 2003). In this scenario, production and consumption decisions are not separable (Benjamin, 1992). Thus, farmers exposed to negative shocks may need to resort to more intensive use of non-traded inputs, like land and domestic labor,

[34] A model with factor biased productivity shocks (i.e., extreme temperatures affecting relatively more one factor of production), could also generate changes in input ratios and, potentially, increase use of some inputs. However, it is unlikely to explain the observed increase in land and domestic labor. To see this, consider an alternative model with competitive input and output markets, two inputs (land and labor), and a CES production function $f(T, L) = [AT^\rho + BL^\rho]^{\frac{\gamma}{\rho}}$, where T and L refers to land and labor, and A and B are factor-specific productivity shifters. Cost-minimization requires that the input ratio (T/L) is equal to $(\frac{Aw}{Br})^{1/(1-\rho)}$, where w and r are the input market prices. Note that if extreme temperature affects only land then the land-labor ratio would decrease (because of a drop in A/B). This prediction together with the reduction in output (due to higher costs) imply a reduction in land, T. The effect on labor is, however, ambiguous.

Table 4: Temperature and labor use

Dep. variable:	Domestic labor: No. HH members work in farm (1)	Domestic labor: Child labor (2)	Domestic labor: No. HH members work in farm (3)	Domestic labor: Child labor (4)	Hired labor: ln(wage bill) (5)
Average DD in growing season	-0.015***	-0.017***			0.021
	(0.005)	(0.004)			(0.015)
Average HDD in growing season	0.033*	0.017*			-0.067
	(0.017)	(0.009)			(0.056)
Average DD in spring			-0.014**	-0.018***	
			(0.007)	(0.004)	
Average HDD in spring			0.027	0.028***	
			(0.020)	(0.010)	
Sample	Full sample		Spring & summer		Full sample
Endowment controls	Yes	Yes	Yes	Yes	Yes
Mean outcome	2.311	0.407	2.294	0.432	2.536
No. obs.	53,619	28,744	26,714	14,352	53,618
R-squared	0.448	0.271	0.464	0.312	0.244

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2. Columns 2 and 4 restrict the sample to farmers interviewed during the growing season (spring and summer). Columns 1 and 3 also restrict the sample to households with at least one child aged 6 to 15 years. HH = household.

to offset undesirable drops in output and consumption. In this sense, changes in input use are akin to other consumption smoothing mechanisms, such as selling disposable assets or increasing off-farm work (Kochar, 1999, Rosenzweig and Wolpin, 1993).

To the best of our knowledge, this margin of adjustment, namely increasing land use on the extensive margin, has not been previously documented in the consumption smoothing literature, nor in existing studies of the effect of temperature on agriculture. However, it may be particularly relevant for farmers in less developed countries due to the presence of several market imperfections and limited coping mechanisms, such as crop insurance or savings.[35]

[35] We examine the importance of market imperfections in Table B.10 in the Appendix. This table estimates heterogeneous effects of HDD on area planted by several indicators of market development, such as share of output sold in market, share of farmers hiring workers, and number of branches of agricultural banks. The evidence is consistent with the positive effect driven by market imperfections. However, we recommend caution to the reader when interpreting these results due to potential endogeneity of the indicators of market development.

Our findings have at least two important implications. First, it suggests a potential dynamic link between weather shocks and long-run outcomes. Leaving land uncultivated, i.e., fallowing, is a common practice in traditional agriculture to avoid depleting soil nutrients, recover soil biomass, and restore land productivity (Goldstein and Udry, 2008). If the increase in area planted as a response to extreme temperature comes at the expense of fallow land, then this short-term response could affect land productivity in the medium- or long-term. To explore this hypothesis, we evaluate whether past weather shocks affect current agricultural yields. We do so by adding to our baseline regression values of HHD from the last 8 previous years (see Table B.9 in the Appendix).[36] For most lags, we cannot rule out their effect are statistically insignificant. However, the effect of HDD lagged 7 years is negative and marginally significant (p-value= 0.083). While suggestive of medium-term effects, we interpret these findings cautiously. We do not have information on the fallow history of a plot or a farm, so we cannot directly link changes in fallowing in the past to current productivity. Similarly, we do not have reliable information on the use of uncultivated land.[37] Thus we cannot satisfactorily examine the effects of temperature on fallow duration or extent.

Second, this farmer response may affect estimations of the damages of climate change on agricultural output. These estimates are usually based on the effect of temperature on crop yields (Y/T). This is a correct approach if land use is fixed. In that case, changes in crop yields are the same as changes in output. However, using crop yields may be less informative in contexts in which farmers respond to weather shocks by changing land use. As we show in Section 6, taking into account this adaptive response reduces, in a non-trivial magnitude, the predicted damages.

4.4 Additional checks

4.4.1 Alternative specifications

Table 5 presents several checks of the robustness of our main results to alternative model specifications. We report only the estimate associated with the measure of extreme heat (HDD). Each row uses a different specification.

Row 1 restricts our sample only to farmers interviewed in fall and winter. By that time, the main growing season has passed and farmers have reaped the main harvest of the year. This specification drops almost half of the baseline sample, but it reduces concerns of measurement error due to mismatch of planting and harvesting decisions, confounding of current and previous weather shocks, or recall bias. Row 2 estimates a more parsimonious model without any individual or household-level controls, only district and region-by-year fixed effects, while row 3 implements

[36] We choose this time span based on the fallow duration of 6 to 8 years documented for subsistence farmers in Peruvian highlands (Brush et al., 1981, Orlove and Godoy, 1986). We present results adding one lag at a time, and also all of them simultaneously. This last specification is quite demanding due to correlation between past weather shocks.

[37] Farmers report fallowing in only a quarter of uncultivated land. The rest is reported as covered with bushes, grasses, and forest. These uses are also consistent with fallowing and crop rotation (Denevan, 2003, Ch. 3). However, we do not know if this land is left fallow or is non-agricultural land.

a more conservative clustering at province (n= 159) instead of district level (n=977). In all three cases, our results are similar to the baseline specification.

Our results are also robust to alternative ways to measure exposure to extreme heat. Row 4 uses the number of days in growing seasons with HDD, while row 5 uses average HDD during the last 12 months instead of during the last completed growing season. We also obtain similar results when allowing for different HDD thresholds by climatic region, i.e., coast and highlands (row 6).[38] Figure A.5 in the Appendix further assesses the sensitivity of our results to different values of the threshold (τ) ranging from 26°C to 42°C. These results show that lower thresholds produce similar results, while higher thresholds increase the magnitude of our baseline estimates and reduce their precision.

4.4.2 Prices as omitted variables

An important concern is that our results might be driven by changes in relative prices. Extreme heat shocks can reduce aggregate supply and increase agricultural prices. This price increase would, in turn, create incentives to increase production and input use. In our baseline specification, we address this concern by including a set of climatic region-by-growing season fixed effects. To the extent that agricultural markets are national or circumscribed to climatic regions, this approach would control for agricultural prices. However, if agricultural markets are narrower, we could have an omitted variables problem.

We examine the relevance of this issue in two ways (see rows 7 to 8 in Table 5). First, we add province-by-growing season fixed effects (row 7). This is a much richer set of time-varying controls than our baseline specification and, under the assumption that agricultural markets are province-wide, effectively controls for prices. Second, we add proxies of local prices at district level (row 8). We focus on tubers and cereals: the two main types of crops in our sample. For each crop type, we construct a price index at the district level and add it to baseline regression.[39] In both cases, our results remain similar to the baseline specification.

4.4.3 Regional differences

As discussed in Section 2.1, our sample has two distinct climatic regions: coast and highlands. The coast has a warm semi-arid climate with very little precipitation, especially in the central and southern coast. In contrast, the highlands are cooler and receive more rain. These climatic differences are apparent when observing the distribution of daily temperature in these two regions (see Figure A.6 in the Appendix). The two regions also differ in their agricultural practices. Coastal farmers are, on average, substantially better off, are more productive, more educated, and more

[38]These region-specific thresholds were chosen by replicating the analysis shown in Figure 4 in the coast and highland observations separately. The results from this exercise are presented in Figure A.6, in the Appendix.

[39]The price index for each crop type is a Laspeyres index using self-reported unit prices and output shares of each crop (within a crop group) in baseline year 2007. We then take natural logarithms.

Table 5: Robustness checks

Dep. variable:	ln(output per ha) (1)	ln(area planted) (2)	Tubers % output (3)	No. obs. (4)
1. Interviewed in fall and winter	-0.106**	0.079***	0.019***	26,799
	(0.045)	(0.026)	(0.006)	
2. Excluding individual controls	-0.120**	0.065***	0.023***	53,493
	(0.046)	(0.020)	(0.005)	
3. Clustering by province (n=159)	-0.114***	0.055***	0.022***	53,493
	(0.036)	(0.020)	(0.005)	
4. Using no. of HHD days during growing season	-0.529**	0.313**	-0.118***	53,493
	(0.212)	(0.126)	(0.042)	
5. Using average HDD in last 12 months	-0.165***	0.095***	0.043***	53,493
	(0.051)	(0.030)	(0.009)	
6. Diff. thresholds by region 33°C Coast, 36°C Highlands	-0.113***	0.046**	0.021***	53,493
	(0.043)	(0.018)	(0.005)	
7. Adding province-by-growing season FE	-0.121***	0.052***	0.022***	53,480
	(0.042)	(0.018)	(0.005)	
8. Adding local prices	-0.122***	0.061***	0.024***	49,713
	(0.044)	(0.021)	(0.005)	

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications, except in row 2 include the same controls as baseline regression in Table 2. Row 1 restricts the sample to farmers interviewed in fall and winter (i.e., April to August). Row 7 adds province-by-growing season fixed effects while row 8 includes logs of price indexes for tubers and cereals at district level.

likely to have access to irrigation. Compared to highland farmers, coastal farmers are also more likely to specialize on fruits and cereals, less likely to own livestock and cultivate a larger share of their land.

Given these regional differences, a relevant question is whether our baseline specification, which pools all observations, may be hiding relevant heterogeneity in the effects and responses to extreme heat. We address this question by relaxing the baseline specification and allowing for different effects of weather variables (DD, HDD, and precipitation) by climatic region. In particular, we modify the baseline specification by including interaction terms of weather variables with an indicator of being located in the highlands. Table 6 shows the estimates of the effect of HDD for each region, and displays the p-value of the test of equality of both estimates.

Our main conclusions still remain the same after allowing for regional differences: in both regions, extreme heat has a negative effect on productivity and a positive effect on the quantity of land used. Surprisingly, despite coastal farmers being normally exposed to higher temperatures, there are no statistical differences in the magnitude of the effect on yields in both regions.[40] There are, however, some quantitative differences on the effect on land use. In particular, the increase in area planted is smaller in the coast. In this region, there is also no significant change in crop mix, measured by the share of tubers in total output.

A possible interpretation of these findings is that mitigation and adaptive responses vary by baseline climate.[41] For instance, warmer areas could have developed different ways to cope with extreme heat other than using their land more intensively. This interpretation is in line with recent papers that combine high-frequency temperature variation with long-run climate differences to study adaptation to climate change (Auffhammer, 2018, Barreca et al., 2015, Heutel et al., 2017).

There are, however, other possible explanations that we cannot rule out. For instance, these findings may reflect lower land availability in the coast. In this region, agriculture occurs in densely populated valleys, surrounded by very arid deserts, and depends heavily on access to irrigation.[42] These features can constrain the expansion of agricultural land. Similarly, they may be driven by coastal farmers having access to other, non-agricultural, coping mechanisms. This is plausible given that coastal farmers tend to be better off and are closer to cities and other urban areas. For these reasons, we interpret with caution as only suggestive evidence of different responses by climatic region.

4.4.4 Very cold days

Our previous results focus on the effect and responses to high temperatures. However, as hinted in Figure 4, low temperatures could also have a negative effect on agricultural productivity. This is especially relevant in the Highlands where around 6% of days in the growing season have temperatures below 8℃. To examine this issue, we replicate our main results adding a measure of low-temperature degree days. This measure is similar to our variables DD and HDD, but uses only temperatures below 8 ℃

Table 7 shows the results. There are two relevant observations. First, our baseline results of the effect of HDD on yields and land use remain unaffected. Second, similar to extreme heat, low

[40] This result echoes findings by Burke and Emerick (2016) among U.S. corn farmers. Using a long difference approach, they find that extreme heat has similar detrimental effects on crop yields across time, despite the observed increase in average temperatures. Burke and Emerick (2016) interpret this finding as suggestive evidence of limited long-term adaptation to higher temperatures.

[41] Indeed, we observe similar results when using an indicator of cool and warm regions instead of a climatic region dummy (see Table B.8 in the Appendix).

[42] The share of uncultivated land is almost 45% in the highlands and 11.5% in the coast (see Table 1).

Table 6: Effect of HDD on land productivity, output and land use - by climatic region

	ln(output per ha) (1)	ln(total output) (2)	ln(area planted) (3)	Tubers % output (4)
(A) Average HDD × Coast	-0.114**	-0.063	0.034*	0.006
	(0.047)	(0.047)	(0.019)	(0.004)
(B) Average HDD × Highlands	-0.142**	0.016	0.118**	0.038***
	(0.057)	(0.044)	(0.047)	(0.010)
Diff. (B)-(A) p-value	0.706	0.226	0.097	0.002
No. obs	53,493	53,619	53,493	53,619
R-squared	0.336	0.348	0.443	0.526

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2.

temperatures have a negative effect on yields, and increase land use and share of tubers. These last results are consistent with our interpretation that farmers increase land use as a response to negative productivity shocks.

Table 7: Effect of low temperatures on land productivity, output, and land use

	ln(output per ha) (1)	ln(total output) (2)	ln(area planted) (3)	Tubers % output (4)
Average low DD	-0.122*	0.071	0.212***	0.047***
	(0.067)	(0.051)	(0.053)	(0.014)
Average DD	0.010	0.017	0.012	-0.024***
	(0.013)	(0.010)	(0.009)	(0.003)
Average HDD	-0.105***	-0.047	0.040**	0.018***
	(0.039)	(0.041)	(0.017)	(0.004)
Observations	53,389	53,515	53,389	53,515
R-squared	0.336	0.348	0.444	0.525

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2. Low DD = degree days below 8 °C.

5 Other coping mechanisms

Our main results suggest that farmers adjust input use as a mechanism to cope with the negative effects of extreme temperatures. In this section, we study other coping mechanisms previously documented in the consumption smoothing literature, such as working in non-agricultural activities (Colmer, 2018, Kochar, 1999, Rosenzweig and Stark, 1989), migrating (Feng et al., 2012, Jessoe et al., 2017, Kleemans and Magruder, 2017, Munshi, 2003) or selling livestock (Rosenzweig and Wolpin, 1993). Then, we examine how these coping mechanisms interact with changes in land use.

We start by examining whether farmers in our context use other coping mechanisms (see Table 8). Our first set of outcomes focuses on the use of livestock as a buffer against income shocks (columns 1 to 3). We find that HDD is associated with an increase in the probability that a farmer reports a decrease in livestock value.[43] This reduction seems to come from households selling, rather than consuming their livestock. These results are consistent with farmers selling livestock to offset the adverse effects of extreme heat.

Next, we focus on indicators of off-farm work (columns 4 and 5). We use an indicator of a household member having a non-agricultural job, as well as the total number of hours worked off-farm (conditional on having a non-agricultural job). As in Table 4, we restrict the sample

[43]Our definition of livestock includes cattle, horses, sheep, llamas, and pigs.

to households interviewed during the growing season (i.e., spring and summer). These outcomes capture supply of off-farm employment in the extensive and intensive margin. In the extensive margin, the estimate is insignificant. However, the estimate on the intensive margin is positive and statistically significant: farmers with off-farm jobs seem to increase the number of hours worked in that activity. While suggestive of off-farm employment as a coping strategy, this result is not robust to using the whole sample of farmers.

In columns 6 and 7, we look for evidence of short-term migration. Due to data limitations, we cannot measure migration directly. Instead, we use proxy variables such as an indicator of whether any member has been away for more than 30 days and household size. Similar to the results on off-farm employment, none of these outcomes seems to be affected by extreme temperature. However, we should interpret these last results with caution. Our analysis focuses on a short period (within a year), and these adjustments may happen over a longer time frame. In addition, our measures of labor and migration may be noisy proxies of actual behavior. These factors likely reduce the power of our statistical analysis and could explain the insignificant results.

Table 8: Other responses to extreme heat

	Livestock buffer			Off-farm work		Short-term migration	
Dep. variable:	Decrease in livestock value	Sold livestock	Consumed livestock	HH member has off-farm job	ln(hours worked off-farm)	HH member away 30+ days	HH size
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average DD	-0.008***	-0.012***	-0.013***	0.009**	0.026***	0.003**	-0.006
	(0.002)	(0.002)	(0.003)	(0.004)	(0.009)	(0.001)	(0.014)
Average HDD	0.022***	0.016*	0.007	0.006	0.054**	-0.002	0.016
	(0.007)	(0.009)	(0.009)	(0.011)	(0.025)	(0.002)	(0.033)
Mean outcome	0.332	0.517	0.476	0.464	57.548	0.085	4.339
No. obs.	48,169	48,169	48,169	26,726	12,377	53,619	53,619
R-squared	0.077	0.146	0.240	0.213	0.169	0.083	0.244

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2. Columns 1 to 3 restrict the sample to farmers who reported having livestock 12 months ago. Columns 4 and 5 restrict the sample to farmers interviewed in spring and summer. Column 5 further restricts the sample to households in which at least one member has an off-farm job. All regressions are estimated using OLS. All regressions, except in columns 5 and 7, have a binary outcome variable.

5.1 Interactions with productive responses

Our results suggest that, in our sample, farmers seem to use livestock sales as a coping strategy to smooth negative weather shocks. A natural question is how this coping strategy interacts with the productive responses, such as increasing input use, identified in our main results. Does having livestock eliminate the need to change land use, or do they complement each other? These are relevant questions to better understand the portfolio of coping strategies available to subsistence farmers.

We examine these issues by estimating heterogeneous responses to extreme heat for farmers with different ability to use other coping strategies. Based on our previous findings, we interact HDD with indicators of owning livestock 12 months ago and having at least one household member employed in a non-agricultural activity. We use these indicators as proxies of farmers' ability to use livestock and off-farm employment as buffers to negative income shocks.

Our results in Table 9 suggest that the effect of HDD on land use (area planted and relative share of tubers) is qualitatively similar between farmers with and without livestock (columns 2 and 3). However, the magnitude of the effect is larger among farmers who do not own livestock. This result is not driven by these latter farmers experiencing a larger negative productivity shock. As shown in column 1, the effect of HDD on agricultural yields is similar for both types of farmers and, if anything marginally smaller for farmers without livestock. In the case of off-farm employment (columns 4 to 6), there are no significant quantitative differences in the effect of HDD in any outcome.

We interpret these results as evidence that farmers do not use one strategy exclusively but instead use a combination of responses to cope with extreme heat. These responses include both sale of disposable assets (such as livestock) and adjustments in production decisions (such as changes in land use).

Table 9: Interaction with changes in land use

	Livestock buffer			Off-farm work		
Dep. variable:	ln(output per ha) (1)	ln(area planted) (2)	Tubers % output (3)	ln(output per ha) (4)	ln(area planted) (5)	Tubers % output (6)
(A) Average HDD × $D = 0$	-0.087*	0.055***	0.024***	-0.100**	0.041**	0.017***
	(0.044)	(0.019)	(0.005)	(0.048)	(0.018)	(0.005)
(B) Average HDD × $D = 1$	-0.121**	0.018	0.015***	-0.112**	0.040**	0.020***
	(0.047)	(0.018)	(0.005)	(0.046)	(0.018)	(0.005)
Diff. (B)-(A) p-value	0.059	0.002	0.000	0.392	0.956	0.113
D is indicator = 1 if	HH owns livestock			Any HH member has off-farm job		
No. obs.	53,493	53,493	53,619	53,493	53,493	53,619
R-squared	0.336	0.452	0.525	0.335	0.444	0.525

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regressions in Table 2. Regressions includes interaction of HDD with an indicator variable D of whether household owned livestock 12 month ago (columns 1 to 3) or has a member with a non-agricultural job (columns 4 to 6). All regressions also include the interaction of HDD with an indicator of climatic region. The third row reports the p-value of test of equality of estimates in first two rows.

6 Implications for estimating damages from climate change

Most models assessing climate change damages use estimates of the effect of temperature on crop yields to calculate the loss of agricultural output and, hence, rural income. This approach is correct if, among other things, the amount of land used is constant. However, if farmers increase land use, as we have documented above, this approach would ignore an important margin of productive adaptation and overestimate the actual fall in agricultural output.

In this section, we quantitatively assess the magnitude of this overestimation of damages. To do so, we obtain end-of-the-century predictions of temperature over our study area from current climate change projections. Then, we calculate the predicted change in agricultural output by extrapolating the effect of these temperatures on agricultural yields. This is the approach commonly used in the literature.[44] Finally, we compare these results to predictions obtained using our estimates of the effect of temperature on output. These latter estimates take into account changes in land use.

[44]See, for example, Deschenes and Greenstone (2007)

Importantly, this exercise only assumes changes in temperature (DD and HDD) and keeps everything else constant. Thus, it does not account for other potential factors and responses associated with climate change such as changes in CO_2, increase risk of natural disasters, changes in water availability, degradation of land quality, migration, changes in sectoral employment, etc. For that reason, our results should be interpreted with caution: they do not attempt to predict the effect of global warming on Peruvian agriculture, but only to highlight the importance of accounting for farmers' changes of land use when estimating damages from climate change.

6.1 Climate change projections

We obtain temperature projections from two climate change scenarios: RCP45 and RCP85. These scenarios, used in the IPCC's Fifth Assessment Report (IPCC, 2014), represent two different sets of assumptions about the future trajectory of global greenhouse gas emissions.[45] RCP85 is a 'business as usual' framework in which no additional policies to reduce greenhouse gas emissions are introduced. This scenario forecasts an increase of 4.9 ℃ in global temperatures by the end of the century. RCP45 is a more optimistic scenario that assumes increased efforts to curb emissions at a global scale and forecasts an average 2.4 ℃ increase in global temperatures.[46]

For each scenario, we obtain gridded data at a resolution 1.25 x 1.875 degrees of monthly temperatures for the baseline year 2005 and the forecast for the year 2099. We then adjust for model-specific error in a similar way to Deschenes and Greenstone (2011) to account for the fact that the historical temperatures (from MODIS) and predicted temperatures (from the HadGEM2-ES model) are from different sources.[47] Then, we use the predicted temperature distribution for each scenario j and location k to calculate DD_{jk} and HDD_{jk} for the end of the century. [48]

Panel A in Table 10 presents the predicted average ΔDD and ΔHDD for our whole sample and each climatic region in both scenarios.[49] Note that the increase in average HDD is 0.639 ℃ in the RCP45 scenario and more than double, 1.323 ℃ in the 'business as usual' scenario. The increase in temperature will create substantially more harmful temperatures in the coast than in the highlands. While the coast is expected to experience 3-5 additional harmful degrees a day during growing season months, the highlands are expected to experience just up to 0.7 HDD a day, in the most pessimistic scenario. These results are a natural consequence of the current distribution of

[45] We use the model output produced by the Hadley Centre Global Environment Model version 2 (HadGEM2-ES).

[46] In Table B.12 in the Appendix, we also include precipitation projections. While the results are qualitatively similar, we focus on temperatures only as there is less consensus ('low confidence') about the sign and the magnitude of projected precipitations patterns (IPCC, 2014, Ch. 27).

[47] We calculate the implied temperature change (i.e., 2099 compared to 2005) for each month-location according to each HadGEM2 scenario, and then add this to the average temperature in our (MODIS) dataset for each day of the year.

[48] We assume the same optimal temperature threshold as discussed in the previous section, 33℃. In both scenarios, average precipitation is predicted to stay within one standard deviation of its natural internal variability, so we do not assume any change in this respect (IPCC, 2014).

[49] Formally, $\Delta HDD_{jk} = HDD_k - H\bar{D}D_k$ where $H\bar{D}D_k$ is the average historical HDD in location j. We use a similar procedure to calculate the change in degree-days ΔDD_{jk}.

temperatures in both regions: as previously mentioned, the coast is already drier and hotter than the highlands. Thus, a shift in the distribution of temperature has a larger effect on the frequency of extremely hot days.

6.2 Predicted effects on agriculture

We calculate the predicted change on agricultural yields and output using the estimated effect of temperature on agricultural outcomes and the predicted changes in temperatures from climate change forecasts. In particular, we calculate the predicted effects as follows:

$$\Delta y_{ijk} = \hat{\beta}_1 \Delta DD_{jk} + \hat{\beta}_2 \Delta HDD_{jk}$$

where y is the outcome (i.e, yield or output) of farmer i in location k, while $\hat{\beta}_1$ and $\hat{\beta}_2$ correspond to the estimated effect of DD and HDD for each climatic region (coast and highlands) taken from columns 1 and 2 in Table 6.

Panels B and C in Table 10 present our results. The main observation is that using yields to predict the effect of climate change can lead to a substantial *overestimation* of the loss of agricultural output. This finding suggests that taking into account farmers' adjustments in land use is quantitatively important when estimating damages associated with climate change.

For instance, assuming the quantity of land used is fixed, we would predict that drops in output are equal to drop in yields. This implies a drop in output of around 5 to 9 percent (columns 1 and 4). However, the predicted drop in output is much smaller: around 0.6 to 1.2 percent. Overestimation is particularly salient in the coast. In that region, assuming land used is fixed, output losses are estimated to range from 29 to 48 percent. These magnitudes are almost twice as large as when allowing for changes in land used. In the highlands, the differences when using both types of approaches are much smaller, but they produce qualitatively different results: a drop in yields, but an increase in output.

Naturally, land is a finite resource, and thus this particular strategy is not dynamically consistent. In other words, farmers will not be able to offset output losses in the face of higher temperatures by adding more land to their production function indefinitely. Nevertheless, note that the farmers in our sample keep large amounts of unused land during any given growing season (see Table 1). In the case of highland farmers this is as high as 40% of their land holdings. It is, therefore, a productive adaptation with a significant margin over the near term.

As a final point, our predictions highlight potentially heterogeneous impacts on agricultural production: while the coast will experience sizable output losses, the impact in the highlands would be slightly positive. This result is consistent with other studies that predict large negative effects of climate change on warm (lower latituted) areas but smaller (albeit less conclusive) effects on cooler (higher latitude) areas (Auffhammer and Schlenker, 2014, Deschenes and Greenstone, 2007, 2012).

Table 10: Predicted effects of temperature on agriculture under two climate change scenarios

	RCP 4.5			RCP 8.5		
	All (1)	Coast (2)	Highlands (3)	All (4)	Coast (5)	Highlands (6)
A. Predicted change of temperature						
Δ DD	1.132	1.232	1.115	3.402	1.789	3.668
Δ HDD	0.639	3.034	0.244	1.323	4.927	0.728
B. Predicted effect on agriculture						
Δ Yields (ln Y/T)	-0.053	-0.288	-0.014	-0.098	-0.477	-0.035
Δ Output (ln Y)	-0.012	-0.154	0.011	-0.006	-0.256	0.035
C. Differences on estimate of damages						
Δ yields - Δ output	-0.040	-0.133	-0.025	-0.092	-0.220	-0.071

Notes: Table presents predictions of the effect of increased temperatures on agriculture under two climate change scenarios (RCP 4.5 and 8.5). Predictions uses region-specific estimates of the effect of temperature on yields and output from columns 1 and 3 in Table 6. Precipitation is assumed to remain constant.

7 Conclusion

This paper examines how subsistence farmers respond to extreme temperature. Using micro-data from Peruvian farmers, we show that extreme temperatures decrease agricultural productivity, but increase area planted. The expansion of area planted is coupled with changes in crop mix. We also find suggestive evidence of an increase in domestic labor.

We interpret these results as evidence that farmers use productive adjustments, such as changes in input use, as strategies to attenuate drops in output and consumption. This interpretation is consistent with predictions of producer-consumer models in the presence of incomplete markets.

Our results point out to a margin of adjustment not previously documented in the literature. This response could be relevant in other contexts with subsistence farmers and incomplete markets. In addition, this paper highlights the importance of high temperature realizations, expected to keep increasing due to climate change, as an income and productivity shock. This measure could be used alongside other standard measures, such as rainfall, to study farmers' decisions and would require new policy instruments that would address the consequences of heat exposure among subsistence farmers.

There are, however, several unsolved issues. First, due to data limitations, we cannot investigate other important topics such as the potential long-term effects, interactions with other long-run adaptive strategies (like defensive investments or adoption of new technologies), Second, we cannot directly examine the role of different market distortions on shaping this response to extreme temperatures. Finally, while our findings are specific to the Peruvian case (with distinct regional differences), our methodology could be used to study similar phenomena in other contexts. Examining these issues warrants future research.

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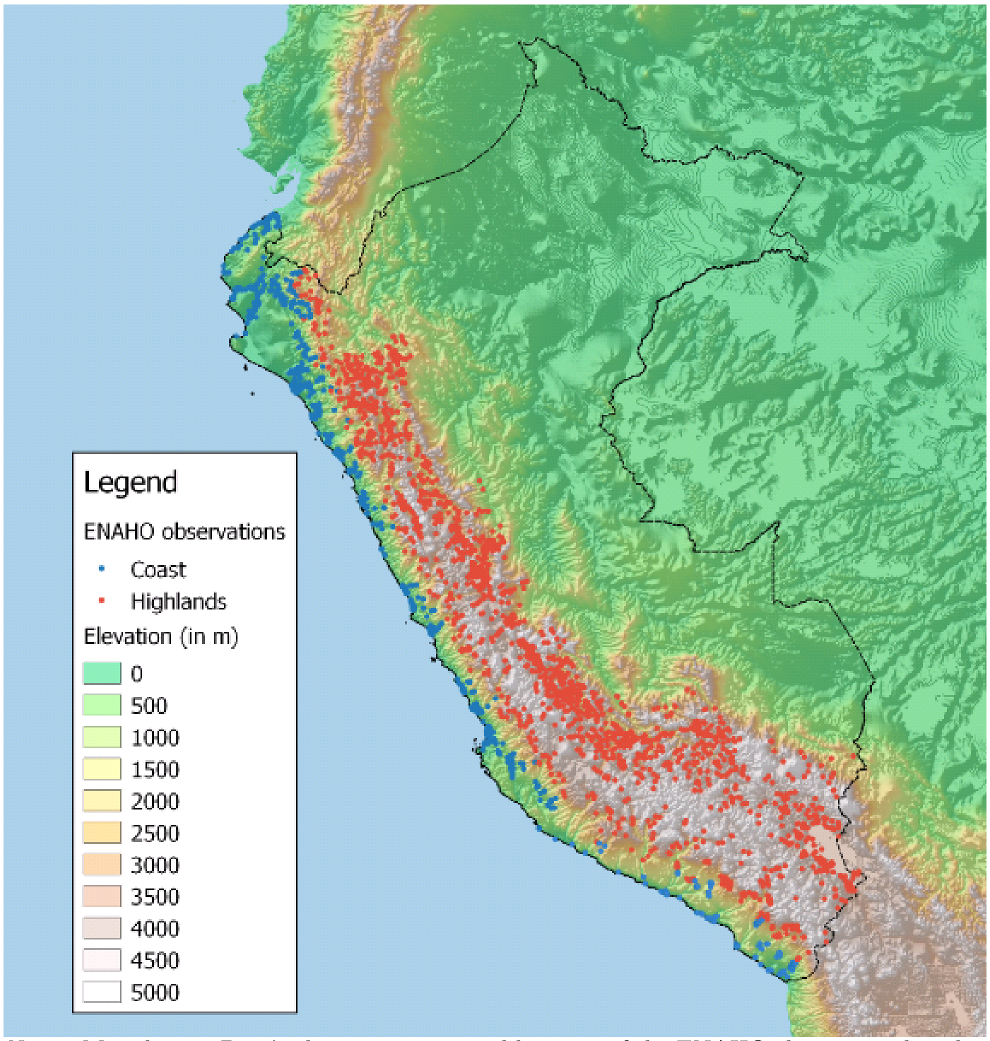
ONLINE APPENDIX - Not for publication

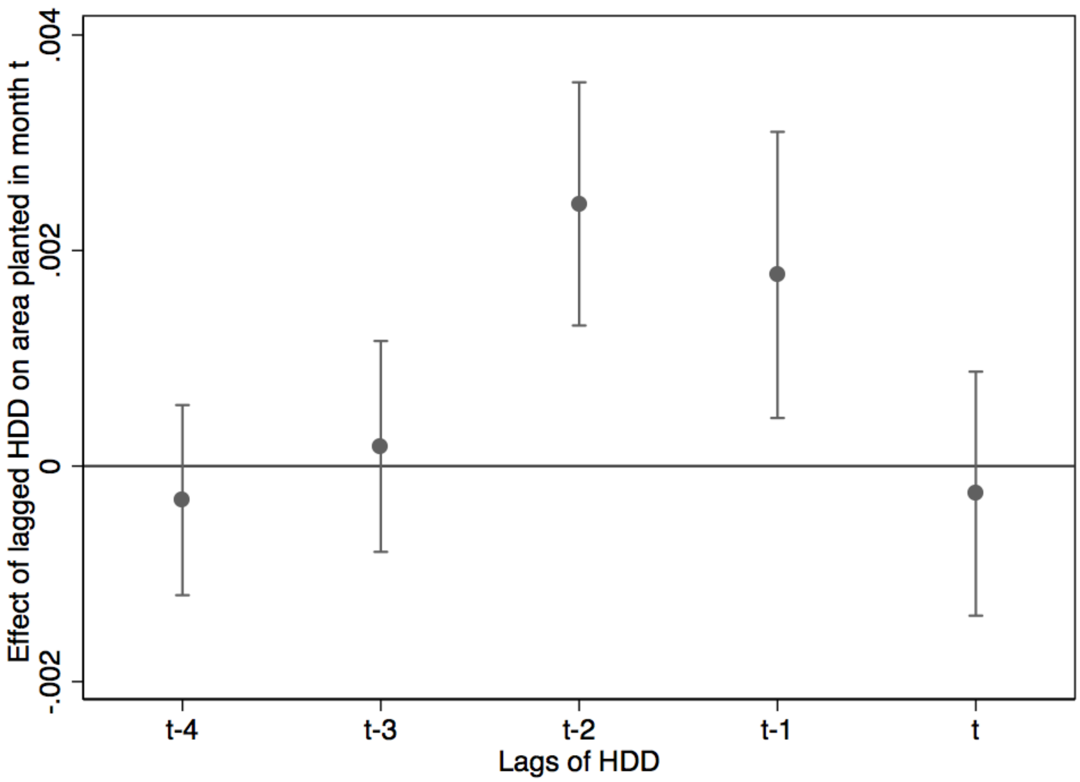
A Additional Figures

Figure A.1: ENAHO observations 2007-2015



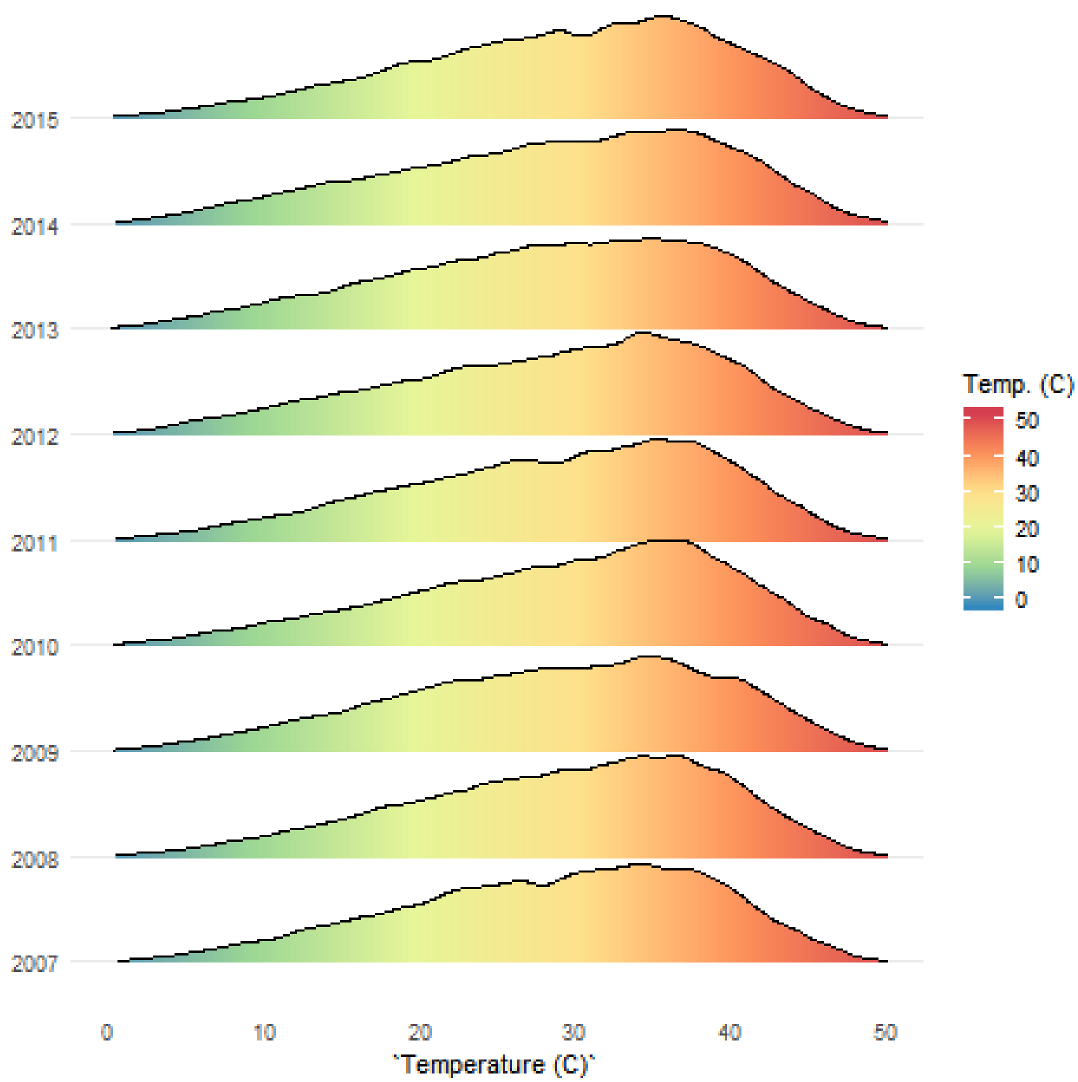
Notes: Map depicts Peru's climatic regions and location of the ENAHO clusters used in this study.

Figure A.2: Effect of lagged HDD on area planted in a given month



Notes: Figure displays results of regressing area planted with transitory (annual) crops in month t on lagged values of HDD (t to $t-4$). Regression uses data from the Peruvian National Agricultural years 2014 to 2017. This dataset has farm-level data of monthly planting over a 12-month period. Regression includes farmer, month-by-strata, and year-by-strata fixed effects. Dots are point estimates and lines indicate 95% confidence intervals. Standard errors clustered at the farmer level. Estimates and additional checks are available in Table B.1.

Figure A.3: Distribution of daily average temperature by growing season



Notes: Figure depicts the share of days spent in each temperature bin by the farmers in our sample, during the 2007-2015 growing seasons (i.e., October to March).

Figure A.4: Optimal temperature threshold using the iterative regression approach

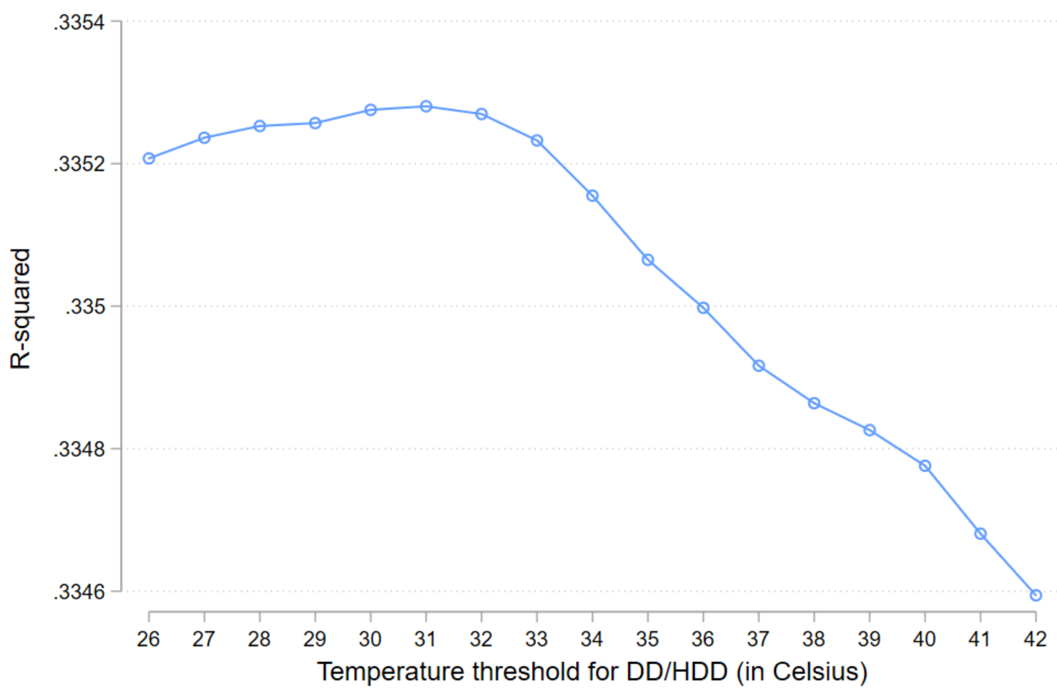
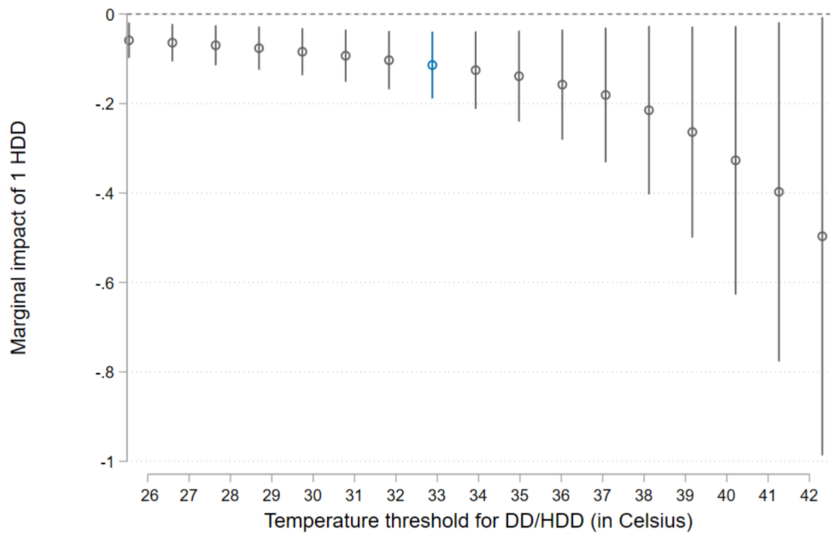
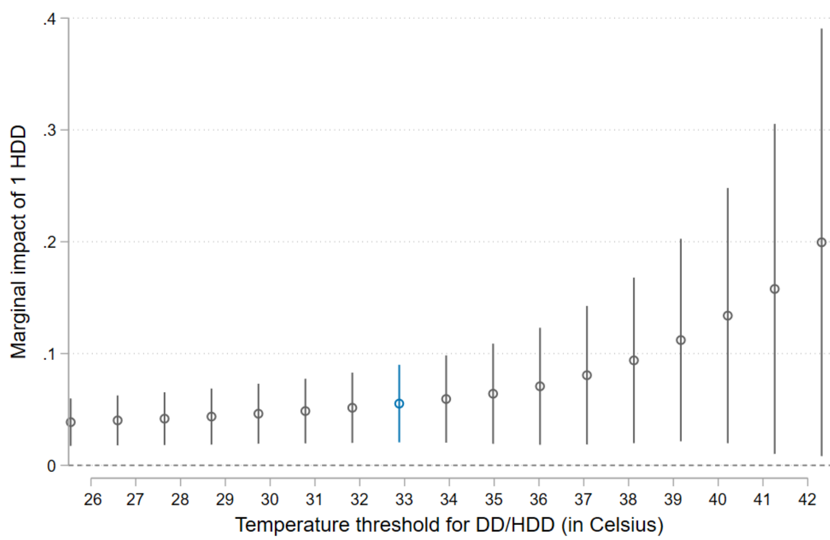


Figure A.5: Effect of HDD on yields and land use using alternative DD/HDD thresholds

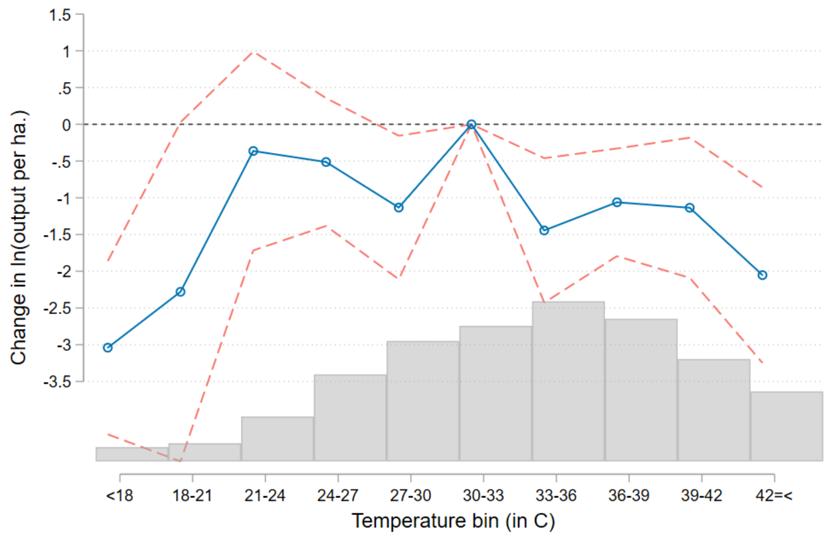


(a) Impacts on ln(output per hectare planted)

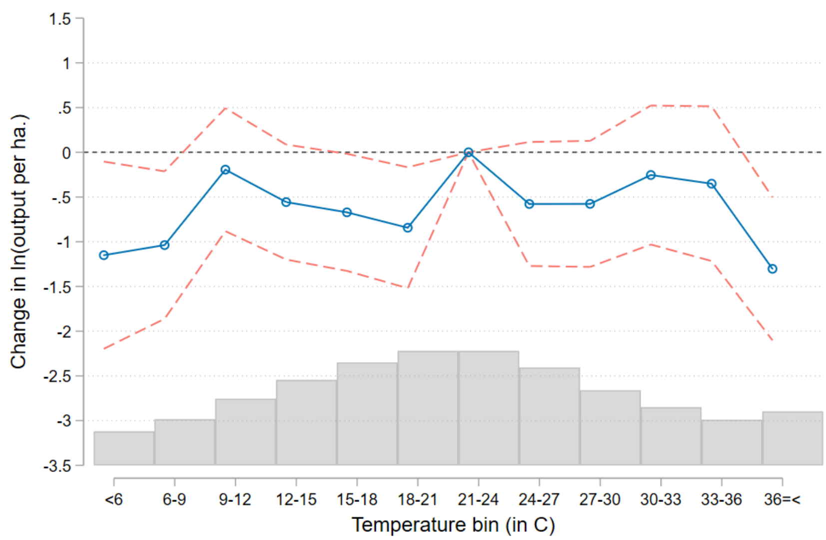


(b) Impacts on ln(hectares planted)

Figure A.6: Non-linear relationship between temperature and agricultural yields by region



(a) Coast



(b) Highlands

B Additional tables

Table B.1: Effect of HDD on area planted in a given month

	Area planted with transitory crops (has) in month t					% annual area planted
	(1)	(2)	(3)	(4)	(5)	(6)
HDD_{t-4}	-0.0003	-0.0016**	-0.0003	-0.0024	-0.0014***	0.0388***
	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.011)
HDD_{t-3}	0.0002	-0.0001	0.0004	0.0020	-0.0014**	0.0831***
	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.013)
HDD_{t-2}	0.0024***	0.0039***	0.0010	0.0033**	0.0017***	0.1257***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.015)
HDD_{t-1}	0.0018***	0.0022**	0.0017*	0.0024**	0.0024***	0.0486***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.016)
HDD_{t}	-0.0003	-0.0003	0.0002	-0.0004	0.0017**	-0.1069***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.015)
HDD_{t+1}					-0.0028***	
					(0.001)	
HDD_{t+2}					-0.0011*	
					(0.001)	
HDD_{t+3}					-0.0021***	
					(0.001)	
HDD_{t+4}					0.0005	
					(0.001)	
Specification	Baseline	Only Coast	Only Highlands	Spring planting	Adding leads	Alternative outcome
No. obs.	480,462	98,317	382,145	192,348	438,298	480,280
R-squared	0.023	0.023	0.033	0.012	0.026	0.118
No. farmers	38,485	7,908	30,577	38,467	38,471	38,472

Notes: Standard errors clustered at farmer level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* Regression uses data from the Peruvian National Agricultural years 2014 to 2017. This dataset has farm-level data of monthly planting over a 12-month period. All specifications include farmer, month-by-strata, and year-by-strata fixed effects. Columns 2 and 3 restrict sample to a climatic region (Coast or Highlands). Column 4 restricts sample to planting done in months of August to December. Column 5 adds leads of HDD, while column 6 uses the share of annual area planted in a given month (i.e. area planted in month t / total area planted in a year) as outcome variable.

Table B.2: Temperature variation under various sets of fixed effects (in ℃)

	DD			HDD		
	R^2	σ_e	$\lvert e\rvert > 1$℃	R^2	σ_e	$\lvert e\rvert > 1$℃
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
No fixed effects (FE)		4.81	100.0%		1.34	28.6%
District FE	0.90	1.50	37.7%	0.86	0.44	23.2%
District + growing season FE	0.91	1.41	36.5%	0.86	0.43	23.1%
District + growing season-by-region FE	0.92	1.40	36.2%	0.87	0.42	23.1%

Notes: This table replicates Table 2 of Fisher et al. (2012), It summarises regressions of measures of temperature on various sets of fixed effects and shows how much of the variation they absorb. The first three columns use average degree days (DD), and the last three columns use harmful degree days(HDD), using a threshold of 33℃. Columns (a) report the R^2 of the regression; columns (b) report the standard deviation of the residuals (remaining temperature variation) in degrees Celsius during the growing season; and columns (c) report what fraction of the observations have a residual that is larger than 1℃ over the growing season.

Table B.3: Temperature variation under various sets of fixed effects (in ^{o}F)

Variable:	DD			HDD		
Measure:	R^2	σ_e	$\lvert e\rvert > 1$°F	R^2	σ_e	$\lvert e\rvert > 1$°F
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
No fixed effects (FE)		8.66	100.00		2.40	39.27
District FE	0.90	2.70	46.30	0.86	0.79	25.73
District + growing season FE	0.91	2.54	45.54	0.86	0.77	25.43
District + growing season-by-region FE	0.92	2.52	44.98	0.87	0.76	25.34

Notes: This table replicates Table 2 of Fisher et al. (2012), It summarises regressions of measures of temperature on various sets of fixed effects and shows how much of the variation they absorb. The first three columns use average degree days (DD), and the last three columns use harmful degree days(HDD), using a threshold of 33^{o}F . Columns (a) report the R^2 of the regression; columns (b) report the standard deviation of the residuals (remaining temperature variation) in Farenheit degrees during the growing season; and columns (c) report what fraction of the observations have a residual that is larger than 1^{o}F over the growing season.

Table B.4: First stage of 2SLS regression (column 3 in Table 2)

Dep. Variable:	ln(area planted)	ln(no. HH members members work in farm)
	(1)	(2)
ln(area owned)	0.165***	0.007***
	(0.005)	(0.001)
ln(HH size)	0.195***	0.494***
	(0.013)	(0.006)
No. obs.	53,487	53,487
R-squared	0.478	0.481

Notes: Standard errors clustered at district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* Table presents first stage of 2SLS regression presented in column 3 in Table 2. Regression has all included such as district, month of interview, and climatic region-by-growing season fixed effects, and a set of farmer controls.

Table B.5: Temperature and agricultural productivity (TFP), alternative specifications

Dep. Variable:	ln(output)		
	(1)	(2)	(3)
Average DD in growing season	0.014*	0.014*	0.013*
	(0.007)	(0.007)	(0.007)
Average HDD in growing season	-0.064*	-0.063*	-0.062*
	(0.033)	(0.033)	(0.033)
Inputs controls	Yes	Yes	Yes
Endowment controls	Yes	No	Yes
3rd degree Taylor expansion of inputs	No	Yes	Yes
No. obs.	53,487	53,487	53,487
R-squared	0.550	0.552	0.552

Notes: Standard errors clustered at district level (in parenthesis). Stars indicate statistical significance: **p* <0.10, ** *p* <0.05, *** *p* <0.01.* All specifications are estimated using OLS and include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as regression in column 2 of Table 2. Input controls: log of area planted, number of household members working in agriculture, and amount spent on hired labor. Endowment controls: log of household size and area of land owned. Columns 2 and 3 include a 3rd degree Taylor expansion of two inputs: log of area planted, number of household members working in agriculture.

Table B.6: Effect of HDD on other farm inputs

	Fertilizers		Pesticides	
	(1)	(2)	(3)	(4)
Dep var:	Extensive	Intensive	Extensive	Intensive
Average DD	-0.003	-0.021	0.001	0.002
	(0.003)	(0.022)	(0.004)	(0.018)
Average HDD	0.003	0.002	0.005	0.029
	(0.010)	(0.052)	(0.008)	(0.043)
No. obs.	53,619	53,618	53,619	53,618
R-squared	0.272	0.375	0.245	0.354

Notes: Extensive margin use is studied using a dummy variable equal to one if the farmer reports to have used fertilizers/pesticides during the last growing season. Intensive margin use is defined as the logarithm of total amounts spent on fertilizers/pesticides. Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2.

Table B.7: Effect of temperature on farm labor inputs, by type of farmer

	Household Labor			Hired Labor
	(1)	(2)	(3)	(4)
Dep var:	HH members in farm	HH hours in farm	Child labor	ln(wage bill)
Average HDD x Owns livestock	0.019	0.032*	0.024*	-0.095
	(0.012)	(0.019)	(0.012)	(0.061)
Average HDD x No livestock	0.014	0.016	0.029*	-0.038
	(0.014)	(0.024)	(0.015)	(0.055)
No. obs.	26,724	26,726	14,358	53,618
R-squared	0.513	0.361	0.315	0.247

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2. Sample restricted to interviews conducted during the growing season (i.e. October to March) in columns 1 and 2, since dependent variable is defined as work conducted over the past week. In column 3, we restrict the sample to households with children between the ages of 6 and 15.

Table B.8: Effect of HDD on land productivity, output and land use - by baseline climate

	ln(output per ha) (1)	ln(total output) (2)	ln(area planted) (3)	Tubers % output (4)
(A) Average HDD x	-0.126***	-0.066	0.039**	0.009**
Hot areas	(0.040)	(0.041)	(0.018)	(0.004)
(B) Average HDD x	-0.228**	0.038	0.221**	0.050***
Cool areas	(0.102)	(0.068)	(0.097)	(0.019)
Diff. (B)-(A)	0.305	0.130	0.054	0.026
p-value				
No. obs	53,493	53,619	53,493	53,619
R-squared	0.336	0.348	0.443	0.527

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2. Cool areas = clusters with average growing season temperature in period 2007-2015 below the sample median (22.4°C). Hot areas = clusters with average growing season temperature in period 2007-2015 above the sample median.

Table B.9: Effect of lagged HDD on land productivity

Dep. Variable:	ln(output/ha)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Average HDD in growing season t	-0.105**	-0.106**	-0.096**	-0.092*	-0.111***	-0.102***	-0.071**	-0.077**	-0.042
	(0.042)	(0.041)	(0.038)	(0.047)	(0.041)	(0.039)	(0.034)	(0.033)	(0.039)
Average HDD in growing season t-1	-0.015								0.026
	(0.025)								(0.033)
Average HDD in growing season t-2		-0.016							0.028
		(0.027)							(0.039)
Average HDD in growing season t-3			-0.031						0.003
			(0.028)						(0.039)
Average HDD in growing season t-4				-0.042					-0.043
				(0.031)					(0.038)
Average HDD in growing season t-5					-0.007				0.014
					(0.020)				(0.026)
Average HDD in growing season t-6						-0.036			-0.020
						(0.024)			(0.027)
Average HDD in growing season t-7							-0.049*		-0.045
							(0.028)		(0.032)
Average HDD in growing season t-8								-0.044	-0.047
								(0.030)	(0.040)
No. obs.	53,493	53,493	53,493	53,493	53,493	52,056	46,636	41,465	41,465
R-squared	0.335	0.335	0.335	0.335	0.335	0.332	0.333	0.330	0.330

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2.

Table B.10: Effect of temperature on land uses, by proxies of market development

	ln(area planted)					
	(1)	(2)	(3)	(4)	(5)	(6)
Average HDD	0.180***	0.075**	0.279**	0.211*	0.150**	0.573**
	(0.068)	(0.034)	(0.138)	(0.113)	(0.068)	(0.280)
Average HDD $\times W$ (region level)	-0.297**	-0.098	-0.438*	-0.315	-0.631	-0.184*
	(0.143)	(0.142)	(0.255)	(0.224)	(0.397)	(0.098)
$W =$	% output sold	% land with registered title	% farmers hire workers	% use pesticides	% apply to agric. credit	ln(no. branches per 100,000 inhab. 2009)
Mean W	0.276	0.158	0.497	0.449	0.082	2.570
No. obs	53,493	53,493	53,493	53,493	53,493	53,493
R-squared	0.443	0.443	0.443	0.443	0.443	0.443

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01*. All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2. W are proxies of market distortions calculated at region (n=24) level. Data for constructing these measure comes from the ENAHO survey, except in columns 5 and 6 which were obtained from the National Agricultural Census 2007 and the Superintendencia de Banca, Seguros y AFP (SBS). Column 6 refers to the number if of branches of banks providing credit to farmers.

Table B.11: Effect of temperature on household income, consumption and poverty rates

	ln(inc/capita)			ln(cons/capita)			Poor (Yes=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample:	All	Coast	Highlands	All	Coast	Highlands	All	Coast	Highlands
Average DD	0.023***	0.010	0.024***	0.021***	0.013	0.021***	-0.014***	-0.009	-0.013***
	(0.004)	(0.012)	(0.004)	(0.004)	(0.014)	(0.004)	(0.003)	(0.012)	(0.003)
Average HDD	-0.017	-0.015	-0.008	-0.014	-0.016	0.001	0.003	0.009	-0.008
	(0.013)	(0.013)	(0.022)	(0.010)	(0.010)	(0.017)	(0.007)	(0.008)	(0.015)
No. obs.	53,619	7,439	46,180	53,619	7,439	46,180	53,619	7,439	46,180
R-squared	0.380	0.388	0.335	0.452	0.451	0.416	0.264	0.282	0.244

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, month of interview, and climatic region-by-growing season fixed effects, and the same farmer controls as baseline regression in Table 2.

Table B.12: Predicted effects of temperature and precipitation on agriculture under two climate change scenarios

	RCP 4.5			RCP 8.5		
	All	Coast	Highlands	All	Coast	Highlands
	(1)	(2)	(3)	(4)	(5)	(6)
A. Predicted change of temperature						
Δ DD	1.132	1.232	1.115	3.402	1.789	3.668
Δ HDD	0.639	3.034	0.244	1.323	4.927	0.728
Δ Precipitation	0.910	0.137	1.038	0.122	-0.560	0.235
B. Predicted effect on agriculture						
Δ Yields (ln Y/T)	-0.113	-0.299	-0.082	0.031	-0.545	0.126
Δ Output (ln Y)	0.030	-0.169	0.063	0.067	-0.391	0.143
C. Differences on estimate of damages						
Δ yields - Δ output	-0.143	-0.130	-0.145	-0.036	-0.154	-0.016

Notes: Table presents predictions of the effect of increased temperatures on agriculture under two climate change scenarios (RCP 4.5 and 8.5). Predictions uses region-specific estimates of the effect of temperature and precipitation on yields and output from columns 1 and 3 in Table 6.