# Climate Change and Agriculture: Farmer Adaptation to Extreme Heat*

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**Abstract**

This paper examines how farmers adapt in the short-run to extreme heat. Using a production function approach and micro-data from Peruvian households, we find that high temperatures induce farmers to increase the use of inputs, such as land and domestic labor. This reaction partially attenuates the negative effects of high temperatures on output. We interpret this change in inputs as an adaptive response in a context of subsistence farming, incomplete markets, and lack of other coping mechanisms. We use our estimates to simulate alternative climate change scenarios and show that accounting for adaptive responses is quantitatively important.

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 conservative predictions, 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 adaptation strategies and the scope for mitigation. Some studies suggest that a possible response to climate change would be re-allocation of economic activity, in the form of migration, changes in trade patterns or sectoral employment (Colmer, 2016, 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 (Akpalu et al., 2015, Di Falco et al., 2011, Gbetibouo, 2009, Hisali et al., 2011).

Less is know, however, about productive adaptations, i.e., changes in production decisions to attenuate the negative effects of extreme temperatures. Existing studies from the U.S. and India find that farmers do not seem to change crop mix or agricultural practices in response to rising temperatures, even though crop yields are negatively affected by both short-term weather shocks and long-term changes in climate patterns (Burke and Emerick, 2016, Guiteras et al., 2015). This finding has been interpreted as evidence that farmers do not engage in long-run productive adaptation.

This paper examines how farmers adapt to extreme heat in the context of a developing country. Our main contribution is to show that an important adaptive response is to increase the use of farm inputs, such as land and domestic labor. This response to a negative productivity shock, can be rationalized in a context of traditional subsistence farming characterized by thin input markets and limited outside opportunities. To the best of our knowledge, this margin of adjustment to extreme temperatures has not been documented before. It has, however, relevant implications for the quantification of predicted economic losses due to climate change, and for understanding the potential long-term effects of weather shocks.

To separate the effects of temperature on agricultural productivity, output, and productive decisions, we use a production function approach combined with a novel dataset. We match micro-data from Peruvian farming households for 2007-2015 with high-frequency temperature data obtained from satellite imagery. The granularity of our data allows us to estimate the relationship between temperature and agricultural outcomes –such as total factor productivity (TFP), yields, output

[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. (2017a).

and input use– using observations at the farm level.[2]

Our approach has several advantages over existing studies examining the effect of temperature on agriculture using crop yields. First, crop yields capture both biological and human responses, such as changes in labor and other inputs. However, by construction, they cannot reflect changes in land use, missing a potentially important margin of adjustment. Second, most of the existing evidence comes from farmers in the U.S. These farmers engage in mostly intensive, monocropping agriculture and have access to ex-ante risk coping mechanisms, such as crop insurance. These features may reduce incentives to adapt to climate change (Annan and Schlenker, 2015). Hence, their responses may not be informative of farmers' adaptation in other contexts. Finally, household and satellite data like the ones used in this paper are publicly available for most developing countries. Thus, our analysis can be replicated in contexts that lack rich weather station data.

We find that farmers respond to extreme temperature by *increasing* use of land and domestic labor. This occurs despite extreme temperatures reducing agricultural productivity. The magnitude is economically significant and partially offsets the drop in total output. This result is robust to a variety of specification checks and is not driven by changes in agricultural prices.

This is a surprising finding: in standard production models lower productivity would weakly reduce input use. However, it is consistent with decisions of consumer-producers facing incomplete markets as in agricultural household models (De Janvry et al., 1991, Taylor and Adelman, 2003). In this view, subsistence farmers, lacking other consumption smoothing mechanisms, may use their inputs more intensively to attenuate drops in output and consumption. With this framework in mind, we interpret our results as evidence of productive adaptation, i.e., changes in production decisions to reduce the negative effects of extreme temperature.

We then exploit the richness of our data to examine other possible adaptive responses. First, we document changes in crop mix associated with extreme temperatures: we find a reduction in cereals (such as rice and corn) and an increase in tubers. This response, however, occurs in addition to changes in land use, and is not enough to offset the drop in productivity. Second, we 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, although the evidence is less conclusive regarding other coping mechanisms. Interestingly, the increase in land as a response to extreme heat only occurs among farmers who do not have livestock, even though cattle owners do seem to have available land. This result suggests, by a revealed preferences argument, that adjusting land may be a costlier strategy than selling disposable assets.

Our findings have important implications for the quantification of the potential economic costs

[2] A similar approach has been used for manufacturing plants in China in Zhang et al. (2017b).

of climate change, especially for developing countries. Most current predictions rely on estimates of the effect on crop yields from studies in developed countries or performed in controlled conditions. These estimates fail to take into account changes in land use, and thus may overestimate the effects of climate change on agricultural output.

To illustrate this point, we use our estimates to predict the potential effect on yields and output of evenly distributed increments of 1.5°C to 3°C in average daily temperatures.[3] We conduct this analysis separately for the two main climatic regions of Peru, i.e., coast and highlands. We obtain two important results. First, the effects of increased temperature are heterogeneous. The coast, with an arid semi-tropical climate, would suffer large losses (between 8-19% of total output). In contrast, the highlands, with a cooler and wetter climate, would benefit slightly from the warmer temperatures. Similar heterogeneous effects have been document for U.S. agriculture (Deschenes and Greenstone, 2007, Mendelsohn et al., 1994, Schlenker et al., 2006) but not for a developing country. Second, accounting for farmer adaptation is relevant to quantify output losses. In the case of the coast, failing to account for adaptive behavior would overestimate the estimated losses by almost 15%.

The rest of this paper is organized as follows. Section 2 discusses our analytical framework and empirical strategy. Section 3 presents the main results on productive adaptation and other coping mechanisms, while Section 4 explores in more detail changes in land use. Section 5 presents simulations of climate change scenarios. Section 6 presents a variety of robustness checks. Section 7 concludes.

# 2 Methods

## 2.1 Analytical framework

This section describes a simple framework to analyze farmers' adaptation to changes in temperature. We focus on short-run productive adaptation, that is, changes in production choices (such as input use) as a strategy to attenuate the negative effects of weather shocks.

We start by considering a producer-consumer model in which agricultural output is defined by production function $Y = f(A, T, L)$, where $A$ is total factor productivity (TFP), $T$ is land and $L$ is labor. In this framework, a natural way to analyze temperature is through its effects on TFP. This effect is likely non-linear. Existing studies, in both the biological and economic literature, find that at moderate levels increases in temperature are beneficial for crop yields. However, at higher levels, temperature can be harmful.[4]

How would farmers respond to this shock? In a standard production model, with well-functioning

[3]These increments are consistent with scenarios RCP2.6 and RCP8.5 of the 4th IPCC Assessment Report. See, for example, IMF (2017).

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

markets, we could expect that producers adjust to lower productivity by reducing input use. This reduction in input use would exacerbate the drop in TFP, and lead to a larger drop in agricultural output.

These predictions, however, could be different in a context with incomplete markets. In this case, we cannot longer separate consumption and production decisions, as discussed in Benjamin (1992). Consider, for example, a scenario in which some inputs cannot be traded and households' consumption is close to subsistence levels.[5] This scenario is similar to the environment used in standard agricultural household models (De Janvry et al., 1991, Taylor and Adelman, 2003). In this case, a negative productivity shock, and the subsequent drop in agricultural output, could push household consumption below subsistence levels. In the absence of other coping mechanisms (such as crop insurance, savings, or access to credit) or limited off-farm opportunities (such as migration or non-agricultural jobs), the only way to attenuate the drop in output, and avoid an undesirable reduction in consumption, would be to *increase* the use of non-traded inputs, such as land or domestic labor. This has been documented recently in a report by Damania (2017). The authors show how, as a response to shortfall in precipitation of one standard deviation, farmers from Madagascar expand their productive units into forests, increasing the rate of deforestation by 10% to 20%.

The argument laid out above focuses on a particular type of productive adaptation, i.e., changes in input use. There are, however, other possible adaptive 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 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)).

With this framework in mind, our empirical analysis examines the effect of extreme heat on TFP, input use, and agricultural output. We also examine potential heterogeneous responses, as those with availability of alternative coping strategies may be more likely to use them instead of changes in input use. Finally, we also examine other productive adaptations, such as changes in crop mix, and consumption smoothing mechanisms.

### 2.2 Data

Our empirical analysis focuses on two climatic regions of Peru: the coast and the highlands (see Figure 1 for a location map).[6] The two regions exhibit a rich variety of climatic, socioeconomic

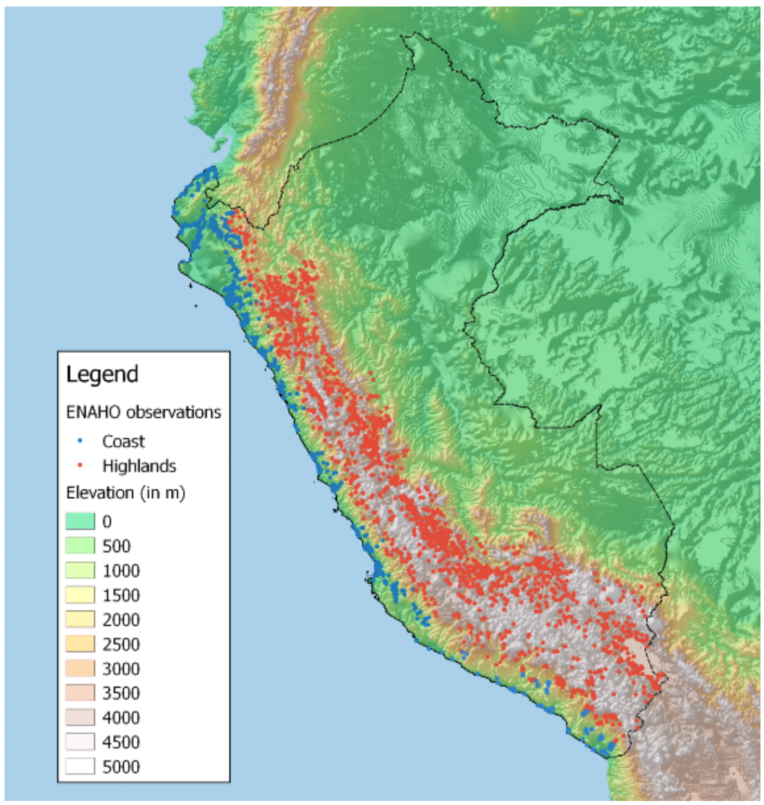
[5]These features are certainly present in the Peruvian case: more than 50% of households are poor, only around 10% of farmers rent land, and family members work mostly on the household farm (see Table 1).

[6]Peru has three main climatic regions: the coast to the west, the Andean highlands, and the Amazon jungle to the east. The coast is the region from 0 to 500 meters above sea level (masl) on the west range of the Andes. Highlands range from 500 to almost 7,000 masl, while the jungle is the region of low lands (below 1000 masl) to the east of the Andes. We drop the jungle due to small sample size and poor quality of satellite data: many observations are missing due to cloud coverage.

and agronomic characteristics. Similar to other developing countries, modern farming (usually capital intensive and export-oriented) co-exists with small-scale, subsistence, farmers. This latter group encompasses most rural households but has been neglected in previous studies on the effect of temperature on agriculture. We argue that these features make the Peruvian case an ideal testing ground of the effect of extreme heat on agriculture. By providing a snapshot of the effects on different climates and subsistence farmers, it can be informative of potential effects in other developing countries.

We combine household surveys with satellite imagery to construct a comprehensive dataset with information on agricultural, socio-demographic, and weather variables at the farm level. The dataset includes around 55,000 households and spans from 2007 to 2015.[7]

Figure 1: ENAHO observations 2007-2015




Notes: Location of the ENAHO observations used in this study by climatic region.

[7]We restrict the sample to households with some agricultural activity in each survey year. We drop 282 farmers reporting land holdings larger than 100 hectares. We also drop observations from the jungle due to small sample size and poor quality of satellite data due to cloud cover.

**Temperature and precipitation** A main limitation in Peru, and other developing countries, is the lack of high resolution weather data: in the period of analysis there were just 14 stations in the whole country. This lack of data also introduces a significant measurement error in gridded products, such as reanalysis datasets, which use weather station data as their main input.[8]

To overcome these limitations, we use satellite imagery.For temperature, 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 $0.05 \times 0.05$ degrees, equivalent to 5.6 km squares at the Equator, and is already cleaned of low quality readings and processed for consistency.[9]

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).

Precipitation data comes 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 daily precipitation with a resolution of $0.05 \times 0.05$ degrees.

We combine the weather data with household's location to obtain daily measures of temperature and precipitation for each farmer during the last completed growing season.[10] Follwing the Peruvian agricultural calendar, we define the growing season to span from October through March. This period corresponds to the southern hemisphere's Spring and Summer. The distribution of temperatures in the relevant locations over the growing season are shown in Figure 2.

**Agricultural and socio-demographic data** We use 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 guarantees that the sample is evenly distributed over the course of the calendar year. Importantly, the ENAHO includes geographical coordinates of each primary sampling unit or survey block.[11] In rural areas, this corresponds to a village or cluster of dwellings. We use this information to link the household data

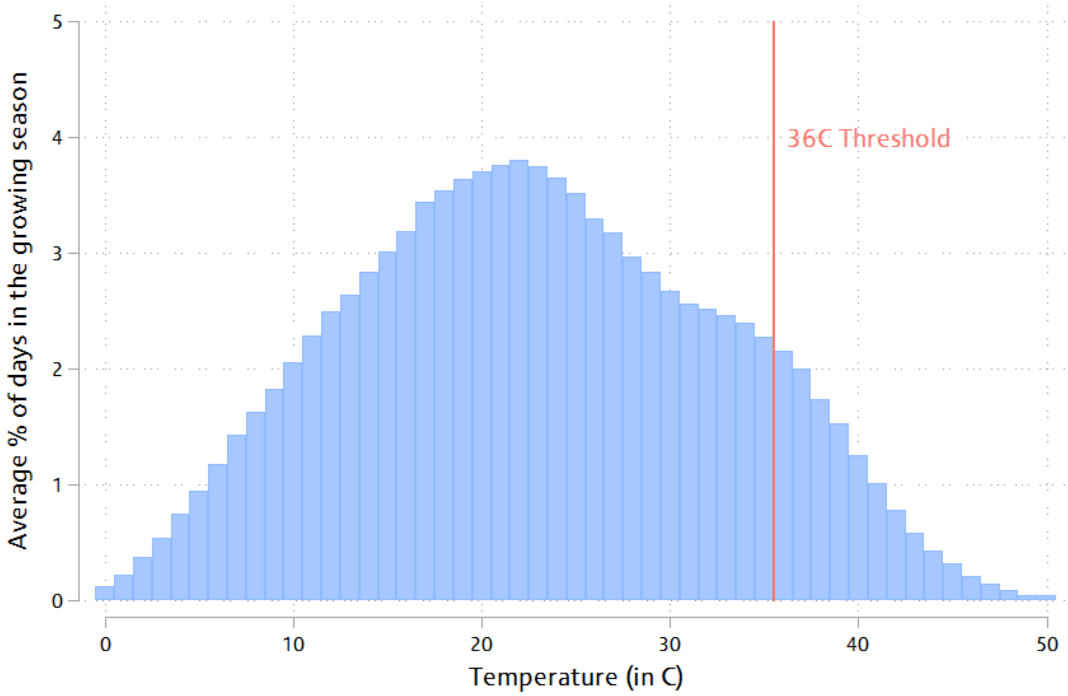
[8]Two commonly used examples are published by the European Center for Medium-Range Weather Forecasting (ECMWF) and the National Center for Environmental Prediction (NCEP). These products rely on weather station data and interpolate it on a global grid using general circulation models.

[9]The satellite estimates are very precise. Validation studies comparing satellite and ground readings find a discrepancy of only 0.1-0.4°C (Coll et al., 2005, 2009, Wan and Li, 2008).

[10]We assign the outcomes for growing season $t$ (October $t = 1$ through March $t$), to any household interviewed as of April $t$ and up to March $t + 1$. We believe this approach is conservative since it only assigns weather outcomes to households once the growing seasons has finished.

[11]There are more than 3,400 unique coordinate points.

Figure 2: Distribution of daily average temperature




Notes: Figure depicts the share of days spent in each temperature bin by the farmers in our sample, during the 2007-2015 growing seasons. The 36°C threshold indicates the temperature beyond which additional heat becomes detrimental for agricultural yields (see Figure 3).

to satellite imagery. Figure 1 depicts the location of the observations used in this study.

The ENAHO contains rich information on agricultural activities in the 12 months prior to the interview. We use this information to obtain measures of agricultural output and input use. To measure real agricultural output, we construct a Laspeyres index with quantity produced of each crop and local prices.[12] Land use is obtained by adding the size of parcels dedicated to seasonal and permanent crops. We observe the size and use of each parcel, but not which specific crops are cultivated in each one. Since most farmers cultivate several crops, this prevents us from calculating crop-specific yields.

We use self-reported wage bill paid to external workers as a measure of hired labor use. Labor information on household members is available for the week prior to the interview.[13] Use this information we calculate the number of household members working in agriculture and build an

[12] As weights, we use the median price of each crop in a given department in 2007.

[13] Given that interviews can occur after the growing season, these measures of domestic labor may not reflect actual input use during the period of interest. We address this concern in the analysis of input use by using only observations interviewed during the growing season.

indicator of child labor.[14] These variables serve as proxies for domestic labor.

We complement the household survey with data on soil quality from the Harmonized World Soil Database (Fischer et al., 2008). This dataset provides information on several soil characteristics relevant for crop production on a 9 km square grid.[15]

Table 1 present some summary statistics for our sample of farming households. There are several relevant observations for the empirical analysis. First, most farmers are poor and depend on agriculture as their main economic activity. 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%. Poverty and reliance in agriculture as the primary economic activity are higher in the highlands than in the coast. Second, farmers have small scale operations (the average farm size is around 2 ha), and use 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. This feature is consistent with fallowing and crop rotation.

Finally, climatic conditions are drastically different in both regions in the sample. The coast has a sub-tropical climate with mild to hot temperatures and very little rainfall. Not surprisingly, most of the agriculture in this region occurs in irrigated lands.[16] In contrast, the highlands have cooler temperatures and more rain during the growing season. These differences do not entail substantially different results in the key components of our analysis, but have important implications when thinking in terms of the potential effects of greater temperatures due to climate change.

### 2.3 Empirical strategy

The aim of the empirical analysis is to examine how farmers adjust their production decisions as a response to extreme heat. As discussed in Section 2.1, we adopt a producer-consumer approach and analyze weather shocks as changes in total factor productivity, $A$. In this framework, extreme heat reduces $A$, and through that channel, it can affect input use and agricultural output. Input use and agricultural output can be modelled as reduced form functions of $A$ and a set of given parameters such as local prices and return to land fallowing. Assuming that $A$ is a function of local weather and other factors, such as household and district characteristics, we can approximate these

[14] 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.

[15] The soil qualities include nutrient availability and retention, rooting conditions, oxygen availability, excess salts, toxicity and workability.

[16] Given the potential importance of irrigation as a method to counteract the damage from high temperatures, a branch of the literature decides to exclude areas with high irrigation coverage, see for instance Schlenker and Roberts (2009). We keep these observations but control for the share of irrigated land.

reduced forms 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 $j$ during growing season $t$, and $y$ is an outcome such as agricultural output, or quantity of input used. $g(\gamma, \omega_{it})$ is a non-linear function of local weather conditions ($\omega_{it}$), to be specified later. $Z_i$ is a set of household characteristics, and $\rho_j$ and $\psi_t$ are district and year fixed effects.[17] We cluster the standard errors at district level to account for spatial and serial correlation in the error term.[18] In this baseline specification, we are interested in $\gamma$: the reduced-form estimate of the effect of weather on agricultural outcomes.

Due to data limitations, we do not include other determinants of agricultural outcomes such as local prices, endowments, or returns to land fallowing. However, to the extent that these variables are captured by the set of fixed effects and household controls, potential endogeneity is less of a concern. In addition, we verify the robustness of our results in alternative specifications by including a richer set of covariates, such as input endowments and department-by-growing season fixed effects. We also examine the effect of weather shocks on local prices, as a way of testing for this possible channel of impact.

### 2.3.1 Estimating the effect on productivity

At the core of our analysis is the assumption that extreme heat affects total factor productivity. We examine this assumption in two ways. First, we estimate regression (1) using as dependent variable total output per hectare ($Y/T$), a proxy for agricultural yields. This approach is similar to previous studies in the literature which use crop yields.[19]

A main limitation of this approach is that yields is a measure of partial productivity which captures both changes in TFP *and* relative use of inputs. If inputs are fixed, for instance in lab conditions, this approach is informative of effects on TFP. However, in the presence of adaptive responses, it can overestimate the effect productivity shocks on agricultural productivity.

For that reason, we complement our results by estimating a production function. Assuming a Cobb-Douglas production function $Y_{ijt} = A_{ijt} T_{it}^{\alpha} L_{it}^{\beta}$, applying logarithms, and using the functional form assumption of $A$, we obtain the following regression model:

$$\ln Y_{ijt} = \alpha \ln T_{it} + \beta \ln L_{it} + g(\gamma, \omega_{it}) + \phi Z_i + \rho_j + \psi_t + \epsilon_{ijt}, \tag{2}$$

[17] 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.

[18] Results are robust to clustering standard errors at provincial level (see Table 12). A third alternative often discussed in the literature is to correct spatial and serial correlation using the procedure suggested by Conley (1999). However, this approach is not feasible in our case due to conformability errors as described in Hsiang (2016).

[19] Due to data limitations we are unable to calculate crop-specific yields, except for a small share of farmers.

where $Y$ is agricultural output, and $T$ and $L$ are quantities of land and labor. This model is similar to equation (1), however, by controlling for input use, $\gamma$ can now be interpreted as the effect of weather on TFP.

A potential concern with this specification is that $\epsilon$ does not simply reflect unanticipated shocks but unobserved determinants of farmer's productivity. Since output and input use are both affected by productivity, this would lead to a problem of omitted variables. To address this concern, we estimate (2) using both OLS and IV models. In the latter case, we use endowments (i.e., household size and area of of land owned) as instruments for input use. The motivation to use these instrument comes from the observation that, in the absence of input markets, the quantity used of land and domestic labor would be proportional to the household endowment.[20] The validity of these instruments would rely on the assumption that endowments affect output only through its effect on input use, i.e., endowments should not be conditionally correlated to unobserved heterogeneity, $\epsilon_{ijt}$.[21]

#### 2.3.2 Modeling the relation between weather and productivity $g(\gamma, \omega_{it})$

Following previous economic and agronomic findings, we model the relation between weather and agricultural productivity as a function of the farm's cumulative exposure to heat and water.[22] This approach is based on the assumption of time separability, i.e., weather outcomes have the same impact on output per hectare whenever they occur within a given growing season. Similar to Schlenker et al. (2006), we construct two measures of cumulative exposure to heat during the growing seasons: degree days (DD) and harmful degree days (HDD). DD measures the cumulative exposure to temperatures between a lower bound, usually 8°C up to an upper threshold $\tau_{high}$, while HDD captures exposure to extreme temperature (above $\tau_{high}$), The inclusion of HDD allows for potentially different, non-linear, effects of extreme heat.

Formally, we define $DD = \frac{1}{n}\sum_d g^{DD}(h_d)$, with

$$g^{DD}(h) = \begin{cases} 0 & \text{if } h \leq 8 \\ h - \tau_{low} & \text{if } 8 < h \leq \tau_{high} \\ \tau_{high} - 8 & \text{if } \tau_{high} < h, \end{cases}$$

$h_d$ is the average daytime temperature in day $d$ and $n$ is the total number of days in a growing

[20]With perfect input markets, we would obtain the standard result of separability of consumption and production decisions and there would be no correlation between endowments and input use (Benjamin, 1992). Empirically, this would create a problem of weak instruments.

[21]The interpretation of this IV strategy would be as a local average treatment effect, since the coefficients would be identified from farmers subject to input market imperfections.

[22]See, for example Schlenker and Roberts (2006).

season. Similarly, $HDD = \frac{1}{n}\sum_d g^{HDD}(h_d)$, with

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

After calculating total degree days, we estimate the average degree days by day over the entire growing season, by dividing over the number of days with non-missing temperature data, for consistency. This re-scaling makes interpretation easier and does not affect the results. Similarly, we measure exposure to precipitation using the average daily precipitation (PP) during the growing season and its square.[23] With these definitions in mind, we parametrize the function relating weather to productivity $g(\gamma, \omega_{it})$ as:

$$g(\gamma, \omega_{it}) = \gamma_0 DD_{it} + \gamma_1 HDD_{it} + \gamma_2 PP_{it} + \gamma_3 PP_{it}^2. \tag{3}$$

A key remaining issue is to define the value of the upper threshold above which temperature has a negative effect ($\tau_{high}$) on agricultural yields. Previous studies in U.S. set this value between 29-32°C (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 (1) using log of output per hectare as outcome variable and replacing DD and HDD 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] Based on the distribution of temperatures in the Peruvian case, we define ten bins: $<$ 18°C, $>$ 41°C, and eight 3°C-wide bins in between. Our omitted category is the temperature bin 27-29°C.

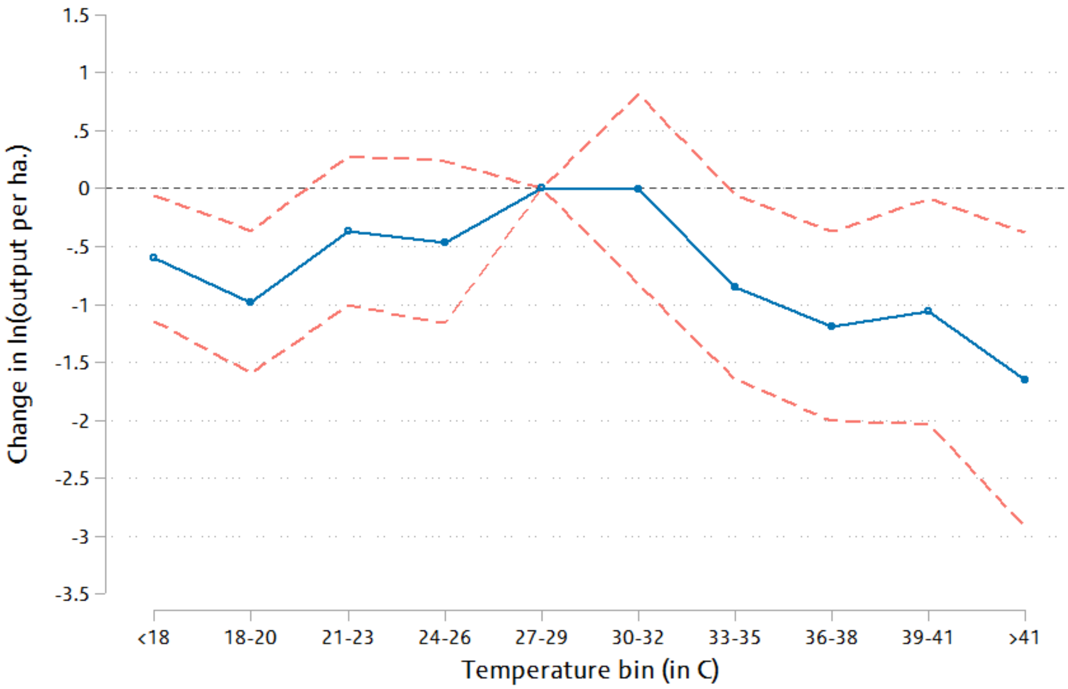
Figure 3 displays the estimated coefficients and their 90% confidence interval. Note that temperatures above 32°C start having a negative effect on agricultural yields. The effect becomes statistically significant for temperature bin 36-38°C. Based on these results, in our preferred specifications we use a value of $\tau_{high}$ equal to 36°C for the whole sample. In Section 6 we verify the robustness of our main results to a threshold of 32°C, selected by an iterative regression method.

[23]Precipitation and temperature are likely to be correlated, so it is important to include this regressor.

[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.

Figure 3: Non-linear relationship between temperature and agricultural yields




Notes: Points represent coefficient estimates of the effect of increasing the share of days in the growing season in each of the temperature bins, relative to the 27-29°C bin, on log of output per ha. Dashed lines show the 90% confidence interval.

Table 1: Summary statistics (ENAHO 2007-2015)

| | All (1) | Coast (2) | Highlands (3) |
|---|---|---|---|
| *A. Household characteristics* | | | |
| Poor (%) | 50.8 | 26.2 | 55.0 |
| Household size | 4.33 | 4.41 | 4.31 |
| Primary education completed by HH head (%) | 51.2 | 59.0 | 49.8 |
| Child works (%) | 21.5 | 9.5 | 23.6 |
| Main job in agriculture (%) | 78.4 | 68.6 | 80.0 |
| *B. Agricultural characteristics* | | | |
| Value of agric. output (Y), 2007 USD | 1025.3 | 3053.0 | 682.0 |
| Output per ha. (Y/T), 2007 USD | 1256.4 | 2319.3 | 1077.3 |
| Land used (T), in ha. | 2.0 | 2.4 | 1.9 |
| No. HH members work on-farm | 2.3 | 2.2 | 2.3 |
| Hire workers (%) | 48.4 | 55.8 | 47.1 |
| Uncultivated land (% of land holding) | 40.1 | 12.1 | 44.8 |
| Irrigated land (% land holding) | 36.5 | 82.3 | 28.7 |
| Tubers (% total output) | 31.4 | 5.6 | 35.6 |
| Cereals (% total output) | 31.2 | 30.2 | 31.4 |
| Legumes (% total output) | 10.75 | 7.82 | 11.23 |
| Own livestock (%) | 76.8 | 54.6 | 80.6 |
| Value of livestock, 2007 USD | 678.1 | 450.3 | 716.7 |
| *C. Weather during the last growing season* | | | |
| Average temperature (°C) | 22.9 | 33.1 | 21.2 |
| Average DD | 14.8 | 23.8 | 13.2 |
| Average HDD | 0.34 | 1.37 | 0.16 |
| % days with HDD | 10.3 | 35.4 | 6.1 |
| Precipitation (mm/day) | 3.1 | 0.9 | 3.5 |
| Observations | 54,981 | 7,961 | 47,020 |

*Notes:* Sample restricted to farming households from the coast and highlands. Cereal, tuber and legumes are the biggest contributors to household agricultural income. Other sources include garden crops, fruits, and forage.

# 3 Results

This section presents our empirical results on farmers' responses to extreme heat. We begin by documenting the non-linear effect of temperature on agricultural productivity. Then we examine productive adaptations, such as changes in input use and crop mix. Finally, we evaluate other coping strategies identified in the consumption smoothing literature.

## 3.1 Temperature and agricultural productivity

Figure 3 sets the scene for our empirical analysis. It provides prima facie evidence of a non-linear relationship between temperature and agricultural productivity: at moderate levels, temperature increases output per ha., but at higher levels, the effect is negative.

Table 2 corroborates this finding using our preferred specification, which includes degree day measures of cumulative exposure to temperature: DD and HDD. Column 1 uses agricultural yields ($Y/T$) as a proxy for productivity. As mentioned above, this approach may not accurately measure the impact of weather outcomes on productivity, since it confounds impacts on both TFP and input use. For that reason, in columns 2 and 3 we estimate a production function, i.e, output conditional on input use, using an OLS and IV strategy, where input use is instrumented with household endowments. By controlling for input use, these latter estimates can be interpreted as the effect of temperature on TFP.

Our estimates suggest that extreme heat has a negative effect on agricultural productivity.[26] The magnitude of the effect is economically significant: the most conservative estimate suggests that an increase of 1°C in the average growing season temperature above the optimal level would decrease agricultural productivity by almost 16%. The standard deviation of this HDD variable is 0.8. To put this figure in further context, note that climate change scenarios envisage that, by the end of this century, average temperatures could increase by 1.5°C to 3°C. Assuming a conservative flat increase of daily average temperatures, these scenarios translate into increases of up to 1.167 average HDD over the growing season in the Peruvian highlands, as we will see in section 5. Negative effects of extreme heat on crop-specific yields of similar magnitudes have been documented in agronomic field trials and using aggregated data in U.S., India, and Sub Saharan Africa, among others.[27]

What happens with total output? Consistent with a drop in productivity, we find that extreme heat reduces agricultural output (column 4). However, the magnitude of this effect is smaller than for TFP or yields. The difference between the two coefficients is not statistically significant. However, it is suggestive that farmers implement productive adaptations (i.e., changes in production

[26] The results are similar using an alternative measure of exposure to extreme heat: the share of days during the growing season with high temperatures (above 36°C). See Table A.1 in the Appendix.

[27] See, for example, Auffhammer et al. (2012), Guiteras et al. (2015), Burgess et al. (2017), Burke et al. (2015), Burke and Emerick (2016), Schlenker and Roberts (2009), Lobell et al. (2011).

decisions) to attenuate the negative effect of extreme heat on total output. We examine this hypothesis in detail next.

Table 2: Impacts of DD and HDD on agricultural productivity and output

| | Y/T | TFP | | Y |
|---|---|---|---|---|
| Dep. var.: | ln(output/ha) | ln(output) | ln(output) | ln(output) |
| | (1) | (2) | (3) | (4) |
| Average DD | 0.009 | 0.007 | 0.009 | 0.006 |
| | (0.009) | (0.008) | (0.008) | (0.009) |
| Average HDD | -0.192*** | -0.164*** | -0.181*** | -0.157** |
| | (0.070) | (0.063) | (0.064) | (0.075) |
| Input controls | No | OLS | IV | No |
| N | 54,981 | 54,972 | 54,972 | 54,981 |
| R2 | 0.241 | 0.405 | 0.390 | 0.244 |

*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 and climatic region-by-growing season fixed effects, and control for 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 number of household members working in agriculture, total land used, and amount spent on hiring labor. Instruments for domestic labor and land used: household size and land owned. First stage joint significance F-test is 360.71.

### 3.2 Productive adaptations: input use and crop mix

Table 3 presents our main results on productive adaptation. We start by examining changes in input use as a response to extreme heat. We focus on three key agricultural inputs: hired labor, household labor, and land.

Consistent with lower productivity, we observe that extreme heat has a negative effect on hired labor (column 1).[28] However, the effect on land and household labor is the opposite (columns 2-5).[29] Extreme heat *increases* land used, quantity of household labor used in the farm (measured both as number of individuals or number of hours), as well as the probability of child labor.[30]

[28]Due to data limitations, we cannot say whether this effect captures lower hours hired or lower hourly wages paid.

[29]Note that the dataset only provides information on labor outcomes in the week previous to the survey. To reduce measurement error, in Columns 3 to 5 we focus only on households that were interviewed during the growing season. This explains the smaller number of observations.

[30]This last result is consistent with findings in the literature on child labor (Bandara et al., 2015, Beegle et al., 2006) that show that poor households may resort to employing children in productive activities when subject to negative income shocks, in line with the luxury axiom proposed initially by Basu and Pham (1998).

These are surprising results. In a standard production model, we could expect negative productivity shocks to reduce use of variable inputs. These findings, however, are consistent with the response of subsistence farmers in a context of incomplete markets, as discussed in Section 2.1. In that scenario, farmers exposed to a negative shock and limited off-farm opportunities may need to resort to a more intensive use of non-traded inputs to avoid undesirable drops in consumption.

To the best of our knowledge, this pattern of productive adaptation has not been documented before. These results uncover an adaptive response (i.e, increase in input use) that may be specially relevant for farmers in less developed countries. This margin of adjustment may have been missed in existing studies of the effect of temperature on agriculture due to their focus on farmers in developed countries. In that context, better access to markets, crop insurance and other coping mechanism may make changes in land use a less relevant response.

This finding has two important implications. First, it suggests a dynamic link between weather shocks and long-run outcomes. To see this, consider that unused land or household labor are not necessarily unproductive, but might have alternative uses. For instance, 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). Similarly, sending children to school, instead of working on the farm, can increase future earnings. Thus, using these inputs more intensively, as a response of a weather shock, could reduce these future benefits. In this sense, this adaptive response is akin to reducing savings/investments.

Second, this adaptive response may affect estimations of the effect of climate change on agricultural production. 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 adapt to weather shocks by changing land use. As we show in Section 5, taking into account this adaptive response reduces, in a non-trivial magnitude, the predicted effects on total output.

**Changes in crop mix** Recent studies have emphasized the possible role of changes in crop mix as an adaptive response to climate change (Burke and Emerick, 2016, Colmer, 2016). A relevant question is how important is this margin of adjustment in our context.

In Table 4 we explore this issue by looking at the effect of temperature on quantities and value shares of three main crop types: cereals (mostly rice in the Coast and corn in the Highlands), tubers (i.e., potatoes) and legumes. These crops represent more than 70% of agricultural production and are widely widespread. Note, however, that farmers in our context practice multicropping: the average farmers grows almost six different crops.[31] This is a commonplace practice among subsistence farmers across the developing world, and is in stark contrast with the modern agricultural

[31] In our sample, less than 10% of farmers report growing only one crop.

Table 3: Impacts of DD and HDD on input use

| | Hired Labor | T | Household Labor | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Dep var: | Wage Bill | Land Used | HH members in farm | HH Hours in farm | Child Labor |
| Average DDs | 0.017 | -0.003 | -0.008* | -0.019*** | -0.020*** |
| | (0.014) | (0.005) | (0.004) | (0.007) | (0.006) |
| Average HDDs | -0.151* | 0.035** | 0.066*** | 0.084** | 0.045** |
| | (0.082) | (0.015) | (0.022) | (0.036) | (0.020) |
| N | 54,979 | 54,981 | 22,500 | 22,503 | 11,990 |
| R2 | 0.222 | 0.313 | 0.261 | 0.257 | 0.308 |

*Notes:* Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. Columns (3) to (5) include only information for households interviewed during the growing season as well as month of interview fixed effects.

practices of the U.S. and other developed countries, which mostly practice monocropping.

We find that extreme heat reduces the quantity (in absolute and relative terms) of cereals, but increases the production of tubers. We interpret these results as suggestive evidence that farmers change crop mix as an adaptive response to extreme heat. In the Peruvian context, tubers (potatoes) may be used as a risk-coping strategy: they have a more flexible planting calendar and may more resilient to extreme temperatures, so they can be used as a way to reduce the drop in income when other crops are failing. Additionally, they provide cheaper calories. Dercon (1996) documents a similar strategy using sweet potato among Tanzanian farmers with no liquid assets in the form of livestock.

Our analysis has two important limitations. First, we cannot distinguish between farmer's actively changing crop mix from crops' heterogeneous response to heat: our results could be similar if potatoes thrive in extreme heat even if farmers do not change crop mix at all. Second, we only observe short-run responses, within a growing season, so our results are not informative of long-run adaptation.

Despite these caveats, these results do suggest a limited role for changes in crop mix as a coping strategy in the short-run. Note, that we focus on total agricultural output, not crop-specific yields. Thus, our estimates of the effect of extreme heat on productivity already include attenuation associated with changes in crop mix. Since our estimates are negative and sizable, these results then suggest short-run changes in crop mix are not enough to offset the harmful effects of extreme heat.

Table 4: Impacts of DD and HDD on crop mix

| Dep var: | ln(output) | | | Share of total output | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Crop group: | Cereals | Tubers | Legumes | Cereals | Tubers | Legumes |
| Average DDs | 0.044*** | -0.079*** | 0.019** | 0.011*** | -0.026*** | 0.002* |
| | (0.009) | (0.015) | (0.009) | (0.002) | (0.003) | (0.001) |
| Average HDDs | -0.207*** | 0.182*** | 0.012 | -0.031*** | 0.036*** | 0.004 |
| | (0.061) | (0.056) | (0.056) | (0.011) | (0.007) | (0.007) |
| N | 43,251 | 40,131 | 34,335 | 54,214 | 54,214 | 54,214 |
| R2 | 0.454 | 0.391 | 0.318 | 0.380 | 0.520 | 0.239 |

*Notes:* Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. Columns (3) to (5) include only information for households interviewed during the growing season as well as month of interview fixed effects.

### 3.3 Other coping mechanisms

The literature on consumption smoothing has identified several mechanisms used by rural households to adjust to income, and weather, shocks. For example, individuals in affected households can seek employment off the farm (Colmer, 2016, Kochar, 1999, Rosenzweig and Stark, 1989), migrate (Kleemans and Magruder, 2017, Munshi, 2003, Feng and Schlenker, 2015) or sell assets, such as cattle (Rosenzweig and Wolpin, 1993).[32]

Table 5 explores these mechanisms. Columns 1 and 2 examine whether households adjust to extreme heat by increasing off-farm employment. We use an indicator of a household member having a non-agricultural job, as well as the total number of hours worked off-farm.[33] These outcomes capture supply of off-farm employment in the extensive and intensive margin. In both cases, the effect of extreme heat on off-farm work is very small and statistically insignificant.

In columns 3 to 5 we look for evidence of 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 from home for more than 30 days, household size, and an indicator of whether the household receives remittances. None of these variables seems to be affected by extreme weather and all the point estimates, albeit small and insignificant, show the opposite sign of what we would expect if migration was a coping mechanism.

[32]We also examine the effect of HDD on two measures of household consumption: per capita expenditure and poverty status. We observe a negative, albeit small, effect of extreme heat on these outcomes. The effect on expenditure is smaller than for agricultural output and the effect on poverty is statistically insignificant. These findings are suggestive of imperfect consumption smoothing (see Table A.3 in the Appendix).

[33]These variables are only reported for the week previous to the interview. As in Table 3, we restrict the sample to households interviewed during the growing season. However, results do not change if we include observations for the whole year.

The lack of significant results on migration and off-farm work should be interpreted with caution. Our analysis focuses on a short time 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.

Finally, we examine cattle sales as a possible coping mechanism (columns 7-10). Consistent with previous findings, such as Rosenzweig and Wolpin (1993), our results show that households reduce their holding of livestock.[34] We find evidence of changes on both the extensive and the intensive margin, as the probability of showing a decrease in value increases (column 7) and the real value of current livestock decreases (column 10). The effect seems to come from households selling, rather than consuming their livestock (columns 8 and 9).

Table 5 shows evidence that households engage in consumption smoothing mechanisms when exposed to extreme temperatures. Together with the findings on adaptation in production, this set of results requires further inspection as different explanations are consistent with what we observe. For example, do farmers use the consumption mechanisms to complement changes in land use or are these strategies substitutes? If the latter, in the context of subsistence farming and imperfect input markets, then farmers would only expand land use if there is no other way to cope with the shock, i.e., if they have no livestock.

[34] This includes cattle, sheep, horses, llamas and pigs.

Table 5: Other adjustments to DD and HDD

| | Off-farm work | | Migration | | | Livestock buffer | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Dep var: | HH member has off-farm job | Hours worked off-farm | HH member away 30+ days | HH size | Receives private transfers | Decrease in livestock value | Sold livestock | Consumed livestock | Current livestock value |
| Average DDs | 0.007* | 0.038** | 0.002** | -0.000 | 0.005** | -0.006*** | -0.012*** | -0.012*** | -1.509 |
| | (0.004) | (0.016) | (0.001) | (0.013) | (0.002) | (0.002) | (0.002) | (0.003) | (4.824) |
| Average HDDs | -0.005 | 0.030 | -0.003 | 0.002 | -0.001 | 0.028*** | 0.024* | 0.009 | -34.124* |
| | (0.020) | (0.085) | (0.004) | (0.049) | (0.009) | (0.011) | (0.013) | (0.013) | (20.174) |
| Mean outcome | 0.469 | 1.745 | 0.084 | 4.325 | 0.195 | 0.331 | 0.515 | 0.474 | 887.436 |
| N | 22,503 | 22,503 | 54,981 | 54,981 | 54,981 | 49,094 | 49,094 | 49,094 | 41,745 |
| R2 | 0.223 | 0.248 | 0.058 | 0.245 | 0.148 | 0.077 | 0.146 | 0.239 | 0.553 |

*Notes:* Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. Columns 1 and 2 include only information for households interviewed during the growing season as well as month of interview fixed effect. Livestock value from Columns (6) and (9) are measured in 2007 USD.

# 4 Understanding changes in land use

In this section we explore more carefully the nature of the changes in land use as an adaptive response to high temperatures. We focus on the increase in land use as an important adaptation mechanism for at least three reasons. First, land is an important agricultural input which, due to factors such as ill-defined property rights, is usually subject to severe market imperfections. Second, since unused land can be part of a dynamic productive decision (such as fallowing), adjustments in land to attenuate current weather shocks may impose productivity losses in the future. Finally, by focusing on crop yields, the current literature on climate change and agriculture, has neglected this margin of adjustment. This coping mechanism has also been overlooked by the literature examining ex-post consumption smoothing.

## 4.1 Who adapts?

As a first step, we study the interplay between consumption smoothing and productive adaptation to understand which types of farmers adjust their land use. As discussed in Section 2.1, it is possible that this adaptive strategy is shaped by the availability of other coping mechanisms, such as off-farm work or disposable assets. To examine these heterogeneous responses, we run our baseline regressions interacting HDD with an indicator of whether farmers had livestock before the start of the growing season or not. The choice of this interaction term is driven by our previous finding (see Table 5) that selling cattle seems to be among the set of relevant consumption smoothing mechanism. As a robustness check, we also examine interactions with indicators of availability of off-farm work.

Our results (see Table 6) suggest that the increase in land use is significantly larger for farmers who did not have livestock (column 1). This occurs despite both types of farmers experiencing similar drops in TFP (column 2). We observe similar pattern when comparing farmers with and without off-farm jobs (columns 3 and 4).[35]

In other words, the farmers who respond by increasing land use are the ones who lack other coping mechanisms. [36] This result is not mechanically driven by cattle owners lacking unused land that could be put into production. Closer examination shows that cattle owners actually have more uncultivated land than non-cattle owners. While some of this land may be used for foraging, it is suggestive that increasing land is a feasible strategy for cattle-owners and that they decide against it. In that case, our results would indicate that, by a revealed preferences argument, adjusting land

[35]Result are robust to using number of days during the growing season with extreme temperatures instead of HDD (see Table A.2 in the Appendix).

[36]We observe similar heterogeneous responses on child labor (see Table A.4 in the Appendix). In particular, the increase in child labor is larger for households *without* cattle. This is consistent with previous evidence by Beegle et al. (2006) from Tanzania, where the authors find that households respond to shocks by increasing child labor but manage to offset most of negative impact of the shock if they hold durable assets. Interestingly, they also find that land does not play a similar mitigating role.

is a more costly (more undesirable) strategy than selling disposable assets.

Table 6: Temperature impacts on land use and TFP, by type of farmer

| | Livestock | | Farmer Only | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Dep var: | ln(land used) | TFP | ln(land used) | TFP |
| Average HDD x owned livestock | 0.019 | -0.175*** | | |
| | (0.016) | (0.067) | | |
| Average HDD x no livestock | 0.042*** | -0.173*** | | |
| | (0.015) | (0.065) | | |
| Average HDD x Other activity | | | -0.003 | -0.311*** |
| | | | (0.015) | (0.072) |
| Average HDD x Farmer only | | | 0.048*** | -0.106* |
| | | | (0.016) | (0.059) |
| Difference | 0.023 | 0.002 | 0.051 | 0.205 |
| *p-value* | 0.030 | 0.956 | 0.000 | 0.000 |
| N | 54,981 | 54,972 | 54,981 | 54,972 |
| R2 | 0.326 | 0.410 | 0.323 | 0.412 |

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

An alternative explanation is that cattle owners cannot, or do not need to, implement productive adaptations. We can test this explanation by examining the heterogeneous effects of high temperatures on crop mix, by cattle ownership (see Table 7). Contrary to this hypothesis, and in contrast to the results on land use, we find that both types of farmers, with and without cattle, change crop mix as a response to extreme heat.[37] This finding also rules out concerns that changes in crop mix, documented in Table 4, were mechanically reflecting an increase in land use.

## 4.2 When do they adapt? Early and late shocks

The ability to adapt to weather shocks may vary during the growing season. For instance, farmers may be able to clear land and plant new crops at the beginning of the growing season, but this response may be more difficult to implement in later stages.

To investigate how timing of the shocks may affect farmers' adaptive behavior, we construct separate measures of DD and HDD according to whether the temperature shock happened in the first (October to December) or the second half (January to March) of the growing season (early

[37]We obtain similar results when interacting HDD with an indicator of having off-farm job instead of an indicator of cattle ownership. Results available upon request.

Table 7: Impacts of DD and HDD on crop mix, by type of farmers

| Dep var: | ln(output) | | | Share of total output | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Crop group: | Cereals | Tubers | Legumes | Cereals | Tubers | Legumes |
| Average HDD x owned livestock | -0.252*** | 0.140** | -0.009 | -0.023* | 0.030*** | 0.006 |
| | (0.062) | (0.056) | (0.058) | (0.013) | (0.008) | (0.008) |
| Average HDD x no livestock | -0.133** | 0.264*** | 0.060 | -0.042*** | 0.043*** | 0.002 |
| | (0.066) | (0.069) | (0.061) | (0.010) | (0.008) | (0.007) |
| Difference | 0.119 | 0.124 | 0.069 | -0.018 | 0.013 | -0.004 |
| *p-value* | 0.003 | 0.019 | 0.161 | 0.019 | 0.002 | 0.365 |
| N | 43,251 | 40,131 | 34,335 | 54,214 | 54,214 | 54,214 |
| R2 | 0.465 | 0.403 | 0.323 | 0.381 | 0.521 | 0.239 |

*Notes:* Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. Columns (3) to (5) include only information for households interviewed during the growing season as well as month of interview fixed effects.

and late DD/HDD). Then, we examine the effect of temperature on productivity, output and land use.

Table 8 presents our results. Both early and late shocks impact negatively on agricultural productivity (columns 1-3). This negative effect is smaller for early shocks, although the difference with the point estimate for late shocks is not statistically significant. One possible interpretation for this smaller effect is that a wider range of productive adaptations, other than incorporating more land, such as increasing work effort or other the use of other inputs (such as fertilizers), are feasible if temperature shocks occur during this period. A biological channel could also be at play: crops may be more capable to manage high temperatures at this stage.

Interestingly, we find that increases in land use only happen if high temperatures occur during the first half of the growing season (column 5). Extreme heat during the second half of the growing season has virtually no effect on land. We interpret this finding as evidence that farmers are more able to engage in productive adaptations when the shocks happen earlier. Consistent with this interpretation, we observe that early shocks have a small, and statistically insignificant, effect on output. In contrast, the effect is larger, and similar in magnitude to the drop in TFP, when shocks occur late in the growing season.

### 4.3 Adaptive response or increase in prices?

We interpret the increase in land use as a strategy to attenuate the negative effects of extreme heat. An alternative explanation is that areas subject to extreme temperature experience a decrease in the supply of agricultural products. To the extent that there is a positive price effect, then farmers

Table 8: Impacts of early and late HDD on farmer productivity, output and land

| | Y/T | TFP | | Y | T |
|---|---|---|---|---|---|
| Dep var: | ln(output/ha) | ln(output) | ln(output) | ln(output) | ln(land used) |
| | (1) | (2) | (3) | (4) | (5) |
| Average Early HDD | -0.067** | -0.064* | -0.076** | -0.036 | 0.031** |
| | (0.038) | (0.035) | (0.036) | (0.067) | (0.013) |
| Average Late HDD | -0.126* | -0.103* | -0.109* | -0.119* | 0.007 |
| | (0.063) | (0.061) | (0.060) | (0.015) | (0.015) |
| Input controls | No | OLS | IV | No | No |
| N | 54,938 | 54,929 | 54,929 | 54,938 | 54,938 |
| R2 | 0.241 | 0.405 | 0.391 | 0.244 | 0.313 |

*Notes:* Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. **Input controls:** number of household members working in agriculture, total land used and amount spent on hiring labor, all in logarithms. Instruments for labor and land: household size and land owned, both in logarithms. First stage F-test is 651.28. P-values for the difference between coefficients are, in order, 0.42, 0.65, 0.65, 0.27 and 0.32.

may be induced to increase production and thus, also the quantity of inputs. If that is the case, our result may be interpreted as a purely profit-driven decision rather than as an adaptive response.

Formally, by failing to account for output prices, our previous results would suffer from omitted variable bias. This issue would be less of a concern if prices are set in national markets. In that case, their influence would be picked up by the set of growing season fixed effects. The problem would persist, though, if agricultural markets were geographically smaller.[38]

In Table 9, we examine this possibility in two ways. First, column 1 includes region-growing season fixed effects (i.e., a set of around 200 dummies that account for 20 regions in 10 agricultural years). If agricultural markets were indeed regional, then this approach would control for prices. Column 2 goes a step further by controlling for the median log prices of cereals and tubers, calculated at the district level. In both cases, the relationship between HDD and land remains positive and significant. The magnitude of the effect of extreme temperatures is also very similar to the baseline results in Table 2.

Second, we examine the effect of temperature on prices of cereals and tubers (columns 3-6). We observe that prices of both crops increase with extreme temperature when measured in each of the 20 regions in the sample. The effect is slightly stronger for cereals, consistent with the previous result that farmers tend to move away from these crops. In columns 5 and 6, we reduce the level of aggregation to the district level and find no significant effects on prices. Taken together, these

[38]For instance Arag?n and Rud (2013) find evidence that in the northern highlands of Peru prices of agricultural products are determined locally.

results suggest that, while regional prices may increase in extremely hot years, changes in prices cannot fully explain the expansion in land use.

Table 9: Temperature impacts on regional and local prices

| Dep var: | ln(land used) | | ln(regional price) | | ln(local price) | |
|---|---|---|---|---|---|---|
| | | | Cereals | Tubers | Cereals | Tubers |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Average DD | -0.004 | -0.004 | 0.000 | -0.002* | -0.003 | -0.001 |
| | (0.005) | (0.005) | (0.002) | (0.001) | (0.002) | (0.002) |
| Average HDD | 0.038** | 0.043** | 0.022* | 0.009** | 0.004 | 0.007 |
| | (0.016) | (0.018) | (0.012) | (0.005) | (0.008) | (0.016) |
| Region-GS FEs | Yes | No | No | No | No | No |
| Control for local prices | No | Yes | No | No | No | No |
| N | 54,981 | 50,836 | 54,981 | 54,981 | 52,739 | 52,447 |
| R2 | 0.320 | 0.319 | 0.931 | 0.910 | 0.757 | 0.667 |

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

# 5 Predicting the effect of climate change

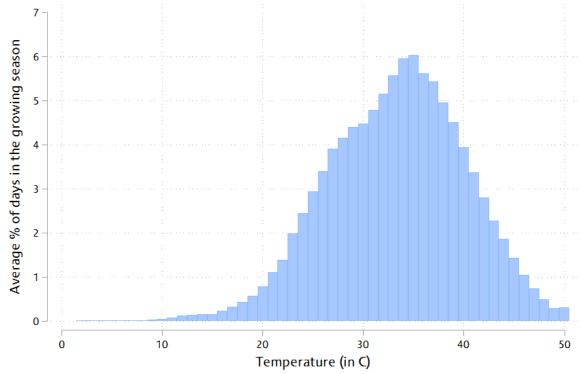
In this section, we use our previous estimates to predict the damages to yields and agricultural output associated with higher temperatures predicted in climate change scenarios. Importantly, we show that these predictions are over-estimated when failing to account for productive adaptations, such as changes in land use.

## 5.1 Peru's climatic regions

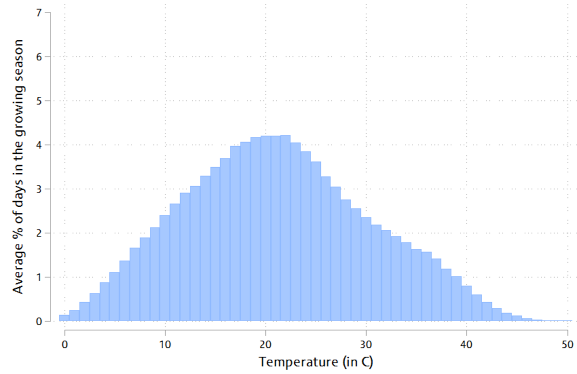
As discussed in relation to Table 1, our sample has two distinct climatic and agricultural regions. On one hand, the coast is hotter and dryer, and farmers are exposed to more harmful degree days. However, and most importantly, farmers are, on average, substantially better off: they are more productive, more diversified, and less poor. This is also reflected in the fact that they specialize on fruits, are more mechanized, and have access to more irrigation. Also, in the coast farmers use a much greater proportion of their land. These climatic differences become more apparent when observing the distribution of daily temperature in these two regions (see Figure 4).

We reproduce our main set of results for both regions to show that, despite these differences, the main set of results remains very similar. In Table 10 we see that extreme temperatures reduce

Figure 4: Distribution of daily average temperature by climatic region




(a) Coast




(b) Highlands

Notes: Figures depict the share of days in growing season in each temperature bin.

yields and output and increase land use. Note that the effect on output is somewhat stronger in the coast while the expansion of land is larger in the highlands. As shown above, this can be explained by the fact that coastal farmers use their land more intensively. With less ability to adapt to the shock, farmers suffer a greater drop in output. In any case, as shown in columns 6 and 9, those differences are not significant between regions.

Table 10: No differential impact of HDD by region

| Dep var: | ln(output per ha) | | | ln(output) | | | ln(land used) | | |
|---|---|---|---|---|---|---|---|---|---|
| Region: | Coast | Highlands | | Coast | Highlands | | Coast | Highlands | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Average DD | 0.004 | 0.007 | | 0.005 | 0.003 | | 0.001 | -0.004 | |
| | (0.040) | (0.008) | | (0.039) | (0.008) | | (0.010) | (0.006) | |
| Average HDD | -0.195** | -0.169* | | -0.171** | -0.084 | | 0.024* | 0.085* | |
| | (0.082) | (0.087) | | (0.084) | (0.092) | | (0.014) | (0.047) | |
| Difference in HDD | | | 0.012 | | | 0.076 | | | 0.057 |
| impact Highlands-Coast | | | (0.121) | | | (0.125) | | | (0.047) |
| N | 7,961 | 47,020 | 54,981 | 7,961 | 47,020 | 54,981 | 7,961 | 47,020 | 54,981 |
| R2 | 0.194 | 0.269 | 0.242 | 0.189 | 0.269 | 0.245 | 0.223 | 0.325 | 0.313 |

*Notes:* Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p* <0.10, *** p* <0.05, **** p* <0.01. All specifications include household controls (age, age squared, gender, and level of education of the household head); soil quality controls (nutrient availability, nutrient retention, rooting conditions, oxygen availability, salinity, toxicity and workability; each indicating severe, moderate or no constraints to plant growth, from Fischer et al. (2008)); and controls for the share of irrigated land owned by the household.

### 5.2 Climate change scenarios

The purpose of this exercise is to highlight two important issues: (1) the heterogeneity of impacts within a country according to their climatic regions and, (2) the importance of accounting for farmers' response when estimating the impact of climate change scenarios. Our exercise does not account for a multitude of factors that might affect agricultural outcomes and thus should be interpreted with caution.[39]

We consider two possible scenarios with increase in average temperature of 1.5°C and 3°C . The first scenario corresponds to the representative concentration pathway (RCP) 2.6 used in IPCC (2014), and assumes a steep reduction of greenhouse emissions due to faster adoption of green technologies. The second is the A1B scenario of the Special Report on Emission Scenarios, and the RCP8.5 model used in IPCC (2014). This is a "business as usual" scenario with predicted increases in Peru's average temperature 3°C to 3.5°C relative to the 1990-2000 period (Gosling et al., 2011). We use the lower bound and assume a country-wide increase of 3°C. In both scenarios, average precipitation is predicted to stay within one standard deviation of its natural internal variability (IPCC, 2014), so we do not assume any change in this respect. For simplicity, we model each scenario as an even increase of the daily temperature.[40]

For each scenario, we calculate the predicted change in DD and HDD. To do so, we use data from 2005-2015 to obtain the average temperature for every day of the growing season for each survey block $k$ in our sample. We use this temperature distribution to calculate the average DD and HDD ($DD_k^{avg}$ and $HDD_k^{avg}$). Then we increase each day temperature by 1.5 or 3 depending of the climate change scenario. Using the new distribution, we predict new DD and HDD ($DD_k^{pred}$ and $HDD_k^{pred}$). For each location, we define the change in HDD as $\Delta HDD_k = HDD_{ki}^{pred} - HDD_k^{avg}$. We use similar procedure to obtain $\Delta DD_k$.

We are interested on assessing the importance of taking into account farmer's responses on estimating the negative effects of climate change on output. To do so, we also consider separately effects on agricultural yields. Specifically, we define the predicted effect on yields (output per ha)

[39] An important omitted factor is the increased concentration of $CO_2$ in the atmosphere and its interaction with changing weather conditions. While lab experiments suggest that higher levels of $CO_2$ could help plant growth, there is significant uncertainty regarding its interaction with other weather variables and its impact on global agricultural yields remains hard to predict (Gosling et al., 2011). We also do not consider any impacts from increased flooding and reduced water access due to glacial melting, nor potential changes of relative food prices.

[40] We can, however, think of many other mean-preserving spreads that would still fit these mean predicted temperatures. Given the non-linear feature of DD and HDD, these different assumptions can alter the predicted impacts. For example, in our "business as usual" scenario we could increase all daily temperatures above the median by 6°C and leave the rest unchanged, resulting as well in an average daily temperature increase of 3°C. This transformation will mechanically result in stronger negative impacts since we would be skewing the distribution of daily temperatures towards more HDDs. While we opted for the most straightforward application of climate change forecasts, it is possible that variance in temperatures might also increase over time, suggesting that our predictions could serve as a lower bound for actual impacts.

and output as follows:

$$\Delta y_i = \hat{\beta}_1 \Delta DD_k + \hat{\beta}_2 \Delta HDD_k$$

where, $y$ is the outcome of interest for farmer $i$ in location $k$. $\hat{\beta}_1$ and $\hat{\beta}_2$ correspond to the estimates for the two regions taken from Table 10.

Table 11 presents our predictions for the whole sample and each natural region (coast and highlands). There observations stand out as relevant. First, the increase in temperature would create substantially more harmful temperatures in the coast than in the highlands. The opposite would be true in terms of good degree days. Columns A and B reflect this results, which is a natural consequence of the current distribution of temperatures in both regions, as presented in Figure 4. The coast is already quite warm and has a larger proportion of days already close to the HDD threshold. Hence, the shift of the distribution due to higher average temperature has a greater impact on HDD in this region than in the highlands. Additionally, the negative impact of the increase in HDD in the highlands is partially offset by the benefitial impact of the increase in DD.

Second, the impacts of increasing temperatures are very heterogeneous: while the coast would experience sizable losses in terms of yields and agricultural output, the effect on the highlands would be negligible and even positive (rows C and D). This result is consistent with other studies finding stronger negative impacts in low-lying areas (Auffhammer and Schlenker, 2014) and strong regional differences (Deschenes and Greenstone, 2007).

Third, despite the fact that we find small effects on land use (i.e. around 4 percentage points increase), taking into account farmers' responses is important. In the coast, ignoring this adaptive response would mean that the negative effect of high temperatures on agricultural output would be overestimated by 1.3%. On the contrary, the beneficial effects of higher temperatures in cold places would be underestimated by 0.3%. Proportionally to the effect on yields, the error is much greater in the highlands, due to the fact that farmers manage to attenuate the drop in output more than in the coast, thanks to a greater use of land. That is, these farmers would benefit doubly, i.e. from higher temperatures and because they engage in more adaptive behavior. This finding is important for the estimation of the economic costs of climate change for developing countries. They suggest that extrapolating estimates of the effect of extreme heat on crop yields from samples of farmers in developed countries or from controlled agronomic studies may significantly bias forecasts of climate change impacts in areas where traditional agriculture is the norm.[41]

[41] As previously noted, the more intensive use of land in the short term might reduce productivity in the long-run. Due to data limitations, we do not include this potential negative effect of climate change in our analysis.

Table 11: Heterogeneous effects of increased temperatures by region

| CC scenario: | Scenario +1.5 Celsius | | | Scenario +3 Celsius | | |
|---|---|---|---|---|---|---|
| Sample: | All | Coast | Highlands | All | Coast | Highlands |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Effect on temperature over the growing season* | | | | | | |
| A. Average DD | 1.383 | 1.007 | 1.450 | 2.724 | 1.833 | 2.881 |
| B. Average HDD | 0.103 | 0.493 | 0.034 | 0.255 | 1.167 | 0.095 |
| *Effect on agricultural productivity and output* | | | | | | |
| C. Change in productivity (ln(Y/T)) | -0.010 | -0.092 | 0.005 | -0.029 | -0.220 | 0.005 |
| D. Change in output (ln(Y)) | -0.010 | -0.079 | 0.002 | -0.027 | -0.190 | 0.002 |
| Over-estimation of effect in Y (\|D-C\|) | 0.000 | 0.013 | 0.003 | 0.002 | 0.030 | 0.003 |

*Notes*: Coefficients to estimate effects are from Table 10.

# 6 Robustness

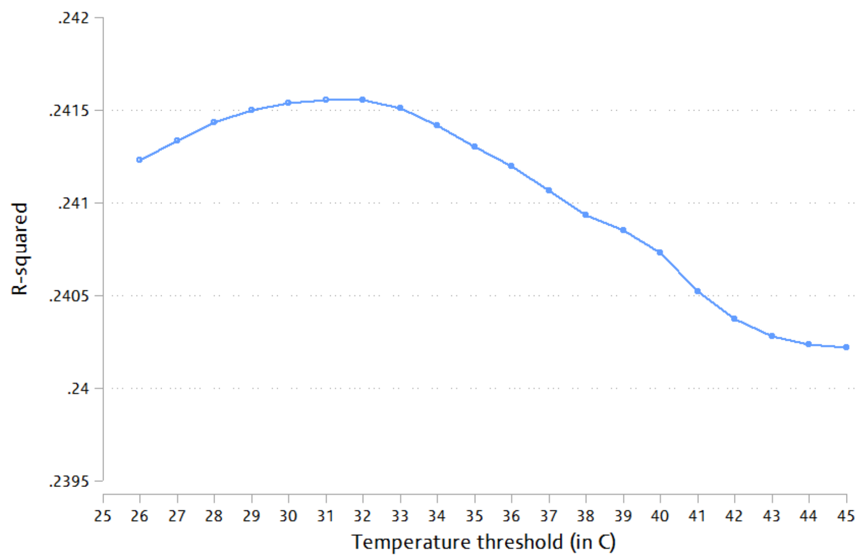
In this section we present several robustness checks on our baseline estimates of the impact of temperature on agricultural productivity, output and inputs presented in Table 2.

## 6.1 Alternative specifications

In Table 12 we present results for a number of alternative specifications. We start by looking into additional controls, such as input endowments (namely land ownership and household size, a proxy for labor force as in Benjamin (1992)), region-growing season fixed effects and month of interview fixed effects (to account for recall bias if the agricultural season is far in the past). This is a very demanding specification that flexibly accounts for department-specific trends in agricultural productivity. Row 1 shows that saturating the regression with these indicators does not substantially change our estimates. Similarly, results hold when we cluster standard error at a higher level of aggregation, allowing for shocks to be correlated within provinces (Row 2).

While controlling for month of interview in Row 1 may attenuate some concerns with respect to the timing of the interview relative to the growing season, we add two more specifications to check the robustness of our main results. First, recall that our baseline results consider exposure to temperature in the last *completed* growing season (October-March). This means, for example, that for households interviewed in March 2010, we are assigning weather variables for the period October 2008-March 2009. However, for households interviewed a month later (April 2010) we would assign weather the outcomes corresponding to the October-2009-March 2010 period. If agricultural output is affected by the most recent weather outcomes, then by assigning households the weather of the last complete growing season we would be introducing a significant amount of measurement error into our estimation. To examine the relevance of this issue, in Row 3 we drop

Figure 5: Model fit ($R^2$) of weather regressions with different temperature thresholds




Notes: Figure plots the model fit ($R^2$) for regressions of Equation 1 using different values of $\tau_{high}$, the thresholds to split between DD and HDD, for the whole sample. Controls include household head's characteristics ( age, age$^2$, gender and education attainment), precipitation, its square, indicators of soil quality, and district and growing season fixed effects.

households interviewed during the growing season. Finally, because the agricultural survey asks about production in the previous 12 months, in Row 6 we use a measure of degree days and hot degree days during that period, instead of just using information for the growing season. While a bit noisier, the main features of our analysis remain very similar in magnitude.[42]

## 6.2 Optimal temperature threshold

In this part we present an alternative way to determine the threshold between DD and HDD, following Schlenker and Roberts (2009) among others. To do so, we estimate equation 1 varying the value of $\tau_{high}$ in 1 degree intervals from 20°C to 40°C . We record the R-square from each regression and select the threshold value that results in the best fit. We perform this analysis using the whole sample and also splitting it by climatic region. Our specification uses log of output per hectare as main outcome but results are robust to using log of agricultural output, controlling for input use, and adding a richer set of fixed effects (department-by-growing season). Figure 5 shows the results of this exercise when conducted over the whole sample. The best fit for this excercise is achieved at a value of $\tau_{high} = 32$°C.

Row 4 in Table 12 shows the results when we apply this alternative threshold to the whole

[42]Additionally, in Figure **??** it was clear that one and two-period lead realizations of HHD did not affect current productivity.

sample. In Row 5 we allow $\tau_{high}$ to be different between the hotter coast and the cooler highlands. In both cases, the main results on yields, TFP, output and land use retain their sign and significance.[43]

Table 12: Robustness checks

| | Y/T | TFP | Y | T |
|---|---|---|---|---|
| Dep var: | ln(output/ha) | ln(output) | ln(output) | ln(land used) |
| | (1) | (2) | (3) | (4) |
| 1. Adding endowment and additional FE | -0.166** | -0.140** | -0.136** | 0.025* |
| | (0.065) | (0.058) | (0.069) | (0.014) |
| 2. Clustering s.e. by province (n=159) | -0.192** | -0.164** | -0.157* | 0.031* |
| | (0.074) | (0.063) | (0.084) | (0.016) |
| 3. Dropping sample October-March | -0.152* | -0.128 | -0.109 | 0.042** |
| | (0.085) | (0.079) | (0.092) | (0.021) |
| 4. Common HDD threshold at 32°C | -0.128*** | -0.112*** | -0.103** | 0.022** |
| | (0.040) | (0.037) | (0.044) | (0.010) |
| 5. Region-specific HDD threshold (32°C and 36°C | -0.156*** | -0.135*** | -0.133** | 0.019* |
| | (0.050) | (0.046) | (0.055) | (0.011) |
| 6. Exposure to temperature in the last 12 months | -0.230** | -0.205** | -0.151 | 0.069** |
| | (0.115) | (0.101) | (0.123) | (0.027) |
| Input controls | No | Yes | No | No |

*Notes:* Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p* <0.10, ** *p* <0.05, *** *p* <0.01. All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. **Input controls:** number of household members working in agriculture, total land used and amount spent on hiring labor, all in logarithms. Each row presents the estimates using a different specification.

# 7 Conclusion

How do poor farmers mitigate the impact of extreme temperature events? We show evidence of adaptation along several margins including livestock depletion, child labor and, ultimately, the expansion of land used for agricultural production. The effect on land use is only present when households do not have alternative sources of consumption or income smoothing. This is consistent with the idea that some land is left unused to recover, and implies that interrupting the process may have deleterious effects in future productivity. In fact, households that can dispose of assets or that do not fully rely on agricultural income do not engage in this practice when exposed to similar shocks.

Taken together, our results have important implications for the analysis of climate change

[43]Results are also robust to the use of quadratic effects of temperature on TFP, as in IMF (2017).

in the context of traditional subsistence farming in developing countries. First, as vulnerable households adapt their production in seasons with extreme temperatures, they successfully offset part of the negative impact on agricultural output. This questions the usefulness of estimates of the link between hot temperatures and yields obtained from other contexts where these short-run responses are not available or unlikely (such as studies from developed countries or from controlled experiments). Second, while in the short run farmers can attenuate shocks by using more land, it is less clear whether this practice is sustainable in the long run, as extreme events become more regular and land is not allowed to fallow as needed. Third, an appraisal of potential effects of climate change in developing countries should allow for regional variation, as warmer temperatures may benefit some regions while harm others. Fourth, our results suggest that instruments such as index-insurance that are linked to the measurement of hot days during the growing season could potentially benefit households engaged in traditional farming.

Some important questions raised in this paper remained unanswered, and may be relevant in terms of understanding the links between short-run adaptation to weather shocks, climate change and welfare. Temporary migration, changes in agricultural practices and methods, and the exact timing of the responses we observe could not be fully addressed due to data constraints, and are likely to play a significant role. Similarly, medium to long run costs of current adaptation in terms of land productivity or other unobserved private costs (e.g. on health, education or well-being) also deserve further attention as well as more appropriate data. Finally, while satellite data provides a good fix for the lack of reliable high frequency data in rural areas in developing countries, improvements in measurement of temperature are necessary to make progress in the understanding of the effects of a changing climate in areas and populations that will likely be the most affected.

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# ONLINE APPENDIX - NOT FOR PUBLICATION

## A Additional tables

Table A.1: Effect of % days with harmful degrees on agricultural productivity and output

| | Y/T | TFP | | Y |
|---|---|---|---|---|
| Dep var: | ln(output/ha) | ln(output) | ln(output) | ln(output) |
| | (1) | (2) | (3) | (4) |
| % days with harmful degrees | -1.065*** | -0.924*** | -1.022*** | -0.867** |
| | (0.316) | (0.294) | (0.286) | (0.360) |
| Input controls | No | OLS | IV | No |
| N | 54,981 | 54,972 | 54,972 | 54,981 |
| R2 | 0.241 | 0.405 | 0.390 | 0.244 |

*Notes:* Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. First stage joint F-test is 365.1.

Table A.2: Effect of days with harmful degrees on land use and TFP, by type of farmer

| | Livestock | | Farmer Only | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Dep. var: | ln(land used) | TFP | ln(land used) | TFP |
| % days with HDD | 0.098 | -0.992*** | | |
| x owned livestock | (0.100) | (0.299) | | |
| % days with HDD | 0.237*** | -1.009*** | | |
| x no livestock | (0.089) | (0.309) | | |
| % days with HDD | | | 0.016 | -1.663*** |
| x Other activity | | | (0.100) | (0.322) |
| % days with HDD | | | 0.261*** | -0.630** |
| x Farmer only | | | (0.095) | (0.287) |
| Difference | 0.140 | -0.017 | 0.245 | 1.033 |
| *p-value* | 0.007 | 0.932 | 0.000 | 0.000 |
| N | 54,981 | 54,972 | 54,981 | 54,972 |
| R2 | 0.327 | 0.411 | 0.323 | 0.413 |

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

Table A.3: Effect of temperature on agricultural output and household consumption

| | Y | C | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Dep. var: | ln(agric. output) | ln(p.c. expenditure) | Poor |
| Average DDs | 0.006 | 0.020*** | -0.012*** |
| | (0.009) | (0.003) | (0.002) |
| Average HDDs | -0.157** | -0.034** | 0.012 |
| | (0.075) | (0.015) | (0.011) |
| N | 54,981 | 54,981 | 54,981 |
| R2 | 0.244 | 0.456 | 0.265 |

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

Table A.4: Effect of temperature on off-farm and child labor, by type of farmer

| | Growing Season | | | All | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dep var: | HH members in farm | HH Hours in farm | Child Labor | HH member in farm | HH Hours in farm | Child Labor |
| Average HDD x owned livestock | 0.069*** | 0.075** | 0.037* | 0.012 | 0.005 | 0.016 |
| | (0.021) | (0.032) | (0.021) | (0.011) | (0.017) | (0.013) |
| Average HDD x no livestock | 0.057*** | 0.095*** | 0.072*** | 0.009 | 0.029 | 0.039*** |
| | (0.022) | (0.035) | (0.022) | (0.012) | (0.026) | (0.014) |
| Difference | -0.012 | 0.020 | 0.035 | -0.002 | 0.025 | 0.023 |
| *p-value* | 0.374 | 0.398 | 0.021 | 0.755 | 0.167 | 0.019 |
| N | 22,500 | 22,503 | 11,990 | 54,974 | 54,981 | 29,366 |
| R2 | 0.301 | 0.310 | 0.318 | 0.270 | 0.275 | 0.270 |

*Notes:* Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include month, district, and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. Columns 1-3 restrict sample to households interviewed during the growing season, while columns 4-6 use all the available observations.