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by

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Abstract

This paper examines how rising temperatures impact the agricultural production value of Thai farmers, compares potential adaptation strategies like agricultural diversification, and analyzes future projections based on IPCC AR6 scenarios. We analyze nationally representative socioeconomic survey data from farm households alongside ERA5 weather data, utilizing econometric regression analysis. Our analysis reveals that higher temperatures lead to a reduction in agricultural output value, with the situation expected to worsen as global warming progresses. Furthermore, we find that households with diversified production practices, such as a variety of agricultural activities or multicropping, exhibit a greater capacity to adapt to rising temperatures. These findings substantiate the importance of the country's policies promoting integrated farming and diversified crop-mix strategies.

Keywords: climate change, agricultural diversification, agricultural households, climate resilience, irrigation, sustainable development

JEL classifications: Q12, Q54, O13, O44

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1. Introduction

Farm households in developing countries frequently confront production risk and income fluctuations due to climatic shocks, worsened by the absence of well-developed farm income support systems and limited financial and agricultural markets. This lack of resources forces households to deprive means to insure themselves, leading to costly coping mechanisms like selling assets or relying on informal borrowing (Dercon and Krishnan, 2000; Gertler and Gruber, 2002; Kazianga and Udry, 2006; among several others). Regional climate shocks can trigger disruptions affecting households in an area. Climate change is altering probability distributions, intensifying coping challenges (McCarl, Villavicencio, and Wu, 2008).

Global average temperature has been increasing since the 1970s and is projected to continue (IPCC, 2021), intensifying climate change implications on farm households worldwide. Previous research confirms significant agricultural sector losses due to climate change, with projections of future damage, especially for developing countries (Mendelsohn, Nordhaus, and Shaw, 1994; Attavanich and McCarl, 2014; Brown et al., 2017). Studies consistently highlight lower adaptation capacity of impoverished farmers (Mano and Nhemachena, 2007; Skoufias, 2012; Hallegatte et al., 2016; Nikoloski, Christiaensen, and Hill, 2018; Sesmero, RickerGilbert, and Cook, 2018). However, few existing studies specifically examine household responses to climate shocks at the country level. Among these, Seo (2012) finds that integrated crop-livestock farms in Africa adapt better than specialized crop farms. Bellora et al. (2018) show that crop biodiversity enhances agricultural production in South Africa. But none exists on a national scale for Thailand.

This paper quantifies the effects of rising temperature on the agricultural production value of Thai farm households and explores agricultural diversification as an adaptation strategy for climate change. We assess diversification's impact by examining diversification across various multiple enterprises: crops, livestock, fisheries, and crop diversification strategies within farms. Thailand is chosen due to its large agricultural workforce, role as a major food exporter, and vulnerability to climate events (Eckstein, Künzel, and Schäfer, 2021).

To fulfill our objectives, we utilize a mix of survey and climate data. Specifically, we use the Agricultural Household Socioeconomic and Labor Survey (2006–2020) by the Office of Agricultural Economics, chosen to capture data over a substantial period. This dataset is matched with sub-district level climate re-analysis data derived from satellite and weather station data. We assess temperature impacts on production output value, exploring whether diversification can mitigate these impacts for Thai farm households. We then project the agricultural outcomes under five climate scenarios from the IPCC (2021) Shared Socioeconomic Pathways (SSPs).

Our analyses show that higher temperatures damage Thai agricultural production. However, diversification across enterprises, including crops and livestock, is an effective adaptation strategy. Moreover, multicropping or planting a variety of crops reduces climate change sensitivity. It's important to note that even if we succeed in limiting global warming to 1.5 degrees Celsius as per the Paris Agreement, the value of agricultural production will continue to be impacted by rising temperatures in any IPCC scenarios.

2. Data

2.1 Agricultural Household Survey Data

The Annual Agricultural Farm Household Socio-economic Survey, administered by the Office of Agricultural Economics, Ministry of Agriculture and Cooperatives, Thailand, were collected over 2006 to 2020 in 14 annual survey rounds. Each survey year starts from 1 May and ends on 30 April of the following year. The data encompass all 76 provinces in Thailand and provide detailed information on household characteristics, income, land usage, and agricultural activities such as crops, livestock and fisheries.

Our outcome variable is agricultural output value, which includes monetary value from both home consumption and products sold from agricultural activities. The survey does not directly report data on the total harvested crop value of each household. Therefore, we estimate the output value using reported price and quantity produced. For households that do not report selling price, we calculate harvested crop value using regional average prices (Golan et al., 2001; Jenkins et al., 2011). We remove outliers exceeding the top 0.5% of our outcome variables. This trimming process does not significantly affect our constructed revenue compared to the reported revenue (see Appendix D for untrimmed results and robustness checks). Additionally, we exclude households with no agricultural output value.

To ensure comparability across time, all monetary variables are expressed in real terms, using 2019 Thai Baht as the base year. Nominal agricultural variables are deflated using the agricultural price index compiled by Thailand's Office of Agricultural Economics.

Table 1 (Panels A-C) presents descriptive statistics for outcome variables, household characteristics, and plot characteristics. Agricultural output value and revenue are skewed, with averages of agricultural output value and revenue roughly double the medians. Half of Thai farmers produce agricultural products for both for their own consumption and commercial sale. These products are valued below 89,000 baht annually, and their revenue from sales is typically under 76,000 Baht. This aligns with the small average and median farm size (23.9 Rai or 9.4 acres, and 16 Rai or 6.3 acres, respectively). Notably, 90% of households less than 30 rai (11.9 acres), and most land is dedicated to cropping. Additionally, less than half of the farmers have access to irrigation. Table 1 also shows that the average Thai farm household consists of 4 people with the average age of household head of 56 years old. Several factors, such as aging households, limited labor, and the relatively higher costs associated with small landholdings compared to larger ones, might discourage farm households from adopting diversification strategies. This aligns with the low diversification rates observed in Table 2.

We explore two types of diversification: (i) across agricultural enterprises, i.e., cropping, livestock, and fisheries (Seo, 2010; Chonabayashi, Jithitikulchai, and Qu, 2020; Chonabayashi, 2021; Jithitikulchai, 2023); and (ii) across crop mix (Attavanich et al., 2019). Table 2 indicates that only 39% of Thai farm households are engaged in more than one type of agricultural activity, and more than half of those who engage in cropping do not diversify their farm activities into livestock or fisheries. Within crops, the majority of Thai farm households grow around 2 different crops per year. Focusing on farm households engaged only in cropping, we find that 30% of them practice monoculture.

2.2 Climate Data

2.2.1 Re-analysis Satellite Remote Sensing Data

The ERA5 Database. We utilize historical reanalysis data from the European Center for Medium-Range Weather Forecasts (ECMWF). This reanalysis incorporates past observations and information from many sources to generate consistent, complete time series of climate variables (Hersbach et al., 2020).

The data contains hourly average weather data at a spatial resolution of 0.10 degrees (approximately 9 kilometers). For each grid cell, we obtained hourly precipitation data in millimeters (mm) and average daily temperature in degrees Kelvin measured at 2 meters above the earth's surface. We then calculated total daily precipitation (mm) and average daily temperatures ($°C$) within each grid.

We generated daily precipitation and temperature for each sub-district (tambon) in Thailand by combining data from all 0.10-degree pixels within each sub-district's boundary. This process yielded daily average temperature and total precipitation at the sub-district level. In cases of adjacent sub-districts sharing the same pixel, we assigned identical precipitation and temperature values. We then used these sub-district-level daily weather data to construct the necessary annual weather variables for our analyses, such as average temperature, total precipitation, number of hot days, and number of wet days.

Weather Variables. For each variable, we aggregated the gridded daily data to annual measures corresponding to the survey period (May 1st to April 30th of the following year) for each survey round. We follow previous studies in choice of weather variables (Attavanich, 2011; Attavanich and McCarl, 2014; Chen et al., 2001; Chen et al., 2004; Jithitikulchai, 2014; Jithitikulchai et al., 2019; McCarl et al., 2008; McCarl et al., 2014; Rhodes and McCarl 2020a, 2020b; Yu and McCarl, 2018). Their descriptive statistics are presented in Panel D of Table 1. Specifically, we constructed the following weather variables:

- *Annual average temperature:* Sub-district-level average temperature, calculated across all days (365 or 366) within each survey year.
- *Annual total precipitation:* Cumulative amount of rainfall measured at the sub-district level for the entire survey period due to potential storage of precipitation in soil or tanks.
- *Number of hot days per year:* Number of days within a survey round where the maximum temperature exceeds $32.22°C$.

- *Number of wet days per year:* Number of days within a survey round where total precipitation exceeds an inch (25 mm).

Validity of the ERA5 Data. To validate our climate data, we compared it with the monthly ground-station data recorded by Thailand's Meteorological Department during 1981–2020. We find strong positive correlations between ERA5 and the ground-station data, as evidenced by high Pearson's correlation coefficients (see Appendix A for details). Appendix A also presents additional test results that demonstrate the close correspondence between ERA5 data and observed data.

2.2.2 IPCC Temperature Projections.

To assess long-term climate change impacts, we rely on projections from the 2021 IPCC report. We specifically focus on the projected ensemble mean global surface temperature changes under five different Shared Socio-economic Pathway (SSP) / Representative Concentration Pathway (RCP) scenarios. These scenarios describe alternative socio-economic trends and the approximate level of radiative forcing and greenhouse gas (GHG) emissions resulting from each pathway by the year 2100 (Arias et al., 2021; IPCC, 2021).

3. Methodology

3.1 Baseline Model Specification

To estimate climate effects on agricultural output, we use the household survey data for the 2006/2007 – 2019/2020 crop years, matched with the sub-district-level weather data. For estimation we use the following base specification:

$$Y_{st}^{i} = \alpha_0 + f(w_{st}) + \alpha_1' X_t^i + \alpha_2 \delta_{t=2012} + \alpha_3 \delta_{t=2015} + \sum_r \alpha_r R_r + \alpha_4 t + \alpha_5 t^2 + \epsilon_{st}^{i} \quad (1)$$

where Y_{st}^{i} is the value of agricultural output for household *i* in sub-district *s* in survey year *t*. $f(w_{st})$ is a flexible functional form depicting the effects of climate on the outcome variable. X_t^i is a set of household-level characteristics which include household size, whether the household head is female, age of the household head, whether the household head completed secondary education (9 years), whether the household has membership in cooperatives or agricultural banks (BAAC), the share of irrigated land, the share of rented land, and the size of agricultural land farmed.

To specifically examine diversification within crop production, we focus on a sub-sample of households engaged only in cultivation. For these crop-producing households, we use the size of land used for cultivation in place of that used for agriculture. Note that we do not include the value of household assets and its squared term due to possible endogeneity issues (correlation between the variable and the error term). Because over half of the households in our sample grow rice and the Thai government often intervenes the rice market, we also include the dummy variable for whether the households grow rice to control for the effect of market price intervention by the government.

To capture country-wide effects of the 2011 major flood and 2015 severe drought, we include dummy variables for cropping years 2011/2012 and 2014/2015, $\delta_{t=2012}$ and $\delta_{t=2015}$. We also include the region dummies (R_r) which control for region-specific time-invariant effects on outcomes. Thailand's Meteorological Department divides the country into six regions deemed to have similar climates. A quadratic time trend is included as a proxy of agricultural technology progress (McCarl, Villavicencio, and Wu, 2008; Attavanich and McCarl, 2014; Ding and McCarl, 2014; Jithitikulchai, Mccarl, and Wu, 2019 among many others). The error term (ϵ_{st}^{i}) captures unobservable factors, measurement errors, and random fluctuations. Finally, we report robust standard errors that account for heteroskedasticity (unequal variance of errors across observations).

Our primary focus is on the effects of temperature on the real value of agricultural output. However, since variations in temperature are likely correlated with precipitation, precipitation is included in the model (Burgess et al., 2017). We define the dependent variable, real value of agricultural output, in three different specifications $f(w_{st})$ described as follow:

Model 1: Linear Weather. Mean annual temperature (in $°C$) and annual total rainfall (in mm) enter the baseline specification linearly and separately:

$$f_1(w_{st}) = \beta_{temp} temperature_{st} + \beta_{prcp} precipitation_{st} \tag{2}$$

Model 2: Quadratic Weather. Since the effects of weather, especially temperature, can exhibit non-linear relationships (Dell, Jones, and Olken, 2014; Deschénes and Greenstone, 2011), quadratic terms of both temperature and rainfall are included:

$$f_2(w_{st}) = \psi_{temp} temperature_{st} + \psi_{temp2} temperature_{st}^2 + \psi_{prcp} precipitation_{st} + \psi_{prcp2} precipitation_{st}^2 \tag{3}$$

Model 3: Including Extreme Weather Variables. We further add indicators which capture extreme weather conditions:

$$f_2(w_{st}) = \theta_{temp} temperature_{st} + \theta_{temp2} temperature_{st}^2 + \theta_{prcp} precipitation_{st} + \theta_{prcp2} precipitation_{st}^2 + \theta_{hot} hotdays_{st} + \theta_{wet} wetdays_{st} \tag{4}$$

We focus on the real value of total output, including both on-farm consumption and sales, to comprehensively analyze household impacts. Almost a third of household output is consumed on-farm, highlighting the importance of considering this aspect. We then transform the outcome variables using the inverse hyperbolic sine function as described below.

Inverse Hyperbolic Sine Transformation and Temperature Elasticity of Output Value

We apply the inverse hyperbolic sine (IHS) transformation, a well-established approach in the literature (Pence, 2006), to the outcome variable. This allows interpretation of the regression coefficients as an approximation of the logarithm transformation while retaining non-positive valued observations (Bellemare and Wichman, 2020). In our case, the 'temperature elasticity of output' derived from the estimated coefficients of the temperature and its squared terms is useful in that it measures the sensitivity of output (percentage change) with respect to a one-percentage change in temperature. Thus, we can compare impacts of temperature across different household cohorts.

Following Bellemare and Wichman (2020), we derive the elasticity for Models 2-3 with quadratic terms [equations (3)-(4)] as follows, and using subscript st to represent sub-district s in year t:

$$Y_{st}^{i} = sinh^{-1}\left(Z_{st}^{i}\right) = \beta_0 + \beta_1 temp_{st}^{i} + \beta_2\left(temp_{st}^{i}\right)^2 + \beta_i X_t^i + \epsilon_{st}^{i}$$

In turn taking the hyperbolic sine transformation:

$$\Leftrightarrow Z_{st}^{i} = sinh\left(\beta_0 + \beta_1 temp_{st}^{i} + \beta_2\left(temp_{st}^{i}\right)^2 + \beta_i X_t^i + \epsilon_{st}^{i}\right)$$

Then taking partial derivative with respect to temperature and rearrange:

$$\Leftrightarrow \frac{\partial Z_{st}^{i}}{\partial temp} = (\beta_1 + 2\beta_2 temp) cosh\left(sinh^{-1}\left(Z_{st}^{i}\right)\right)$$

$$\Leftrightarrow \frac{\partial Z_{st}^{i}}{\partial temp} = (\beta_1 + 2\beta_2 temp)\sqrt{1 + \left(Z_{st}^{i}\right)^2}$$

$$\Leftrightarrow \frac{\partial Z_{st}^{i}}{\partial temp}\frac{temp}{Z_{st}^{i}} = (\beta_1 + 2\beta_2 temp)\sqrt{1 + \left(Z_{st}^{i}\right)^2}\frac{temp}{Z_{st}^{i}}$$

By the definition of elasticity, we have:

$$\Leftrightarrow \xi_{Y_{st}^{i} temp} = (\beta_1 temp + 2\beta_2 temp^2)\frac{\sqrt{1 + \left(Z_{st}^{i}\right)^2}}{Z_{st}^{i}} \tag{5}$$

where $\xi_{Y_{st}^{i} temp}$ is the temperature point elasticity of output at a given temperature calculated from the nonlinear transformation of the estimated parameters.

Both temperature and temperature-squared coefficients affect the elasticity magnitude [as shown in equation (5)]. For calculating of point elasticity, we use the fitted values from the regressions as a corresponding value Z_{st}^{i} for each value of temperature; and for summary measure we do the calculation holding the value of all other control variables constant.

3.2 Assessing the Impact of Agricultural Diversification

We investigate the role of agricultural diversification by determining whether it can help attenuate the global warming impacts. To do this we estimate models for separate cohorts of two levels of diversification: (i) types of enterprises, i.e., cropping, livestock, and fisheries; and (ii) the mix of crops grown.

Firstly, we run models 1–3 using the sub-sample of farm households that state they pursue multiple agricultural enterprises diversification strategies and those that do not. Then we compare the estimated coefficients on temperature and the resulting temperature elasticities as similar to Lien et al. (2006), Birthal et al. (2013), Chonabayashi, Jithitikulchai, and Qu (2020), Chonabayashi (2021), and Jithitikulchai (2023).

One approach to address the above problem is by running a pooled regression with an additional interaction term between a diversification dummy variable and weather variables. Specifically, we use the specification:

$$Y_{st}^{i} = \alpha_0 + f(w_{st}) + \phi D_{st}^{i} + \beta\{D_{st}^{i} * f(temp_{st})\} + \alpha_1' X_t^{i} + \alpha_2 \delta_{t=2012} + \alpha_3 \delta_{t=2015} + \sum_{r} \alpha_r R_r + \alpha_4 t + \alpha_5 t^2 + \epsilon_{st}^{i} \tag{6}$$

where D_{st}^{i} is the dummy variable indicating agricultural diversification in some forms, and $f(temp_{st})$ is the function of temperature variables. The D_{st}^{i} diversification dummy is included to account for the mean difference in the output value between households that do and do not diversify. The estimated coefficient β of the interaction term(s) indicates whether diversification helps reduce the impact of *temperature* changes on output value. Note, however, that the point estimate of β could be subject to potential selection bias in that the decision whether household adopt a diversification strategy is not random. With both approaches potentially having their own threats to identification, we present the results for both for robustness checks.

3.3 Threats to Identification and the Use of Pseudo-panel Settings

One main concern with cross-sectional regression analysis is that the estimates may be biased due to unobserved heterogeneity that are not included in the model but can influence the results (Arellano and Honoré, 2001; Arellano, 2003; Glenn, 2005; Warunsiri and McNown, 2010 among others). To address this concern and leverage the additional time dimension in our data, we use a pseudo-panel approach (Deaton, 1985). This approach leverages the repeated observations across time for groups of individuals with similar characteristics, allowing us to control unobserved heterogeneity to some extent. We defined the cohorts based on the province of residence of farm households as farm location is a time-invariant characteristic that likely influences agricultural practices and outcomes (Attavanich et al., 2019). Our pseudo-panel data consists of 77 province cohorts and covers a span of 14 years of survey data. Following recommendations by Deaton (1985) and Verbeek and Nijman (1992) to mitigate potential bias from sampling errors of small cohort sizes, we exclude groups with less than 10 cohort-year observations from the analysis.

We apply Moffitt (1993)'s estimator which is equivalent to a within cohort estimator. Specifically, we start by averaging equation (1) with individual fixed effects over cohort c at time t:

$$\bar{Y}_{ct} = \alpha_0 + f(\bar{w}_{ct}) + \alpha_1' \bar{X}_{ct} + \alpha_2 \delta_{t=2012} + \alpha_3 \delta_{t=2015} + \sum_r \alpha_r R_r + \alpha_4 t + \alpha_5 t^2 + \bar{\lambda}_{ct} + \bar{\varepsilon}_{ct} \tag{7}$$

Then, we apply within transformation and estimate the following specification:

$$\tilde{Y}_{ct} = \alpha_0 + f(\tilde{w}_{ct}) + \alpha_1' \tilde{X}_{ct} + \alpha_2 \tilde{\delta}_{t=2012} + \alpha_3 \tilde{\delta}_{t=2015} + \alpha_4 \tilde{t} + \alpha_5 \tilde{t}^2 + \nu_{ct} \tag{8}$$

We also apply a similar within transformation to equation (6) as the pooled regression with the diversification dummy variable to examine the role of agricultural diversification.

3.4 Predicting Value of Agricultural Output under Different Temperature Projections

Given the estimated coefficients obtained from the regression analysis, we can simulate the impact of climate change using the IPCC scenarios. To do this, we use five SSP scenarios

(Attavanich et al., 2019; Arias et al., 2021; IPCC, 2021) that capture a range of low and high climate impacts:

- SSP1-1.9: a very low GHG emissions scenario
- SSP1-2.6: a low GHG emissions scenario
- SSP2-4.5: an intermediate GHG emissions scenario
- SSP3-7.0: a high GHG emissions scenario
- SSP5-8.5: a very high GHG emissions scenario

In reporting the scenarios are denoted as 'SSPx-y', and this stands for the socio-economic trend for SSP scenario 'x', with a 'y' radiative forcing level. (IPCC, 2021). We use historical sub-district-level temperature from the re-analysis data to combine with the predicted changes in temperature under different IPCC's scenarios for global surface temperature change to generate subregional temperature projections for Thailand from 2021 to 2050.

With the realizations and projections of the mean temperature during 1981–2020, we can then predict the value of total output in each year and under different scenarios from 2021 onward *ceteris paribus*. That is, we are holding household and plot characteristics (control variables) at their levels in 2020 and then vary temperature to reflect the climate scenarios. Since our fitted value of the outcome variable is expressed in an inverse hyperbolic sine function format, we transform it back by taking the hyperbolic sine function thereby acquiring the predicted output value. We did not consider alterations in other climate variables such as precipitation and extreme weather, because we only had projection data on temperature at the time of analysis.

4. Estimation Results

In this section, we report and discuss the estimated impacts of climate change, particularly focusing on temperature, on real farm output value. We begin by presenting the coefficients that quantify the overall impact of temperature changes. Next, we explore the role of agricultural diversification as a potential strategy to alleviate these negative impacts. Finally, we leverage the estimated coefficients to project the future value of output under various climate scenarios.

4.1. The Effects of Temperature on Agricultural Output

Columns (1) - (3) of Table 3 report the point estimates of the coefficients from cross-sectional analysis for the three model specifications with varying climate variables. The results show that a higher temperature leads to a reduction in the value of agricultural output. We can interpret the coefficient as an elasticity, since the IHS transformation approximates a log transformation in linear models [Bellemare and Wichman (2020)]. In other words, a one-degree Celsius rise in temperature leads to a roughly 3.4% decrease in average real output value.

The significant coefficients on both the linear and squared terms of the temperature and precipitation variables in Model 2 indicate non-linear effects of climate on output value, consistent with findings in the literature [Dell, Jones, and Olken (2014)]. This supports the use of the quadratic specification for a more accurate estimation of the climate impacts.

Our findings remain robust when including controls for extreme weather events (floods and droughts) in Model 3. While the coefficients on temperature terms become less significant (reflected in the wider confidence interval in Figure 1b). This aligns with the conclusion that the temperature elasticity of output weakens as temperature increases. Notably, the coefficients for extreme weather controls are negative and highly significant, indicating a negative impact of such events on output. However, their correlation with temperature reduces the explanatory power for our main temperature terms. Therefore, we adopt Model 2 as the baseline and move the full regression results for Models 1 and 3 to Appendix B.

Given the nonlinear model, the effects of temperature on real output value are best interpreted as elasticity. We calculated elasticity using the estimated coefficients of Model 2 (Table 3). Our results suggest that a one-percent rise in surface temperature would lead to a fall in the value of output of approximately 1.5-2%.

We use estimates from Model 2 to calculate the point elasticity for each annual average temperature and its corresponding fitted output value. Figure 1a illustrates these elasticities with their 95% confidence intervals. We observe that the elasticity becomes negative around the average temperature of 24-27$°C$ and declines at an increasing rate thereafter. Farms with diversified activities, such as those combining cultivation and livestock (24°C) or practicing multicropping (27°C), show greater resilience to rising temperatures compared to non-diversified farms. Non-diversified farms, especially those focused solely on monoculture production (25°C) or cultivation alone (26°C), experience negative impacts on production value at lower temperature thresholds. This highlights the potential benefits of farm diversification as a strategy to adapt to climate change and maintain production value in a warming environment. Despite wider confidence intervals, the point elasticity reaches an estimated maximum of -10 at the highest observed annual average temperature ($33°C$). This suggests that a one percentage point increase in temperature could lead to a 10% decrease in the value of output.

Columns (4) to (6) of Table 3 present the estimates obtained from the pseudo-panel approach. These estimates are largely consistent with those from the pooled cross-sectional data analysis, despite potentially lower significance of some coefficients due to fewer observations in the pseudo-panel data. This reinforces the robustness of our findings and suggests that bias arising from unobserved heterogeneity should not be a major concern. Therefore, we primarily rely on pooled cross-sectional data for our main results.

Across all models (Table 3, columns 1-3), the coefficients of the share of irrigated land are positive and significant, indicating that households with irrigation systems have a higher average output value. This finding, along with the relatively small effect of precipitation, suggests that irrigation is a crucial water source for Thai agriculture. Other noteworthy controls are the survey round dummy variables. The significant negative coefficients for the 2015 dummy variable reflect the severe drought that year. Interestingly, the 2011 dummy has a positive coefficient. While floods can damage crops, 2011's floods might have been short-lived, and the year likely experienced higher overall rainfall which could benefit many agricultural activities. Additionally, positive pass-through effects of flood-induced higher prices for agricultural products might also play a role.

4.2. The Role of Agricultural Diversification amid Climate Change

We now investigate whether agricultural diversification can mitigate the negative impacts of climate change. To capture diversification behavior across two levels - by types of agricultural activities and crop mix - we consider diversification strategies in three forms: (i) the number of agricultural enterprises, (ii) by types of enterprise (cropping, livestock, and fisheries), and (iii) within cropping activities.

Diversification by the Number of Agricultural Activities. Table 4 (columns 1-2) reports the coefficients from a cross-sectional analysis using the model 2 specification. Column1 shows results for households with only one agricultural activity (cropping, livestock, or fisheries), and column 2 reports presents results for those with at least two activities (full results in Appendix B, Table B1). We use these parameter estimates to calculate point elasticities (output response to temperature change) displayed in Figure 1c. Crucially, households with diversified activities (two or more enterprises) exhibit significantly lower sensitivity to temperature changes (in absolute terms) compared to those with just one enterprise.

In fact, the elasticity value of diversified households is close to zero, implying minimal impact of temperature fluctuations on their total output at any given average annual temperature. The temperature elasticity for one-enterprise households evaluated at the mean temperature ($26.4°C$)is -2.04, while for diversified households it is less than half at -0.94. This suggests that, at the long-run average temperature, a one-percent temperature increase would lead to a nearly 2% decrease for non-diversified households. In other words, Thai farm households with higher diversification experience lower output losses due to rising temperatures.

Table 5 presents the estimates from our pseudo-panel regression (full results in Appendix C). Consistent with the cross-sectional analysis, Table 5 (columns 1-2) confirms that households with more than one agricultural enterprise exhibit lower sensitive to temperature changes, compared to those with only one enterprise.

Table B2 (columns 7-8) in Appendix B show that the negative impact of extreme rainfall is smaller for households engaged in more than one enterprise. This is consistent with findings in Chonabayashi, Jithitikulchai, and Qu (2020) or Jithitikulchai (2023) that diversified households can better mitigate the adverse impact of droughts, floods, or a rise in temperature.

Diversification by Type of Agricultural Activities. We now analyze a popular diversification strategy: households engaged in both cropping and livestock, compared to those solely engaged in cropping (Table 4, columns 3-4) with full results in Appendix B, Table B2. The temperature terms have significantly lower magnitudes for households with both enterprises. Figure 1d confirmed this, illustrating that the absolute values of the temperature point elasticity are generally smaller for households practicing crop-livestock diversification. This implies reduced sensitivity to temperature changes for diversified households. Table 5 (columns 3-4) also confirmed this from pseudo-panel regression analysis.

While the focus of our study is not on extreme weather variables, it is noteworthy noting that their coefficients in Table B3 (columns 7-8) are also smaller for households engaged in both cropping and livestock activities compare to solely cropping households. This finding further supports agricultural diversification as a strategy to mitigate the adverse effects of extreme weather on household agricultural production.

Diversification within Cropping Activities. Since most households engage in cropping, we now focus on diversification strategies by crop choices and the number of crop(s) grown. Table 4 (columns 5-6) presents the estimated temperature impact, comparing monoculture with diversified crop mixes. We find suggestive evidence that growing more than one crop might help alleviate the negative effects of temperature changes. The coefficients for temperature terms in column 6 (diversified crops) are smaller in magnitude and statistically insignificant compared to column 5 (monoculture). This suggests that households practicing crop diversification experience, on average, a lesser impact from rising temperature. The findings from the pseudo-panel regression (Table 5, columns 5-6) align with these results. Figure 1e further this, as the absolute value of the temperature elasticity for diversified households is lower than for those growing just one crop type.

4.3. Predicted Value of Agricultural Output under Different Temperature Projections

Using the coefficients and fitted value obtained from our base case Model 2, we can predict the value of agricultural output under the ensemble SSP scenarios as discussed in Section 3.4. Figure 2a depicts the nation-wide annual average temperature projection in Thailand for 2020-2050. Under the intermediate GHG emission scenario (SSP2-4.5), the annual average temperature in Thailand will rise from $26.68°C$ in 2020 to $27.39°C$ by 2050. By contrast, under the worst-case scenario (SSP5-8.5), the surface temperature in Thailand will be $27.7°C$ in 2050.

Figure 2b illustrates the projected total farm household output value by year. Consistent with Figure 1a, which shows a negative temperature elasticity above a certain temperature range (around 24-27°C), the real output value exhibits a gradual decline (driven by rising temperatures) from around 44,000 Baht in the early 2000s to just below 40,000 Baht by 2020 (all else being equal).

It is important to recognize that this projection assumes average characteristics for all households. While holding everything else constant allows us to isolate the temperature effect, it's a strong assumption. Several factors, such as advancements in agricultural technology, infrastructure improvements, market changes, or better policies, could potentially raise output value despite rising temperatures. However, this exercise helps visualize the potential adverse impact of climate change on agricultural production value due to variations in annual average temperature under different emission scenarios. We see a drastic drop in the average annual output value to below 30,000 Baht in the worst-case scenario (SSP5-8.5) with very high greenhouse gas emissions. This projected decline could have significant negative consequences for the Thai economy and household well-being.

Figure 3 illustrates the projected average output value for households with different diversification levels, estimated using Model 2 in Table 5 (columns 4-5). Households engaging in 2 or 3 enterprises (diversified) show significantly higher projected average output value compared to those with only one enterprise (non-diversified). The difference in projected output between the best and worst-case scenarios is most pronounced in 2050, with the gap for non-diversified households being roughly twice as large. Furthermore, even in the worst-case scenario, the projected output for diversified households remains considerably higher than the best-case scenario for the non-diversified ones. These findings highlight the potential of agricultural diversification strategies in mitigating the negative impacts of climate change on farm output, particularly for poor farmers.

Figure 4 compares the projected output between households solely engaged in cropping and those practicing crop-livestock. The results reveal a consistent pattern, suggesting that diversification might play a vital role in buffering households against potential climate changes, particularly rising temperature.

5. Discussion

In developing countries like Thailand, impoverished farm households face challenges due to unpredictable agricultural production and income resulting from climatic and economic shocks. These losses are further compounded by the lack of insurance, social securities, and institutional support. With climate change amplifying these issues, weather-related shocks are expected to increase in frequency and intensity, placing smallholder farm households at even greater vulnerability. While prior studies demonstrate agricultural diversification as a viable strategy for Thai agricultural households to adapt to climate change (Attavanich et al., 2019; Saengavut et al., 2019; Bellora et al., 2018; Forsyth and Evans, 2013; Kasem and Thapa, 2011; Rungruxsirivorn, 2007; Chainuvati and Athipanan, 2001; among others), there is a research gap in country-level analysis.

This paper investigates the impact of temperature changes on agricultural production in Thailand and the effectiveness of agricultural diversification as an adaptation strategy. We achieve this by integrating a nationally representative socioeconomic survey of Thai farm households with reanalyzed temperature and precipitation data.

Our analyses reveal that average annual temperatures exceeding a range of 24°C to 27°C negatively affect Thai farmers' agricultural production. Our results suggest a potential decrease in agricultural production of up to 10% for every one percentage point rise in average annual temperature. Diversification, defined as (a) engaging in two or more activities like cropping, livestock, or fisheries, or (b) mixed crops are more climate resilient. Importantly, our research highlights the critical role of effective irrigation systems. Regardless of farm size, households with a larger portion of irrigated land achieve higher output value. This underscores the reliable irrigation systems for farm households. The land holding characteristics in this study are predominantly small farms. This is an important consideration when interpreting the findings on the relationship between farm size and diversification strategies of Thai farm households.

This paper contributes to the literature on climate change adaptation. We explore how agricultural enterprise diversification and crop diversification impact farm output and climate vulnerability, using sub-district-level weather variations to identify climate impacts. Despite being nationally representative, our use of pooled cross-sectional data means some unobserved factors, like entrepreneurial ability or risk preferences might correlate with both weather and production decisions but remain unaccounted for in our model. However, our pseudo-panel regression results align with regression using pooled cross-sectional data, suggesting minimal bias from unobserved heterogeneity.

It is important to acknowledge the limitations of this study when interpreting its policy implications, that is the potential for over extrapolating the benefits observed in diversified farms to non-diversified ones. For farms within ecoregions or microclimates with unique soil compositions or specific climate patterns that support the growth of particular crops, specialization might be a more strategic choice (Kray et al., 2019). For example, evidence suggests that crop intensification is preferable for rubber farmers in some regions of Thailand (Amornratananukroh et al. 2023). However, if we can identify practices where changing from non-diversification to diversified activities can increase profitability while also offering greater climate resilience in the long run, then pre-emptive adaptation to climate change becomes a reasonable strategy.

For future research, incorporating analyses of soil quality's role in climate change impacts on agriculture holds significant promise. To delve deeper, accessing richer panel-level soil quality data is essential. Currently, our household surveys lack this; limited two-year spatial soil data per subdistrict hinders its inclusion. Further analysis of the CO2 effect, which may have a counterbalancing effect on temperature, is also warranted as the SSPS series provides CO2 projections. While initial studies predicted CO2 fertilization mitigating temperature stress on rice yield, recent research highlights negative interactions between these factors (Ishigooka et al., 2021). This complexity suggests that CO2 enrichment can only partially offset yield decline from rising temperatures (Maniruzzaman et al., 2018; Yamaguchi et al., 2023), and rising night temperatures could diminish the potential gains from CO2 fertilization in rice production (Cheng et al., 2009). Analyzing the effects on rice yields (and other crops, if applicable) from interactions of temperature and rainfall effects, direct physiological effects of increased CO2, and the effectiveness and availability of adaptations is complex, but crucial. Therefore, further research on the intricate interactions between CO2 and temperature on crop yields is crucial for informing adaptation strategies in a changing climate. Another avenue is climate-smart agriculture, but our survey data lacks details. Focusing on smart farming and advanced technology could help farmers mitigate climate impact. Despite limitations, our study contributes nationally representative insights into agricultural diversification's interplay with economic resilience of farm households, using historical and projected climate change impacts.

6. Conclusions and Policy Implications

Our analysis shows that climate change negatively affects Thai farm households' agricultural production. Agricultural diversification, including multiple enterprises and crops, offers potential as an *ex-ante* adaptation strategy.

From a policy perspective, our main results support Thailand's current national climate change strategic plan for agriculture, promoting integrated farming and crop diversification (Attavanich, 2018). In 2020, about 70% of Thai farmers practiced only one agricultural activity, with about 40% focusing on one crop. Our insight highlights diversification's benefits, urging support for farmers to diversify. To encourage the adoption of integrated farming for sustainable agriculture, incentives, financial support, and specific guidance on integrating livestock and crops or selecting profitable and drought-resistant crops are essential.

In practice, implementing a major diversification strategy, like an integrated crop-livestock system (ICLS), could be challenging, particularly in the short run, due to the small size of Thai farmers and the high implementation cost. Nevertheless, it is essential to consider a policy approach that prioritizes immediate actions (high-level policy approach) in the agricultural sector to adapt to observed climate conditions. Meanwhile, the national sectoral policy should encourage long-term, adaptable strategies through well-designed incentives (Kurukulasuriya and Rosenthal, 2013; Makate et al., 2023). When devising incentives and support mechanisms for agricultural diversification, it is important to consider factors like poverty reduction, sustainable development, and climate resilience. These efforts also contribute to broader socio-economic and environmental objectives.

In conclusion, this study highlights the urgency of addressing climate change's negative impact on Thai agriculture through diversified farming practices. While implementing large-scale diversification strategies may be challenging in the short-term, a multi-pronged approach is crucial. This approach should combine immediate actions focused on adapting to current climate conditions with long-term, dynamic adaptation strategies like diversified farming, supported by well-designed incentives and targeted policies. By prioritizing both short-term and long-term solutions while considering diverse objectives from the Sustainable Development Goals (SDGs), Thailand can ensure the long-term viability of its agricultural sector and the well-being of its farming households.

7. Tables & Figures

Table 1: Descriptive Statistics of Thai Farm Households

	N	Mean	S.D.	Min	P25	Median	P75	Max
Panel A: Output value and revenue								
Agricultural output value ('000 Baht)								
Full sample	107,777	2,964	90,6867	0.68	38	90	202	297,718,383
Trimming top 0.5%	107,215	167	226	0.68	38	89	200	1,991
Agricultural revenue ('000 Baht)								
Full sample	107,777	465	7,1894	0.00	25	78	198	23,478,385
Trimming top 0.5%	107,277	165	254	0.00	25	76	196	2,407
Panel B: Household characteristics								
Household head gender (Female = 1)	107,215	0.23	0.42	0.00	0.00	0.00	0.00	1.00
Education of household head (Complete lower secondary school = 1)	107,215	0.25	0.43	0.00	0.00	0.00	1.00	1.00
Age of household head	107,215	56.13	11.50	15.00	48.00	56.00	64.00	102.00
Household size	107,215	4.36	1.77	1.00	3.00	4.00	5.00	20.00
Membership of cooperatives and agricultural banks (being member = 1)	107,215	0.63	0.48	0.00	0.00	1.00	1.00	1.00
Panel C: Plot characteristics								
Land tenured used for agriculture (Rai)	107,215	23.88	24.46	0.01	9.00	17.00	30.00	730.00
Land tenured used for cropping (Rai)	107,215	23.08	23.90	0.00	8.50	16.50	30.00	680.00
Share of agricultural irrigated land	107,215	0.23	0.41	0.00	0.00	0.00	0.19	1.00
Share of rented land	107,215	0.19	0.34	0.00	0.00	0.00	0.24	1.00
Engage in growing rice (0/1)	107,215	0.58	0.49	0.00	0.00	1.00	1.00	1.00
Panel D: Annual weather conditions								
Average temperature (ºC)	107,215	26.40	1.20	19.41	25.77	26.50	27.21	29.16
Total precipitation (mm)	107,215	848.10	258.87	388.52	679.31	786.71	940.10	2,668.94
Number of hot days	107,215	4.51	7.55	0.00	0.00	1.00	6.00	65.00
Number of wet days	107,215	1.21	1.37	0.00	0.00	1.00	2.00	23.00

Note: Panels A to D show summary statistics of trimmed sample. Unit of observation is household. All monetary variables in Panel A are in thousand baht. BAAC stands for Bank for Agriculture and Agricultural Cooperatives. Land tenured includes land that households have full ownership, have partial ownership, rent, and do not have document identified rights (see Attavanich et al. (2019) for further details).

Table 2: Descriptive Statistics of Diversification Strategies

	N	Mean	S.D.	Min	P25	Median	P75	Max
Number of agricultural activities	107,215	1.42	0.56	1.00	1.00	1.00	2.00	3.00
Engage in > 1 agricultural activity (0/1)	107,215	0.39	0.49	0.00	0.00	0.00	1.00	1.00
Engage in cropping (0/1)	107,215	0.97	0.16	0.00	1.00	1.00	1.00	1.00
Engage in cropping only (0/1)	104,428	0.59	0.49	0.00	0.00	1.00	1.00	1.00
Engage in cropping & livestock (0/1)	104,428	0.35	0.48	0.00	0.00	0.00	1.00	1.00
Number of types of crops grown	104,428	2.03	1.05	1.00	1.00	2.00	2.00	13.00
Practice monoculture (0/1)	62,057	0.30	0.46	0.00	0.00	0.00	1.00	1.00

Note: The first three rows of this table present the descriptive statistics of trimmed sample. The other rows except the last row show the descriptive statistics of trimmed sample engaging in cropping. The last row presents the statistics for households doing only cropping. Unit of observation is household.

Table 3: The Effects of Temperature on Agricultural Output Value

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled cross-sectional analysis			Pseudo-panel analysis		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Temperature	-0.034***	0.703***	0.230*	-0.066**	3.474***	2.411**
	(0.004)	(0.092)	(0.104)	(0.023)	(0.786)	(0.774)
Temperature Squared		-0.015***	-0.005*		-0.068***	-0.046**
		(0.002)	(0.002)		(0.015)	(0.015)
Precipitation	8.67×10^{-5}***	-4.78×10^{-4}***	-6.21×10^{-4}***	5.33×10^{-5}	-7.79×10^{-4}*	-0.001**
	(2.23×10^{-5})	(7.45×10^{-5})	(7.53×10^{-5})	(7.45×10^{-5})	(3.37×10^{-4})	(0.003)
Precipitation Squared		2.36×10^{-7}***	3.39×10^{-7}***		2.97×10^{-7}*	3.71×10^{-7}**
		(3.26×10^{-8})	(3.30×10^{-8})		(1.20×10^{-7})	(1.23×10^{-7})
Number of Hot Days in a Year			-0.009***			-0.019***
			(0.001)			(0.002)
Number of Wet Days in a Year			-0.025***			0.014
			(0.003)			(0.012)
Engage in growing rice (0/1)	0.429***	0.439***	0.432***	0.882*	0.862*	0.852*
	(0.009)	(0.009)	(0.009)	(0.340)	(0.348)	(0.347)
Share of irrigated land	0.256***	0.266***	0.268***	-0.130	-0.116	-0.093
	(0.010)	(0.010)	(0.010)	(0.144)	(0.155)	(0.147)
Cropping Year 2014/2015	-0.193***	-0.209***	-0.262***	-0.248***	-0.283***	-0.336***
	(0.011)	(0.011)	(0.012)	(0.029)	(0.030)	(0.034)
Cropping Year 2011/2012	0.165***	0.169***	0.152***	0.112***	0.132***	0.124***
	(0.015)	(0.015)	(0.015)	(0.030)	(0.032)	(0.030)
Constant	11.341***	2.388*	7.932***	13.705***	-31.655**	-19.056
	(0.148)	(1.167)	(1.303)	(0.821)	(10.260)	(9.988)
No. of Observations	107215	107215	107215	1045	1045	1045
R-squared	0.379	0.380	0.381	0.410	0.432	0.454
Adjusted R-squared	0.379	0.380	0.381	0.401	0.423	0.444

Note: Columns (1) to (3) present the coefficients estimated using pooled cross-sectional data, and columns (4) to (6) present the estimates obtained from pseudo-panel regression. The dependent variable is agricultural output value trimmed at top 0.5%. All regressions include a quadratic time trend. A set of region dummies are included only in regression using pooled cross-sectional data. Other household-level controls included but not shown in the table are household size, whether household head is female, age of household head, whether household head completed secondary education, whether household has cooperatives or BAAC membership, share of rented land, and the size of land tenured used for agriculture. For pseudo-panel regression, dependent variable, weather variables, and control variables are averaged across cohort. Robust standard errors are reported in the parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: The Effects of Temperature on Agricultural Output Value by diversification strategies – Pooled cross-sectional analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	By number of agricultural activities		By types of agricultural activities		By number of crops grown	
	1 Activity	2/3 Activities	Cropping	Cropping & Livestock	Monocrop	Multicrop
Temperature	0.852^{***}	0.325^{*}	0.714^{***}	0.421^{**}	1.475^{***}	0.239
	(0.125)	(0.127)	(0.121)	(0.132)	(0.233)	(0.143)
Temperature Squared	-0.018^{***}	-0.007^{**}	-0.014^{***}	-0.009^{***}	-0.028^{***}	-0.005
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)
Precipitation	$-3.76\times10^{-4***}$	$-3.60\times10^{-4***}$	$-3.52\times10^{-4***}$	$-4.47\times10^{-5***}$	-3.02×10^{-4}	$-6.20\times10^{-4***}$
	(9.87×10^{-5})	(1.08×10^{-4})	(9.09×10^{-5})	(1.15×10^{-4})	(1.64×10^{-4})	(1.06×10^{-4})
Precipitation Squared	$2.30\times10^{-7***}$	$1.29\times10^{-7*}$	$2.04\times10^{-7***}$	$1.57\times10^{-7**}$	$1.83\times10^{-7**}$	$3.10\times10^{-7***}$
	(4.17×10^{-8})	(5.03×10^{-8})	(3.86×10^{-8})	(5.35×10^{-8})	(6.86×10^{-8})	(4.52×10^{-8})
Share of irrigated land	0.290^{***}	0.238^{***}	0.284^{***}	0.232^{***}	0.028	0.321^{***}
	(0.013)	(0.014)	(0.012)	(0.015)	(0.022)	(0.015)
Constant	0.486	6.835^{***}	2.057	6.328^{***}	-5.244	17.307^{***}
	(1.594)	(1.629)	(1.543)	(1.671)	(3.385)	(2.055)
No. of Observations	65160	42055	61692	36109	18682	43010
R-squared	0.377	0.413	0.410	0.418	0.353	0.451
Adjusted R-squared	0.377	0.413	0.410	0.417	0.352	0.451

Note: This table presents the coefficients obtained from regression using pooled cross-sectional data. The dependent variable is agricultural output value trimmed at top 0.5%. Unit of observations is household. All regressions include a set of region dummies and a quadratic time trend. Other household-level controls included but not shown in the table are household size, whether household head is female, age of household head, whether household head completed secondary education, whether household has cooperatives or BAAC membership, share of rented land, the size of land tenured used for agriculture, whether household engage in growing rice, dummy variables for cropping years 2011/2012 and 2014/2015. Robust standard errors are reported in the parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: The Effects of Temperature on Agricultural Output Value – Pseudo-panel analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	By number of agricultural activities		By types of agricultural activities		By number of crops grown	
	1 Activity	2/3 Activities	Cropping	Cropping & Livestock	Monocrop	Multicrop
Temperature	3.023***	2.020*	3.104***	2.015*	2.516***	1.848
	(0.704)	(0.953)	(0.665)	(0.789)	(0.694)	(0.997)
Temperature Squared	-0.059***	-0.039*	-0.061***	-0.038*	-0.049***	-0.037
	(0.013)	(0.013)	(0.013)	(0.015)	(0.013)	(0.019)
Precipitation	-6.89×10^{-4}	2.57×10^{-4}	-6.70×10^{-4}	8.66×10^{-5}	-5.76×10^{-4}	-1.02×10^{-3}
	(3.55×10^{-4})	(5.46×10^{-4})	(3.52×10^{-4})	(5.36×10^{-4})	(3.24×10^{-4})	(6.73×10^{-4})
Precipitation Squared	$2.63\times10^{-7*}$	-8.21×10^{-8}	$2.65\times10^{-7*}$	-6.20×10^{-9}	$2.47\times10^{-7*}$	3.70×10^{-7}
	(1.26×10^{-7})	(2.24×10^{-7})	(1.23×10^{-7})	$(2.16\times10^{-})$	(1.17×10^{-7})	(2.26×10^{-7})
Share of irrigated land	-0.052	0.140	0.012	0.164	0.318*	0.066
	(0.172)	(0.151)	(0.193)	(0.123)	(0.122)	(0.160)
Constant	-26.183**	-14.419	-26.183**	-14.419	-26.183**	-14.419
	(9.234)	(12.429)	(9.234)	(12.429)	(9.234)	(12.429)
No. of Observations	1045	1005	1045	1005	1040	1018
R-squared	0.387	0.373	0.387	0.373	0.400	0.364
Adjusted R-squared	0.376	0.362	0.376	0.362	0.390	0.353

Note: This table presents the coefficients obtained from pseudo-panel regression data. The dependent variable is the mean agricultural output value trimmed at top 0.5%. Unit of observations is province-year. All regressions include a quadratic time trend. Other household-level controls averaged across cohort are household size, % of households with female head, age of household head, % of households whose head completed secondary education, % of households that have cooperatives or BAAC membership, share of rented land, the size of land tenured used for agriculture, % of households engaging in growing rice, dummy variables for cropping years 2011/2012 and 2014/2015. For regressions in column (5) and (6), we control for the size of land tenured used for cropping in place of the size of land tenured used for agriculture. Robust standard errors are reported in the parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

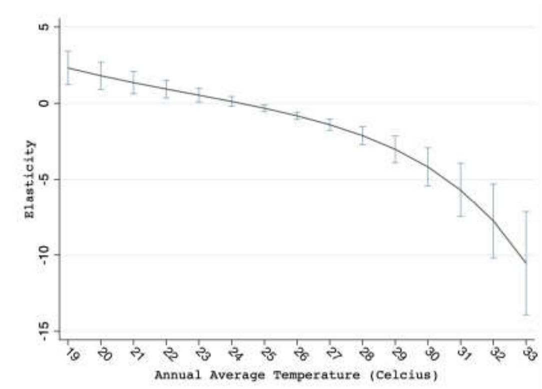
Table 6: Elasticity at Mean of Agricultural Output Value with Respect to Annual Average Temperature

	Whole Sample	By number of agricultural activities		By types of agricultural activities	
		1 Activity	2/3 Activities	Cropping only	Cropping and Livestock
Elasticity	-1.736***	-2.039***	-0.939***	-1.046***	-1.069***
	(-2.04, -1.459)	(-2.421, -1.658)	(-1.316, -0.562)	(-1.396, -0.695)	(-1.475, -0.663)

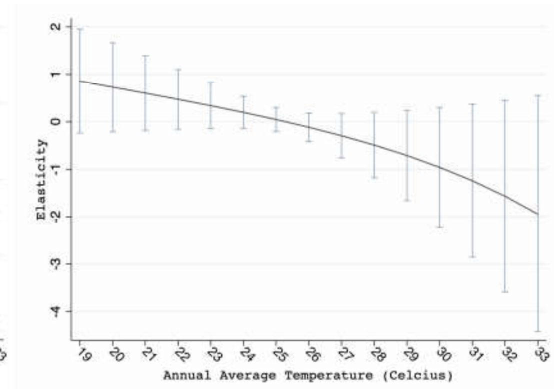
Note: This table presents point elasticity of temperature evaluated at mean temperature ($26.4°C$) over 2006–2020 experienced by households in the sample. The elasticities are calculated from coefficients of temperature and temperature squared in model 2. The 95 % confidence intervals are reported in parentheses. ***$p<0.001$

Figure 1: Point Elasticity of Agricultural Output Value with Respect to Annual Average Temperature

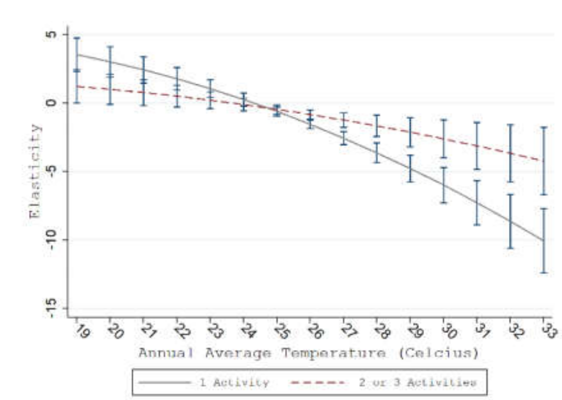
(a) Whole sample (Model 2)



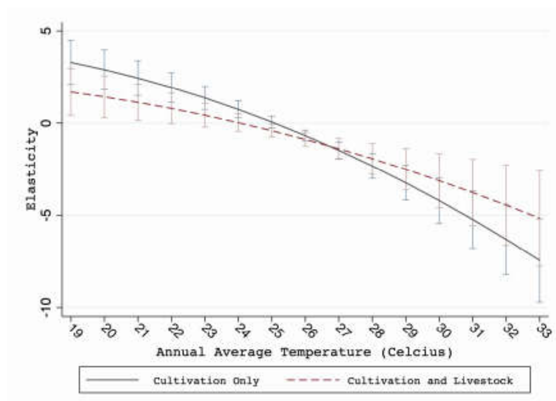
(b) Whole sample (Model 3)



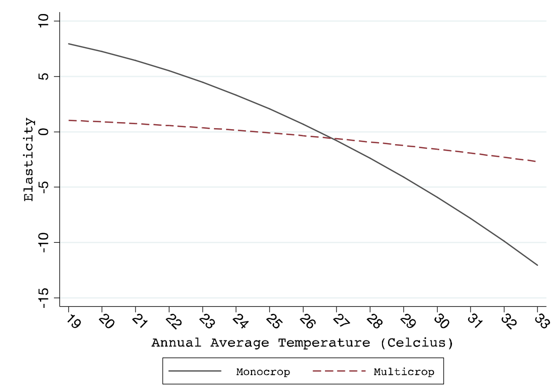
(c) By number of agricultural activities (Model 2)



(d) By types of agricultural activities (Model 2)



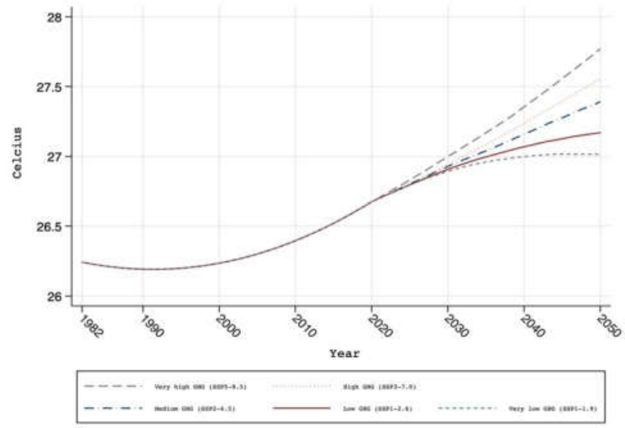
(e) By number of crops grown (Model 2)



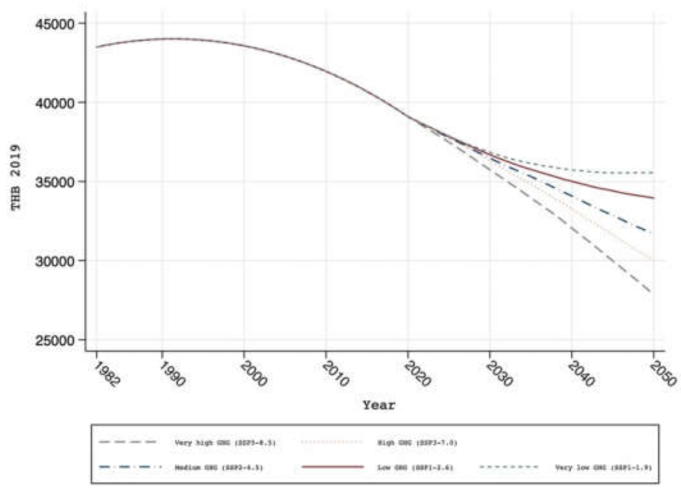
Note: Panels (a) to (e) of Figure 1 illustrate point elasticity of agricultural output value along with 95% confidence interval calculated from the nonlinear combination of estimated parameters.

Figure 2: Agricultural Output Value and Temperature Projection

(a) Temperature Projection

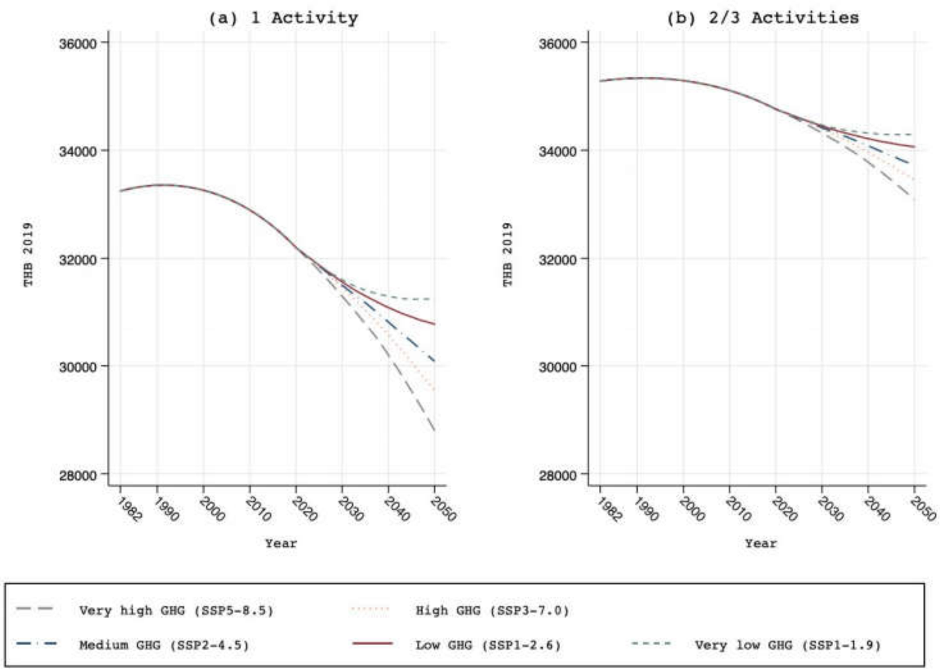


(b) Agricultural Output Value Projection



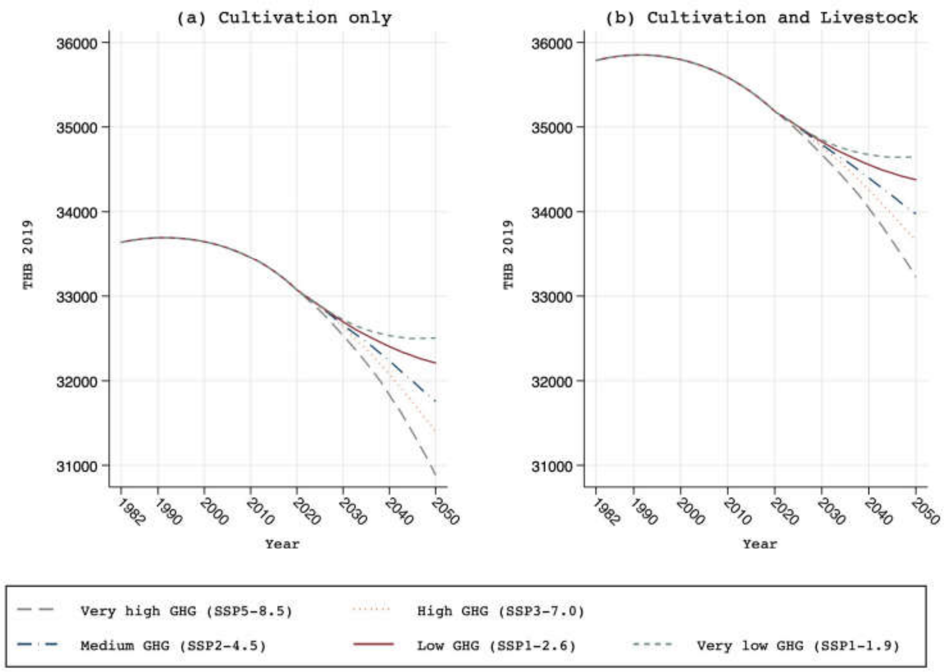
Note: Panel (a) illustrates the temperature predictions from the latest Intergovernmental Panel on Climate Change (IPCC) Assessment Report (AR6). Panel (B) illustrates the projected annual average household's real agricultural output value by different climate change scenarios. The average household and plot characteristics in 2020 were used to calculate the projected values.

Figure 3: Output Value Projection by Number of Agricultural Activities



Note: The figure illustrates the projected annual average household's real agricultural output value by different climate change scenario and by number of agricultural activities. We use the average household and plot characteristics in 2020 to calculate the projected values.

Figure 4: Output Value Projection by Type of Agricultural Activities



Note: The figure illustrates the projected annual average household's real agricultural output value by different climate change scenario and type of agricultural activities. We use the average household and plot characteristics in 2020 to calculate the projected values.

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