Challenges and Opportunities for Climate Adaptation in Thailand Agriculture:

The Rice Sector

March, 2013

Preface

This report is part of a series of research studies into climate risk and adaptation response in Thailand's agricultural sector. In addition to disseminating original research findings, these studies are intended to contribute to policy dialog and public awareness about environment-economy linkages and sustainable growth.

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Introduction

Emerging evidence strongly suggests that global warming will pose serious risks to livelihoods generally and to agriculture in particular. Even small percentage variation of world temperatures could trigger significant and lasting climate changes, including the spatial and seasonal incidence of precipitation, sea levels, tidal and riverine patterns, the severity and frequency of storms, floods, etc. All these factors have important implications for future food security, and policy makers need to better anticipate them and respond proactively.

Evidence from Thailand's Office of Natural Resources and Environmental Policy and Planning (2008) indicates that Thailand's average temperature rose 1 degree Celsius over the last four decades. Meanwhile, rainfall and the number of rainy days decreased in summer but increased in winter. It is estimated that if average temperatures rise by 2 to 4 degrees, the typhoon cycle will probably change direction and increase in destructive potential, with 10 to 20 percent increase in number of typhoons each year.

Although agriculture represents less than 10 percent of current real GDP, this sector still secures Thai livelihoods, and almost 40 percent of population remain directly dependent on agricultural employment. More importantly, the majority of Thailand's poor reside in the agricultural sector and rely on farming for their subsistence. This group is particularly vulnerable because they lack the information, technology, and financial resources needed to cope with the adverse impacts of climate change. Farmers of all sizes will be affected by climate change, but the rural poor majority will require more activist policy engagement to overcome the many constraints they face. With better foresight regarding anticipated climate impacts, it will be possible to more effectively design and deploy extension services, agro-food R&D, water resource management, labor and education policies to facilitate adaptation. To support the necessary policy innovations, the Office of Agricultural Economics (OAE) and the United Nations Food and Agriculture Organization (FAO) have collaborated to develop new capacity for forward-looking economic assessment of climate-agriculture linkages in Thailand. This permits evaluation of different scenarios for Thai economic growth and development in the medium to long term (10 to 50 years), including a spectrum of alternative possible climate trends and policy responses. The present study reports on such an assessment for the rice sector, with a review of historical evidence, projections and identification of climate risk and vulnerability, and a discussion of adaptation options.

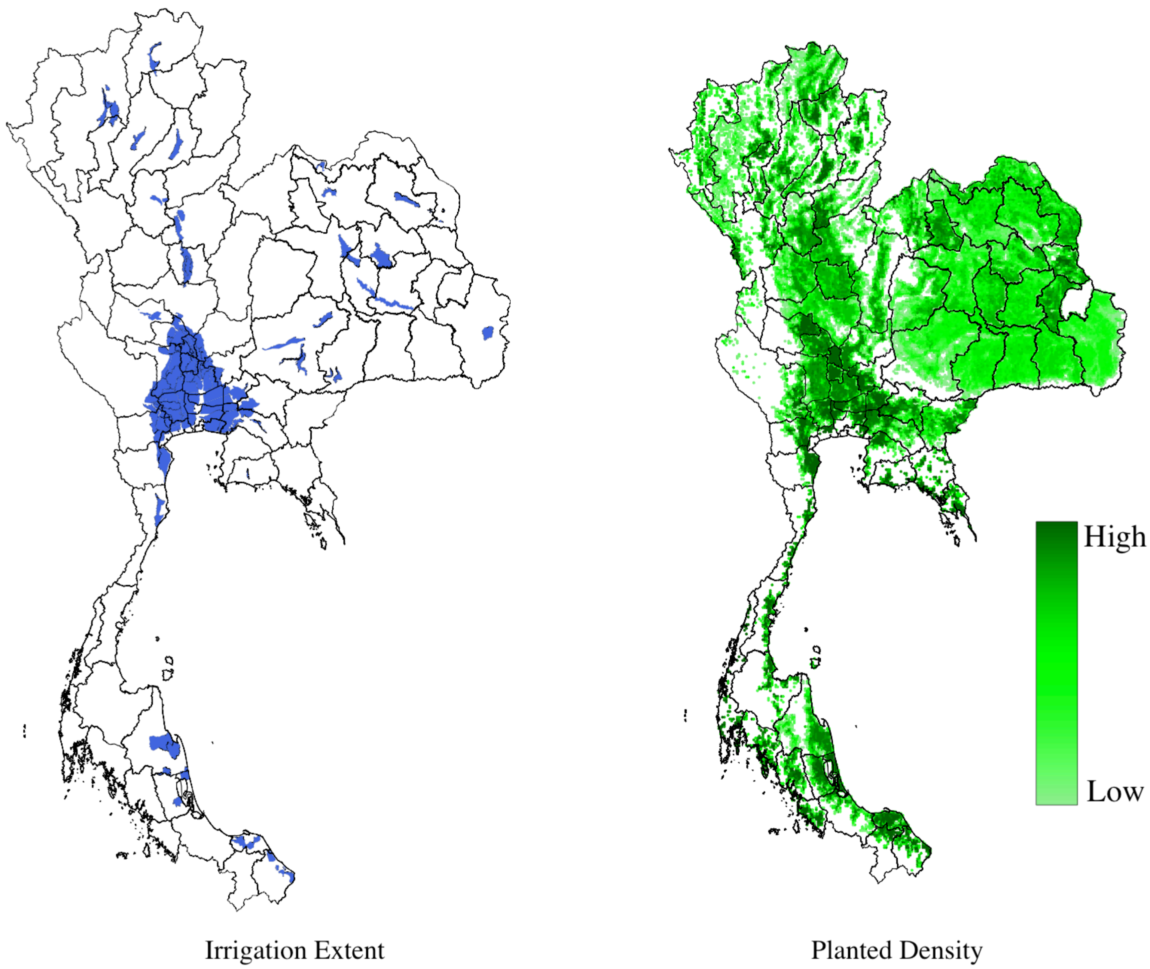
1 Rice Production Systems in Thailand

Rice production in Thailand can be categorized into four types of production systems; lowland rain-fed, irrigated, deep-water, and upland (Kupkanchanakul 2000). Lowland rain-fed is the primary production system, accounting for approximately three-quarters of annual planted area (Kupkanchanakul 2000). Yields in this production system, dependent on rainfall, are highly variable and significantly lower than in irrigated systems. Irrigated rice systems, in turn, benefit from higher yields in the wet season as well as a second production cycle during the dry season. The deep-water production system is historically a production system practiced in areas of the central plains that are subject to a long annual flood season. Yields in this system are low and account for a low percentage of rice production nationally. The final production system, upland rice, produces the lowest yields and has become significantly less common over the past 40 to 50 years. Upland rice now accounts for less than half of one percent of total rice production in Thailand.

The total area under rice in 2010 was estimated to be 11 million ha, accounting for 31.5 million tons of production (OAE). Approximately a quarter of rice production is under irrigated conditions, however, irrigated rice production accounts for well over half of total production. The disproportionate contribution of irrigated areas to total rice production is partly due to higher yields attributed to irrigated production systems, but also because irrigation allows for production in the dry season. Figure 1 illustrates the close relationship between irrigation and rice production, where the left side of the figure maps irrigation extent and the right-hand side illustrates maps production intensity.

The growing seasons for rice depend on yearly conditions and vary by region. In general, there are two seasons: wet season and dry season. The wet season is the primary season where much of the rice is produced with water from rainfall or natural irrigation (i.e., streams and rivers). Rice production in the dry season, however, requires sufficient irrigation in order to support the water requirements of rice production during months with minimal rainfall. The expansion of irrigation networks, and in turn dry season rice production, has significantly increased annual production of rice in Thailand (Tuong et al, 2003). Figure 1 shows the distribution of rice production across Thailand. Production intensity is highly correlated with irrigation extent. Dry-season production is not possible in most regions without irrigation. While the exact dates of production stages in each season vary, even within villages, for the purpose of this study we use average growing season by region. Therefore, when we refer to the “growing season” we are actually referring to each region’s respective growing season.

Figure 1: Rice Production Intensity



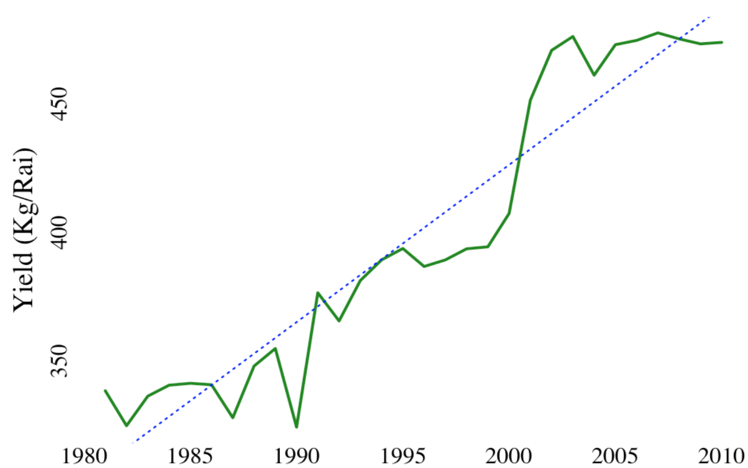
Source OAE

1.1 Weather and Yield Variability

Agriculture is an inherently risky endeavor because many of the essential inputs (i.e., weather) are out of the farmer's control. While technological advances have helped farmers to overcome many of the challenges associated with managing the unpredictable nature of weather, year-to-year weather variability continues to contribute to significant year-to-year variation in yields. Nonetheless, technological progress has led to a steady increase in average yields (Figure 2). On average, rice yields have increased by 40 percent over the study period (1980 -2010). Despite the positive trend in yields, year-to-year variability remains high, sometimes by as much as 20 or 30 percent in a year. Figure 5 illustrates the unpredictability of weather, and in turn, yields, by highlighting the year-to-year deviations from the long-run national trends in weather and wet-season rice yields.

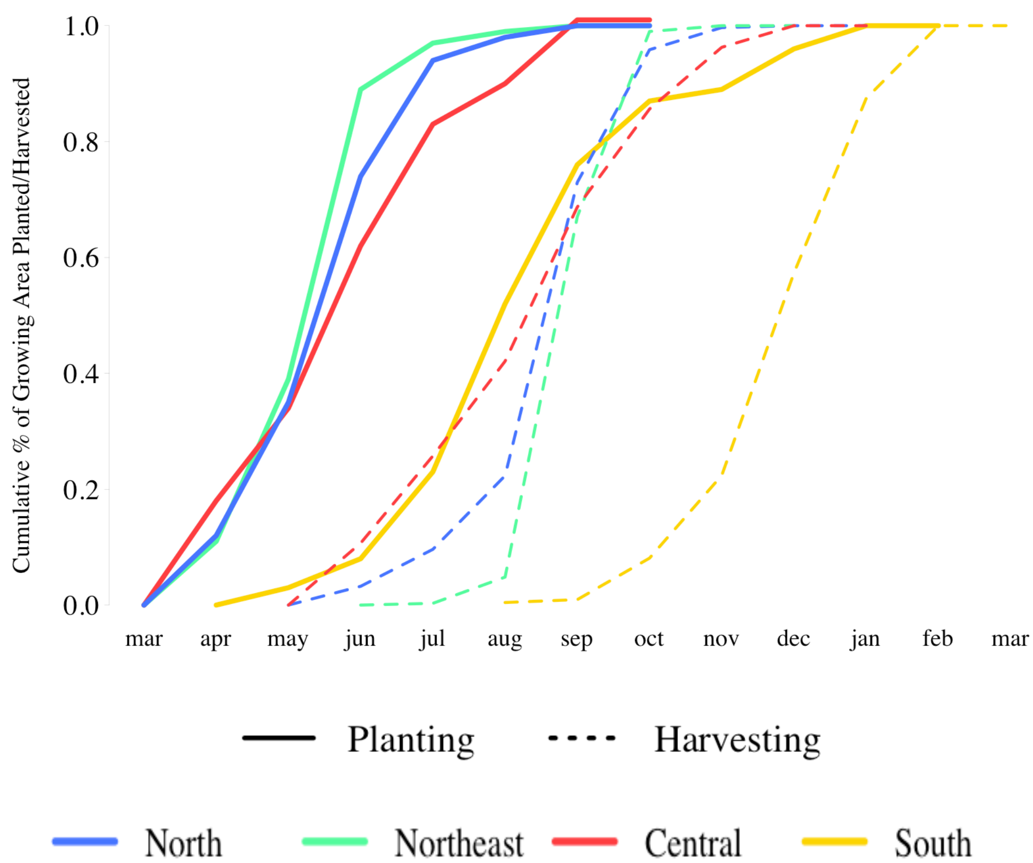
Provinces in the figure are sorted by average yearly deviation from long-run trend, and the 25th, 50th, and 75th percentile provinces are plotted with respect to yield variability. Year-to-year weather variation is large throughout the country, with temperatures often exceeding 50 percent in deviation from the long-run trend and precipitation varying more. In general, provinces in the northeast, where much of the rain-fed production systems are located, tend to have larger year-to-year variation in rainfall.

Figure 2: Average Provincial Rice Yields



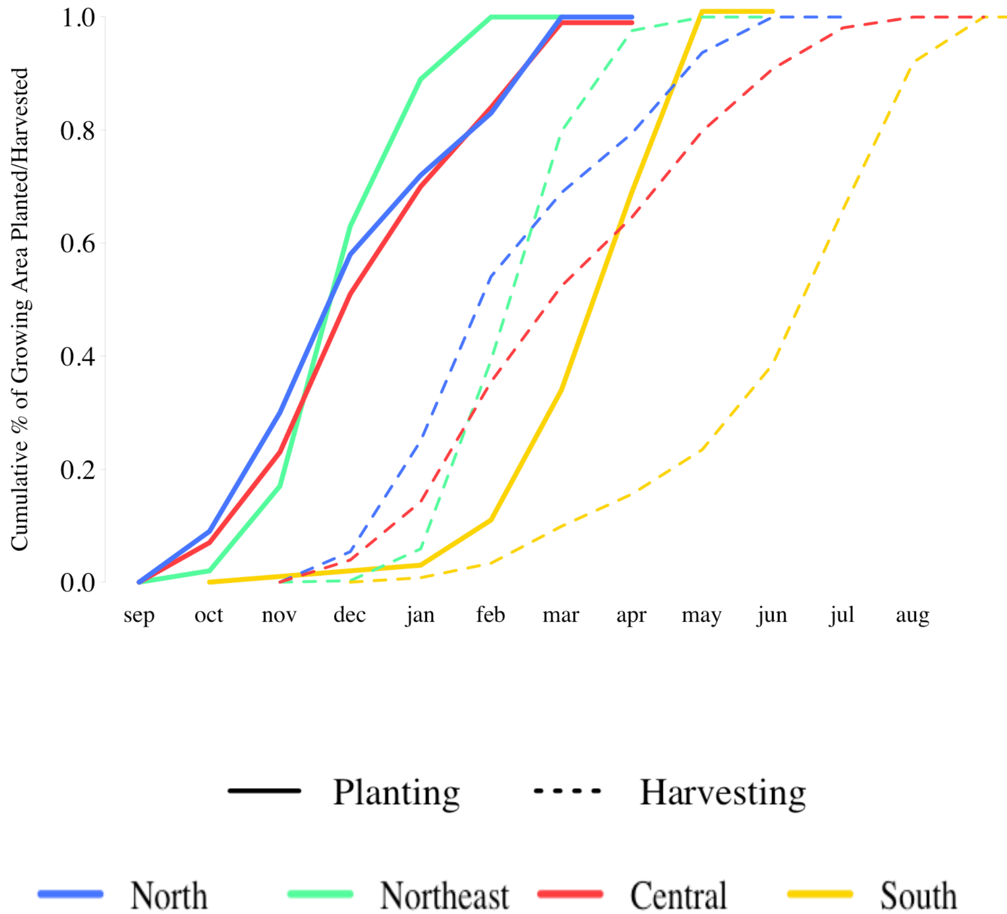
Notes: Average provincial level rice yields (green) and long-run trend (blue).

Figure 3: Distribution of Rice Growing Season (Wet-Season)



Notes: *Figure shows average distribution of wet-season rice planting and harvesting by month. Data are averaged over the available years (2006 – 2010). The earliest planting begins in March in the central region and the latest planting occurs in December in the south. Harvesting begins in late May in the central region and ends the next February in the south.*

Figure 4: Distribution of Rice Growing Season (Dry-Season)



Notes: *Figure shows average distribution of dry-season rice planting and harvesting by month. Data are averaged over the available years (2006 – 2010). The earliest planting begins in September in the northern region and the latest planting occurs in April in the south. Harvesting begins in late November in the north and central regions and ends the next August in the south.*

Figure 5: The Relationship Between Weather and Yield Variability

Notes: The above figure demonstrates the relationship between weather and yield variability for provinces with varying degrees of year-to-year yield variation. Provinces with the 25th, 50th, and 75th percentile of yield variability were selected for comparison. The top panel shows annual yield deviation from the long-run trend. Years where yields were 5 percent or more below the long-run trend are highlighted in red. Those same periods are then highlighted on the equivalent plots for minimum temperature, maximum temperature, and precipitation. In general, yearly high peaks in min and max temperature, as well as low peaks in precipitation, are associated with lower yields.

2 Rice Production and Weather Conditions

In this section, we first review the state of knowledge about the physical relationships between rice growth and weather inputs. Next, we survey past modeling approaches taken to estimate climate impacts on rice growth. Finally, we describe the estimation methods applied here where we use annual provincial-level rice production data over the period of 1981–2010 in order to study the observed relationships between weather and rice yields. The primary environmental inputs to crop production are water, solar radiation, and soil nutrients. Soil characteristics are not considered directly here, but are likely to be relevant to adaptation strategies. For our Thai environmental data, the historical covariation of the other two variables (water in terms of rainfall and radiation in terms of temperature) are summarized in the following table.

Table 1: Correlations Between Climate Variables

	Yield	*Min T*	*Mean T*	*Max T*	*Rad*	*Precip*
Yield	-					
Min T	-0.03	-				
Mean T	0.22	0.82	-			
Max T	0.20	0.39	0.78	-		
Radiation	.013	-0.14	0.30	0.45	-	
Precipitation	.014	0.23	0.04	-0.15	-0.21	-

2.1 The Role of Water

Rice production is much more dependent on water availability than most crops. Yields vary significantly with both the quantity and timing of water application (Bouman et al 2005, 2007). Total Thailand rainfall between May and November ranges from about 500 to 2500 mm. However, as noted, rainfall varies substantially from year to year and over the growing season. Thus, even years with identical levels of total rainfall can have very different growing conditions depending on when the rainfall arrives. Monthly rainfall generally rises each month from the beginning of the growing season until it peaks in August and then decreases thereafter. At some points during the growing season, rainfall is highly beneficial (e.g. prior to planting), while at other times during the season it can be harmful (e.g. harvesting) (Belder 2004). Excessive water can lead to partial submergence of the rice plant, which reduces yields. In one experiment, Yoshida (1981) reports that 50 percent of plant submergence during any of the growth phases led to a 30-50 percent reduction in yields. However, while excessive water can be damaging to rice yields, drought is widely recognized as the primary constraint for rain-fed rice production (Bouman et al 2005, 2007). Insufficient water causes stress on the rice plant and can lead to spikelet sterility, incomplete grain filling, stunting (Yoshida 1981), and delayed heading (Homma et al 2003). For these reasons, we need to develop an approach to characterise yield effects of not only the amount of water, but also when it enters the production system.

Prior to planting, water is also important for rice production because it is an important input to field preparation (Bouman et al 2007). In rain-fed production systems, insufficient rainfall can force farmers to delay planting. Sawano et al (2006) studied the relationship between rainfall and planting date in rain-fed areas of northeast Thailand and concluded that, depending on field-level water availability from rainfall, planting dates were locally distributed over an approximately two-month period; local harvesting, on the other hand, took place around the same time everywhere. The implication was that delayed planting from insufficient early season water resources resulted in a shorter growing season and thus lower yields. It was unclear why farmers who delayed planting did not delay harvest. While the authors did not offer find any conclusive answers for this question, they suggested that farmers may not want to delay harvesting in order to prevent interference with the subsequent growing season.

In addition to the importance of timing, agronomic evidence indicates that extreme (high or low) deviations in rainfall can also be highly disruptive to rice production. Excessive levels of rainfall may result in floods, including plant and soil displacement as well as plant drowning, while very low levels of rainfall (possibly over several years) may lower yields, and even eliminate harvests in droughts. Either type of extreme event has the potential to devastate an entire year's crop. Irrigation systems can help alleviate the drought risk, and investments in conveyance infrastructure can help shed excess water. However, these investments are beyond the means of many smallholders and should be considered for their public goods characteristics.

2.2 The Roles of Temperature and Radiation

Solar radiation is another essential input into rice production, affecting plants directly through photochemistry and indirectly through ambient temperature. Rice plants require heat to grow. There are a number of ways to measure energy requirements, the most basic being intensity for a given level of atmospheric pressure and humidity, i.e. average temperature. Other related measures take account of duration (e.g. daily minimum and maximum), agronomic temperature measures such as Growing Degree Days (GDD), and cumulative radiation measures.

Across some ranges of maximum temperatures, higher daytime temperatures are generally found to positively affect rice growth (Peng 2004; Welch 2010), however, as temperatures continue to rise, they eventually become harmful. The threshold where maximum daytime temperatures become detrimental to rice growth depends largely on genotype and local growing condition (e.g., water availability). For example, depending on genotype and field conditions, Wassmann et al (2009a) estimated a cutoff for maximum temperature of 31 degrees beyond which “growth and productivity rapidly decrease”. Similarly, using a laboratory experiment where they artificially manipulate temperatures, Yin et al (1996) estimate a cutoff for positive effects of maximum temperature of, depending on genotype, 28 - 30 degrees. However, these estimates come from experimental rather than field results, which may not be representative of farmer-managed fields where some precautions may be taken when temperatures become potentially harmful.

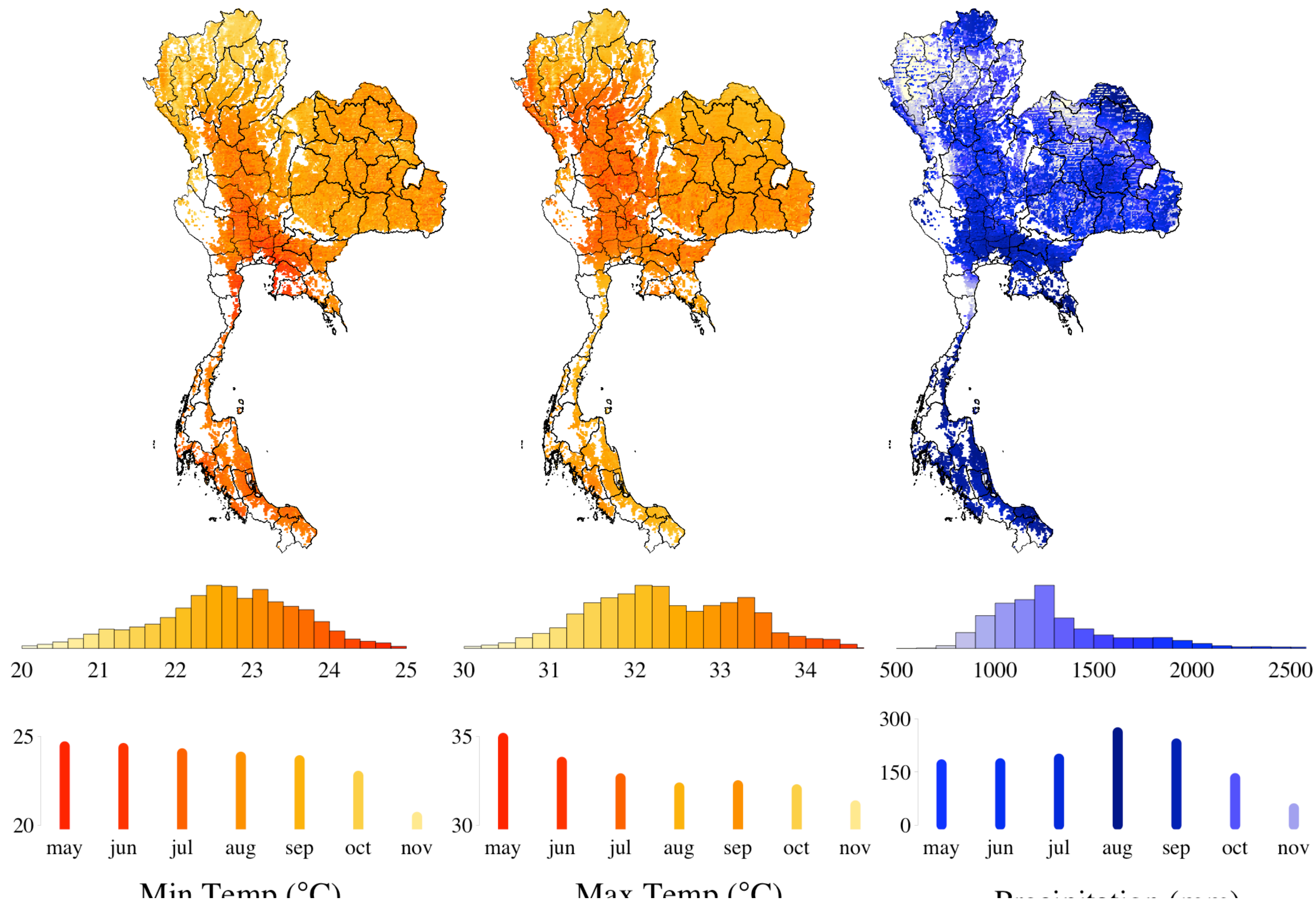
Consequently, if we believe that farmers may be able to ameliorate the effects of extreme temperature through adapted management practices, or that local varieties have been selected for heat resistance, then we might expect observed field data to exhibit higher thresholds. Indeed, in the next section, we discuss our findings that, increases in average daily maximum temperature across the growing season are beneficial to rice growth up to 34 degrees, above which rice growth is strongly harmed. Moreover, extended periods of high temperatures are also found to be harm growth.

Generally, extreme highs and lows are threats to crop growth. However, for the range of temperatures considered in Thailand, extreme lows are unlikely to harm rice growth. Extreme highs are a more serious concern, and they threaten plant growth because heat stress delays the growth process (Yoshida 1981; Wassmann 2009b). Furthermore, consecutive days of high temperatures may be especially harmful because they exacerbate the stress caused by individual extreme days, without allowing time for the plant to recover. Like all organisms, plants have innate resilience that enables them to cope with transitory environmental risks like one day temperature spikes. If extremes persist, however, the plant’s resilience will be overcome. We discuss our approach to addressing this “heat wave” scenario in the next section. In addition, we explore the well-documented differential effects of minimum and maximum temperature, and propose a more comprehensive measure of temperature and radiation’s effect in the rice growth production function.

High levels of solar radiation are also thought to have a negative effect on rice yields. While a certain amount of radiation is helpful (indeed required) for plant growth, high levels are thought to increase heat stress, speed growth, and reduce the length of the growth period, ultimately resulting in lower yields (Wassmann et al 2009b). For our purposes, relatively low-resolution shortwave surface radiation data is included primarily to serve as a control that helps to separate temperature effects of interest from radiation effects.

There is significant variation in growing season temperatures across Thailand. Figure 6 shows the geographic distribution of growing conditions over space and time. Average minimum (nighttime) temperatures during the growing season range between 20 and 25 degrees Celsius, while average maximum (daytime) temperatures range from 30 to 35 degrees, although this varies across the growing season. The beginning of the rice growing season is typically 3-4 degrees hotter than the end.

Figure 6: Average Rice Growing Season Conditions (1980-2010)



3 Changing Climate Conditions

The purpose of this report is to evaluate the future challenges to the Thai rice sector that arise from changing climate conditions, as well as identifying opportunities for adaptation to improve long term food security. Although climate change is generally seen as a prospective risk, in Thailand we have already observed limited changes over the study period 1980-2010. Figure 7 maps the change in average growing season conditions over the study period. Changes are calculated by taking the difference between (5-year) smoothed end points. In particular, baseline conditions were calculated as averages over the period of 1981–1985 and then compared to average conditions over the period 2006–2010. Temperature changes were calculated as absolute degree differences and precipitation changes were calculated as percentages. Statistical tests were also carried out to compare the two samples (Table A1 in the Technical Appendix). Minimum temperatures were found to increase only slightly (~ 0.1 degrees) while maximum temperatures rose by an average of 0.25 degrees and precipitation increased by slightly less than 1 percent. The differences in maximum temperature and precipitation were both statistically significant. Local conditions across Thailand were found to vary significantly, however, and some areas have likely benefitted from the change in weather conditions while others have been adversely affected. [1]

Regional disaggregation suggests even more trend climate variation in some localities. We find that the areas experiencing the greatest increase in average growing temperatures are the north, northeast, and south, while temperatures in the central region were relatively more stable. Temperatures in the central region (typically the hottest) appear to have remained relatively constant, and in some places even decreased. Most observed temperature changes over the study period have been less than 0.5 degrees and happened later in the growing season (Sep – Nov). The most extreme differences in average growing season minimum temperatures across periods approached 1 degree. Most of these cases occurred in the north and northeast, however, these only accounted for 1 percent of all rice-growing areas.

Total precipitation across rice growing areas in recent years was, on average, higher than in the baseline period by about 10-15 percent. While higher levels of rainfall have the potential to benefit rice farming, much of the observed increase has come late in the

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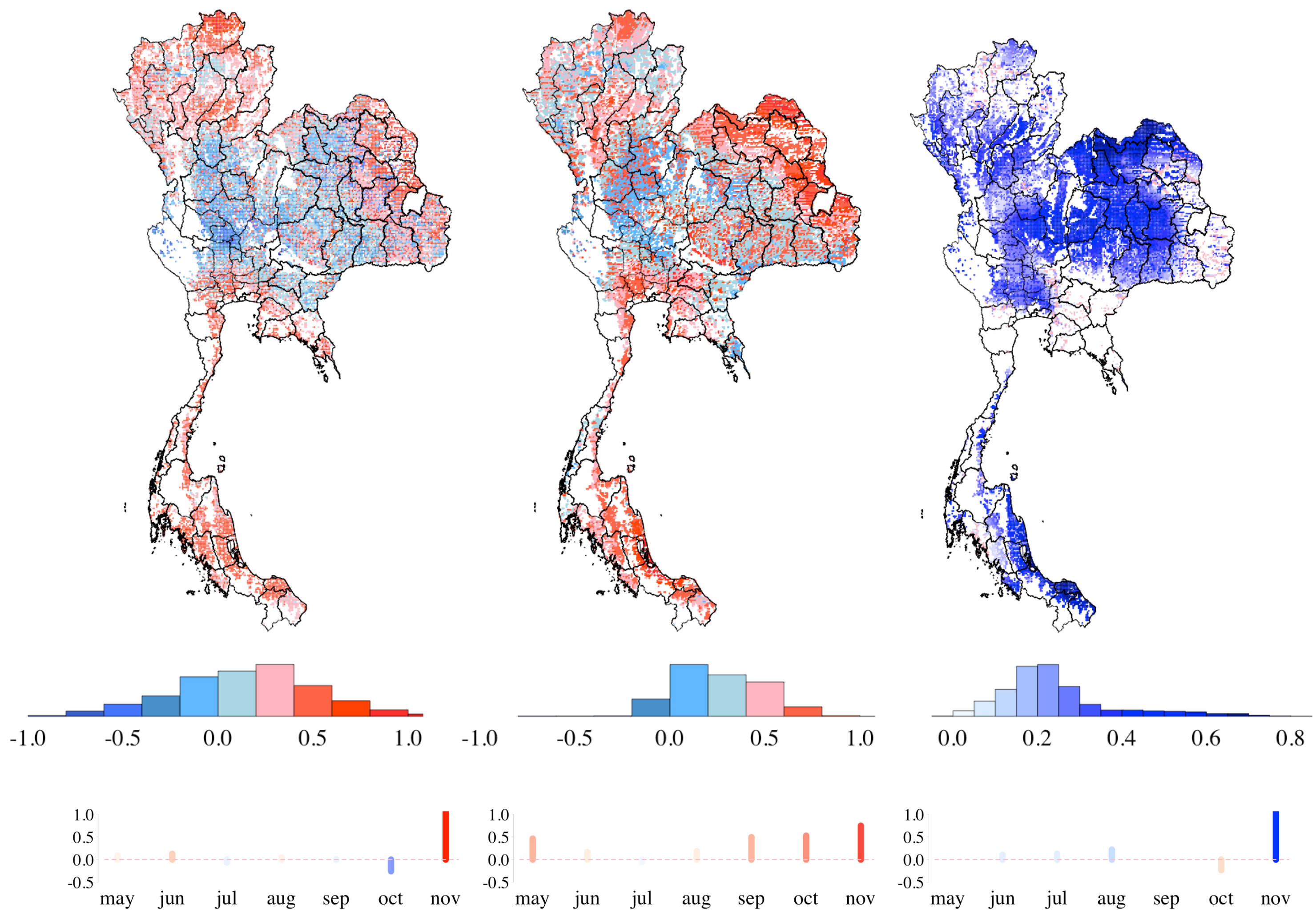
[1] Both daytime and nighttime extreme highs are potentially harmful to rice yields.

growing season when additional water is less useful or even detrimental. Moreover, heavy rains late in the season have contributed to extensive flooding in several of the past few years, leading to extensive crop losses and other damages.

Our comparison of rice growing conditions over the past 30 years suggests that recent conditions (2001–2010) were different from the conditions seen in previous decades (1981-1990). As we discuss in the next section, these are also the types of changes in minimum and maximum temperature are likely to threaten rice yields, while concurrent changes in precipitation have potential to either benefit or harm rice production, depending on the timing and intensity of rainfall patterns.

Figure 7: Change in Climate Conditions (1980 – 2010)



4 Estimating the Impact of Weather on Rice Yields

4.1 State of Knowledge

In general, two approaches have been taken to characterize potential climate change impacts on rice production. First, agronomical studies may involve laboratory or experimental fields where rice plants are placed under different types of environmental stresses in order to measure their physiological responses (e.g., Borrell et al 1997; Belder et al 2004; Homma et al 2004; Yin et al 1996). An extension of this approach is to use field data to calibrate crop models that model the physiological growth process. Perturbing the inputs in these models can in turn provide predictions of crop growth under potential future climate conditions. CIAT (2012) is a recent example of a crop model study used to examine potential impacts of climate change on the Thai agricultural sector.

The second approach, which we take here, applies statistical models using plausibly random variations in weather to estimate the effects of weather conditions on observed rice yields. One of the primary distinctions of the statistical model approach is that the analyses reflect not only physiological responses of rice but also human behavior involving farmers attempting to mitigate potential losses (Lobell and Burke 2010). Although it is difficult to distinguish physiological responses from farmer behavior, we believe that including human behavior in our models is useful considering that future adaptation is likely to depend on improved field management.

Typically, statistical studies use average growing season (or sub-season) conditions, to represent the weather inputs in the production function. The simplest approach estimates log yields as a function of mean temperature, mean precipitation, and their squares. However, several studies have emphasized the differential effects of minimum and maximum temperature (Yin et al 1996; Peng 2004;Welch 2010), the importance of including radiation (Sheedy 2006; Welch 2010), and the differential effects across phases of the growing season (Welch 2010). In addition, there has been extensive research on water requirements for rice production in irrigation (Bouman 2001,2005,2007;) and rain-fed settings (Mackill 1996; Sharma 1994; Wade 1999).

Our goal is to provide a local analysis for Thailand. In order to do so, we seek to incorporate the main methods and findings from these disparate sources into statistical models that estimate the impact of climate on yields. This analysis, in turn, will be used to inform policy prescriptions and highlight the rice production areas that are most vulnerable to adverse changes in growing conditions.

4.2 Estimation Strategy

We begin with a baseline approach of estimating the effects of weather on rice yields using a panel regression with a single growing season metric for each weather covariate (average growing season min T, max T, radiation, and precipitation). Using average seasonal conditions, we estimate both linear and piecewise linear models, which are later used to predict yields under various climate scenarios. Using GIS information on irrigation extent in Thailand , we are able to divide rainfall into two variables: rainfall over rain-fed cropland, and rainfall over irrigated cropland.

In our second approach, we address the evidence that extreme temperatures are especially harmful to yields (Schlenker 2009, Yin 1996) by re-estimating the panel regression models with additional controls for extreme weather events (heat waves, droughts, and floods). In our third approach, we draw heavily on the agronomy literature in an attempt to construct optimal temperature and rainfall profiles for the average rice farm, and then use deviations from these optimal profiles as our weather metrics.

Average Growing Season Conditions

4.2.1.1 (i) Linear Fixed-Effects Panel Model

The first approach that we take is to estimate a linear panel regression fixed-effects model for log yields as a function of weather metrics during the growing season (estimation equations described in Technical Appendix). Minimum temperature, maximum temperature, and radiation are all averaged while the rainfall terms are summed over the growing season. In addition to the separate rainfall terms, we also include their squares. To control for technological change and advances in farm management, we estimate separate regressions with a linear national time trend, separate provincial level linear time trends, and year fixed effects, respectively. The results across models with different controls are qualitatively the same.

All of the regressions are weighted by average production over the study period. Due to the discrepancy between planted area and total production, the choice of weights ultimately causes us to over-weight rain-fed subsistence farms (planted area weights) or intensively managed irrigated farms (production weights). We estimated the model with both sets of weights. The results were qualitatively the same.

The linear panel approach has been widely applied in the literature (e.g., Peng et al 2004; Welch et al 2010) but requires somewhat restrictive assumptions about the linearity of the terms (Lobell and Burke 2010). For example, the linear panel model assumes that the effect of an increase from an average minimum growing season temperature of 20 to 21 degrees is the same as a change from 24 to 25 degrees. Consequently, in our second approach we allow for nonlinearities at higher minimum and maximum temperatures.

4.2.1.2 ii. Piecewise-linear Panel Fixed-Effects Model

The second approach involves estimating a piecewise linear function that allows for extreme seasonal values to have differential effects. In other words, for each temperature variable, we assume that the input is good (bad) up to a certain value, but that eventually too much of that input is harmful (no longer harmful). This approach involves calculating piecewise linear functions for each variable, with an endogenous threshold that is chosen by minimizing the in-sample RMSE. The benefit of this approach is that it allows for differential effects of temperature over higher ranges, which is more consistent with discontinuous effects found in the agronomic literature (Yoshida 1981). This method has previously been used to estimate the effect of extreme temperatures on wheat and maize yields in the United States (Schlenker 2010).

5 Extreme Weather Events

Up to this point, we have discussed the effect of average growing conditions on rice yields. While average conditions are important, extreme events often have disproportionately large negative effects on seasonal output (Choch 2012; Homma 2004; Schlenker 2009). Heat waves, droughts, and floods can all negatively affect a given year's outputs without drastically changing the seasonal temperature averages. For example, a five-day heat wave that is sufficiently hot could severely damage rice crops so that output for that year is significantly lower. However, the heat wave is unlikely to change seasonal average temperatures since the season lasts several months. Similarly, floods and droughts may not have statistical significance in seasonal averages, while they can have devastating one-time effects on crop outputs.

In order to address potential increases in the frequency of extreme events under future climate change, we take two separate approaches to extreme event scenarios. The first approach estimates 3-day, 5-day, 2-week, and 3-week moving averages of our climatic variables and then calculates the hottest periods and incorporate those "heat waves" in the analysis. A similar approach is taken to calculate the driest and wettest periods in each season. The second approach estimates extreme events as a function of standard deviations with respect to historical averages. This coresponds to a behavioral approach that assumes farmers adjust their practices in response to average conditions in their area, and that deviations from expected conditions are harmful to crop growth.

6 Results

Consistent with other statistical studies (e.g., Peng 2004, Welsch 2010), our linear fixed-effects regression model results suggest that elevated minimum nighttime temperatures are highly damaging to rice yields. Under the linear model, we find that, holding all else constant, a 1 degree (1.5 standard deviation) rise in nighttime temperature reduces rice yields by an average of approximately 8 percent over the study period [Table 2]. In addition to being consistent with statistical studies, this finding is also consistent with the current understanding of biological processes in rice such that nighttime temperatures affect respiration in the rice plant and increase spikelet sterility, thereby harming rice growth (Wassmann et al 2009b). With respect to radiation, we find that a 1-mjd^{-1} (equivalent to one standard deviation) rise in radiation results in a yield decline of approximately 2 percent. This is also consistent with previous statistical studies, although Welsch et al (2010) emphasize the differential effects of radiation across rice growth stages. As expected, we find that higher maximum temperatures are associated with 2-3 percent higher rice yields.

As discussed above, we separate rainfall into rainfall over irrigated land and rainfall over non-irrigated (rain-fed) land. This helps to separate the differential effects of irrigation. Under the linear model (where both rainfall terms and their squares are included) we find that rainfall is significant for both rain-fed and irrigated areas, however, the signs of the effects are opposite. For rain-fed rice, we find that an additional 10 cm of rainfall over the course of the growing season increases yield by about 1 percent. However, too much rainfall is harmful (negative squared term). For irrigated rice crops, however, we find that additional rainfall is harmful to irrigated crops where 10 cm of additional rainfall across the growing season reduce yield by about 1 percent. One possible explanation is that irrigated crops have irrigation schedules which call for water to be released strategically, but rainfall disrupts this schedule by adding unplanned water to the production cycle.

In summary, the results from our linear model suggest that minimum temperature is a driving factor in yield loss from temperature, that maximum temperature is positively correlated with higher rice yields, radiation negatively so, and that rainfall over irrigated and rain-fed cropland have opposite effects. Next, we relax our linearity assumption and find that, in fact, the piecewise linear model better explains observed variation in rice yields.

Table 2: Linear Seasonal Average Panel Model Results
Significance levels indicated by ***0.01, **0.05, *0.1

	Model (1)	Model (2)	Model (3)
Min Temp (deg C)	-0.100*** (0.014)	-0.084*** (0.015)	-0.098*** (0.026)
Min Temp (deg C)	0.023** (0.010)	0.018* (0.009)	0.001 (0.027)
Radiation (mjd^{-1})	-0.016** (0.006)	-0.019*** (0.006)	0.011 (0.010)
Rainfall (100 cm rain-fed)	0.123*** (0.029)	0.119*** (0.029)	0.149*** (0.054)
$Rainfall^2$ (100 cm rain-fed)	-0.023** (0.010)	-0.020** (0.010)	-0.028** (0.011)
Rainfall (100 cm irrigated)	-0.141** (0.054)	-0.103* (0.054)	-0.110* (0.057)
$Rainfall^2$ (100 cm irrigated)	0.065*** (0.020)	0.038* (0.021)	0.060*** (0.020)
Fixed Effects	Prov	Prov	Prov, Year
Time Trend	National	Prov	--
Mean Log Yield	5.847	5.847	5.847
No Obs	2067	2067	2067
R2	0.536	0.600	0.587

Table 3: Piecewise-linear Seasonal Average Panel Model Results

	(1)	(2)	(3)
Min Temp (< 24) (deg C)	-0.098*** (0.014)	-0.076*** (0.016)	-0.106*** (0.029)
Min Temp (>24) (deg C)	-0.149** (0.065)	-0.146* (0.073)	-0.060 (0.078)
Max Temp (<34) (deg C)	0.037*** (0.010)	0.026** (0.011)	0.025 (0.025)
Max Temp (>34) (deg C)	-0.205*** (0.069)	-0.182** (0.069)	-0.075 (0.073)
Radiation (<17) (mjd^{-1})	-0.015 (0.010)	-0.010 (0.010)	0.014 (0.013)
Radiation (>17) (mjd^{-1})	-0.020** (0.009)	-0.036*** (0.010)	-0.013 (0.009)
Rainfall (< 3) (10 cm rain-fed)	0.072*** (0.023)	0.072*** (0.024)	0.013 (0.024)
Rainfall (3<r<18) (10 cm rain-fed)	-0.001 (0.002)	0.000 (0.002)	-0.000 (0.003)
Rainfall (>18) (10 cm rain-fed)	-0.004* (0.002)	-0.004* (0.002)	0.000 (0.001)
Rainfall (10 cm irrigated)	-0.015** (0.006)	-0.010* (0.006)	-0.020*** (0.006)
$Rainfall^2$ (10 cm irrigated)	0.001*** (0.000)	0.000 (0.000)	0.001*** (0.000)
Fixed Effects	Province	Province	Province, Year
Time Trend	National	Provincial	--
Mean Log Yield	5.916	5.916	5.916
No Obs	2280	2280	2280
R^2	0.544	0.617	0.596

*Significance levels indicated by ***0.01, **0.05, *0.1*

6.1 Piecewise Linear Panel Model with Average Growing Season Weather

In order to estimate the piecewise linear model, we loop over thresholds for each of the weather variables (minimum and maximum temperature, radiation, and rainfall), selecting the thresholds that minimize in-sample RMSE. Unfortunately, we do not have enough variation in rainfall over irrigated cropland to estimate separate effects over different ranges of that variable. However, we are able to separate rainfall over non-irrigated cropland. In fact, we find that a three-part (two-threshold) specification best fits the non-irrigated rainfall data (i.e., minimizes RMSE). For the irrigated rainfall data, we continue to include the linear and squared terms. Ultimately, the chosen model represents an approximately 8.5 percent reduction in RMSE relative to the comparable linear model.

Under the piecewise linear panel model (Table 23), we estimate a threshold for minimum temperature at 24 degrees. We find that a 1-degree rise in minimum temperature across the growing season decreases yields by 8-10 percent when the average minimum temperature is below 24 degrees, but by nearly 15 percent if the minimum temperature is already above 24 degrees. This suggests that not only are rising minimum temperatures harmful to rice yields, but that over extreme ranges, the effect becomes more negative. Estimation of the minimum temperature threshold is robust to trend controls (national trend, provincial trends, year fixed effects) and the alternative weighting schemes. All of our results for minimum temperature below the threshold are highly statistically significant. Our results for minimum temperature above the threshold are significant in two of three specifications, but not when we include year fixed effects. This is likely because year fixed effects absorb much of the identifying variation and thus we lack the power to identify an effect. In our data, about 25 percent of the 2,280 observations averaged nighttime temperatures above 24 degrees.

When we estimated the linear panel model, we found that higher maximum temperatures are associated with 2-3 percent higher rice yields. However, once we allow for separate impacts across different ranges of temperatures, we find a discontinuity at 34 degrees, above which maximum temperature is highly harmful to rice yields. Under the piecewise linear specification, we estimate that a 1-degree increase in maximum temperature below 34 degrees increases yields by 2-4 percent during the study period. However, a 1-degree increase in maximum temperature above 34 degrees reduces yields by more than 18 percent in two of three specifications. The result is highly significant when we include national or provincial linear time trends, but not when we include year fixed effects. This result is extremely important in the context of future yield projections. While statistical models using linear specifications are likely to find a positive effect of higher maximum temperature on rice yields, our non-linear specification reveals that rising maximum temperatures over the range of temperatures forecast by GCMs are likely to be extremely harmful and need to be accounted for when estimating climate change impacts. Over the past 30 years, average maximum temperatures across the growing season over 34 degrees were observed less than 5 percent of the time. However, with temperatures likely to rise, more and more rice-growing areas are likely to be subjected to harmful ranges of temperatures in the future.

For radiation we find that a threshold of 17mjd-1 minimizes RMSE. Below the threshold, we find no effect on rice yields . However, above the threshold, we find that a one-unit increase in radiation (equivalent to a one standard deviation increase) reduces yields by approximately 3 percent. In our data, approximately 40 percent of our observations averaged over mjd-1 across the growing season.

The thresholds endogenously selected for rainfall over rain-fed crops were 30 and 180 cm. Below 30 cm we find that an additional 10 cm of rainfall is associated with a 7 percent increase in yields. Between 30 and 180 cm, we find no effect of additional rainfall. However, after 180 cm, we find a small negative effect of about 0.4 percent for an additional 10 cm of rainfall. These results are consistent with a process where rainfall is initially helpful, but once rainfall has reached a certain point, it become less useful, although not yet harmful. As rainfall continues, eventually it crosses a second threshold and becomes harmful to rice yields. However, it should be noted that these rainfall results ignore the very important timing component of rainfall.

Irrigated rainfall, which was estimated with linear and quadratic terms, was found to have the opposite relationship with rice yields, where the linear term was negative and significant in every specification. The quadratic term was negative. The magnitudes of the coefficients were similar to the fully linear model.

One caveat about estimating piecewise linear functions over extreme ranges is that, in each case, we use less than 5 percent of the data to estimate an effect size of weather that has crossed a threshold.

A second caveat is that measurement error associated with interpolating precipitation over space is typically large. Aside from these caveats, our results are strongly suggestive that weather has differential effects on rice yields over different ranges. Moreover, the signs of extreme values for all variables suggest that linear models will underestimate potential impacts of climate change, since we find that effect size is drastically increased over extreme ranges. Taking this into account is important when we are estimating potential impacts of climate change on rice yields.

7 Future Climate Forecasts

The Intergovernmental Panel on Climate Change (IPCC, 2007) predicts that Southeast Asia will experience warmer temperatures, increased frequency of heavy precipitation, increased droughts, and lower annual levels of rainfall in the next century. Changes in the climate are most likely to effect Thai rice yields through harmful extreme temperatures, reduction in water availability from lower levels of rainfall, and a reduced growth period attributed to higher temperatures and radiation levels (Welch 2010). Rice in Thailand is presently grown at the upper end of the optimal temperature range for rice production. This suggests that Thai rice production is likely to be harmed if future temperatures rise as expected (Wassmann et al, 2009).

On a global scale, researchers estimate that minimum temperatures have risen faster than maximum temperatures over the last century. Easterling (1997) estimates that minimum temperatures have risen faster than maxima over the last century. He attributes this to increased CO2 concentration in the atmosphere. However, in our Thailand data we observe maximum temperatures are *rising faster* over the last 30 years than minimum temperatures. Rice in Thailand is already grown at the upper end of the optimal temperature range, suggesting it is one of the rice growing areas likely to be hurt by rising temperatures (Wassmann: 2009). Also, warmer temperatures combine with higher radiation to accelerate plant growth and reduce yields.

Global Climate Models (GCM) are mathematical models used to simulate the dynamics of the climate system, including the interactions of atmosphere, oceans, land surface, and ice/snowpack. These dynamic simulation tools take into account the physical components of weather systems and use these relationships to model future climate conditions. While GCM projections still reflect high levels of uncertainty, these models provide useful insights into future climate scenarios.

The IPCC serves as a clearing house for research groups around the world to compare their model results. Each research group must choose an approach to modeling physical climate interactions, spatial and time resolution, and future economic conditions, among other things. Variations in these standards can result in a wide variety of predictions. Fortunately, the IPCC has attempted to standardize economic and emissions scenarios in order to increase comparability across models. However, while these scenarios limit the choices that modelers are faced with, there are still many assumptions to be made about how to model future climate. Differences in these choices present a wide range of predictions across models, even within similar groups of economic scenarios.

In order to improve comparison across GCMs from different research groups across the world, the IPCC publishes baseline greenhouse gas emissions scenarios, the most recent of which is called the Special Report on Emissions Scenarios (SRES), for all groups to utilize. Here we use three of the baseline scenarios established in the IPCC Fourth Assessment Report (AR4), published in 2007 (IPCC, 2007).

The B1 scenario imagines increased emphasis on global solutions to economic, social, and environmental stability, but without additional climate initiatives. It assumes rapid global economic growth, but with transition toward a service and information economy and global population rising to 9 billion in 2050 and then declining thereafter. Clean and resource efficient technologies are introduced that limit future emissions growth. This scenario imagines an increase in global mean temperatures of 1.1-2.9 degrees by 2100.

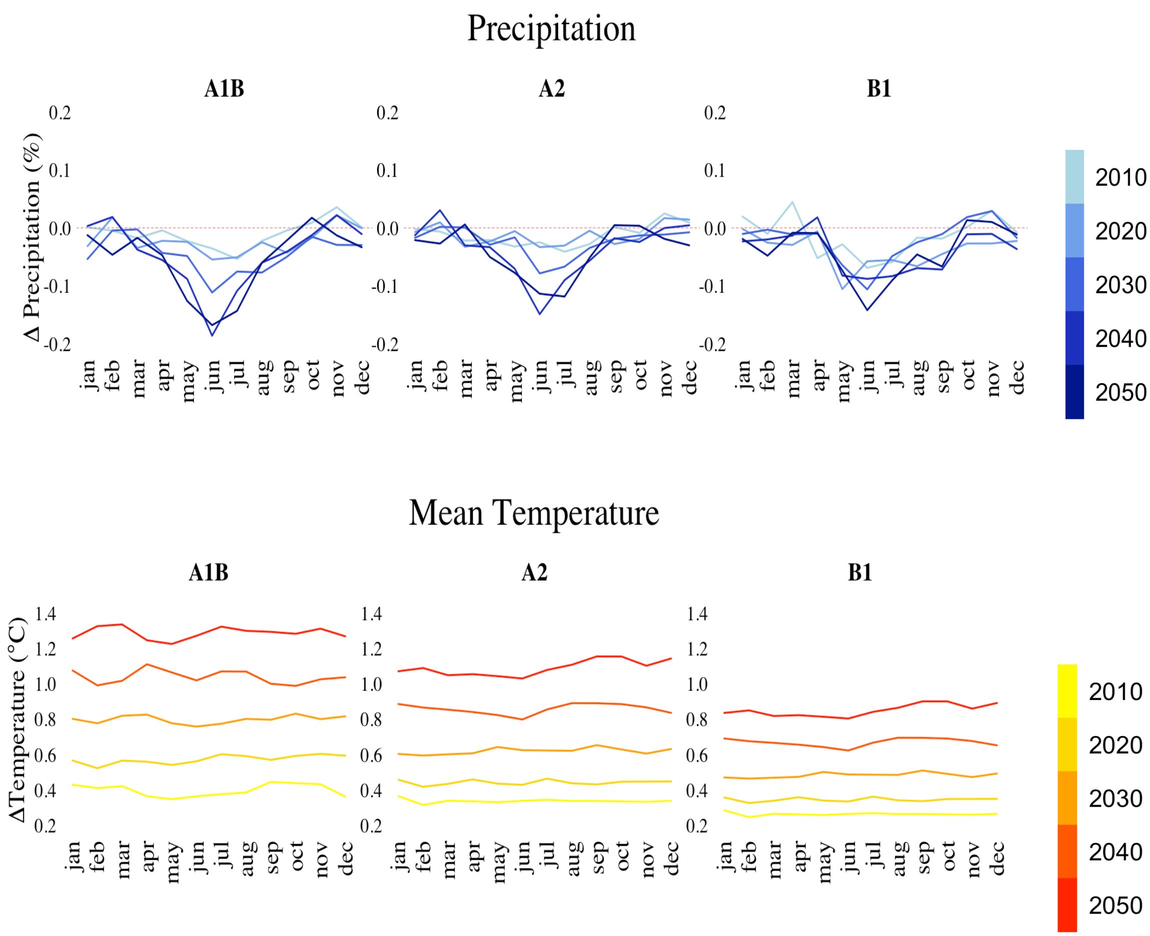
The A1B scenario also assumes global economic growth and a more homogenous future world but with less global emphasis on the information and service economy. Instead, it assumes a continuation of current economic activities, but with more efficient technologies and a balanced emphasis on all energy sources. It assumes similar population increase to 2050 followed by declining global birth rates. This scenario predicts, on average, a 2-6 degree warming of global temperatures by 2100.

The A2 scenario describes a more heterogeneous world, with uneven global economic development and emphasis on self-reliance and preservation of local identities. Fertility patterns across regions converge slowly, resulting in a continuous increase in global population. Economic development is regionally fragmented and there is less global cooperation. This scenario predicts a global increase in temperature of 2-5.4 degrees by 2100.

From 2010 to 2050 the A1B scenario typically predicts larger changes in temperature, however in the longer run (2050-2100), the A2 scenario predicts the largest temperature increase.

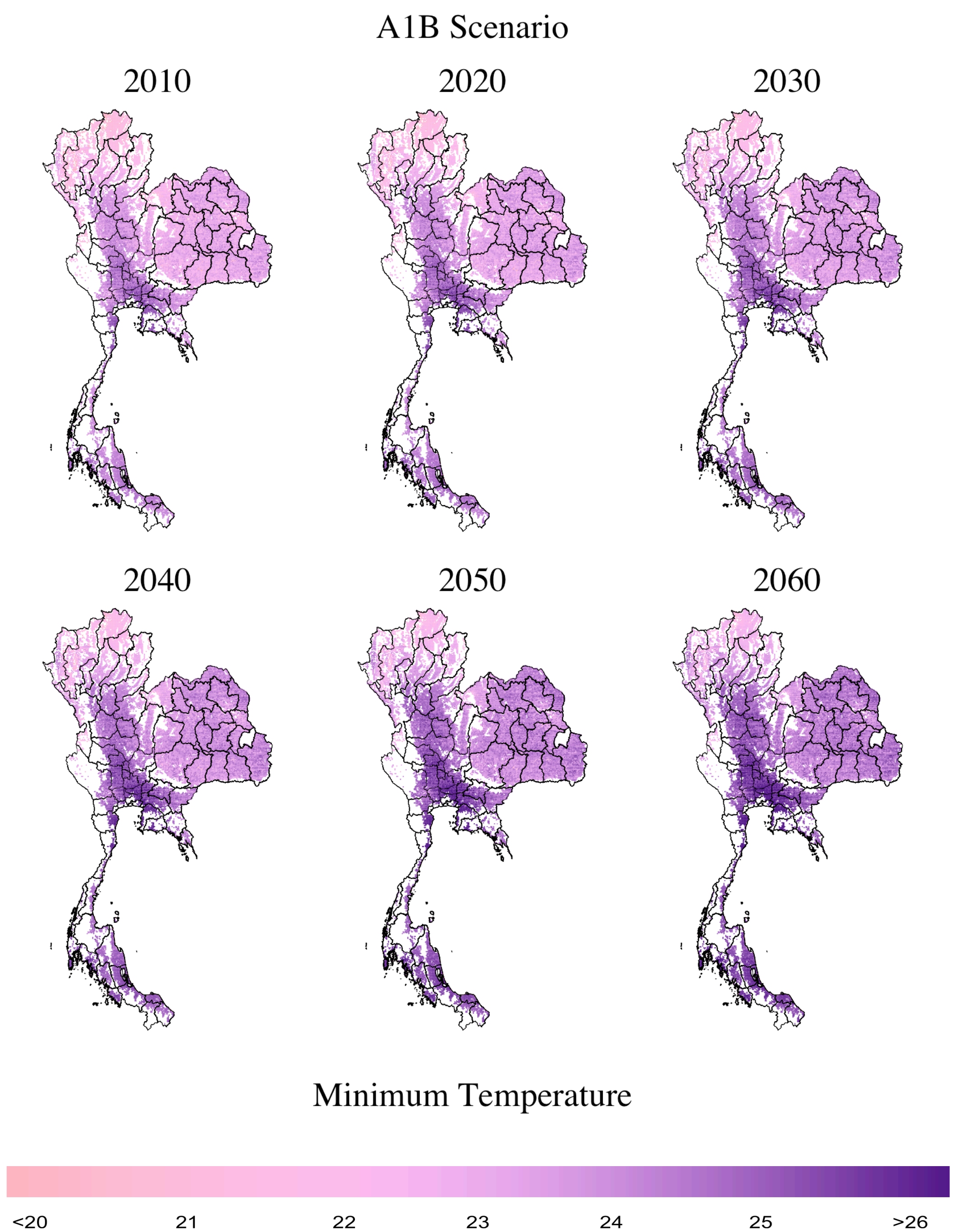
Other studies that downscale global climate models include Johnston et al (2009) and Chinyanno (2009). Both studies … FINISH.

Figure 8: GCM Forecasts of Monthly Changes in Precipitation and Temperature



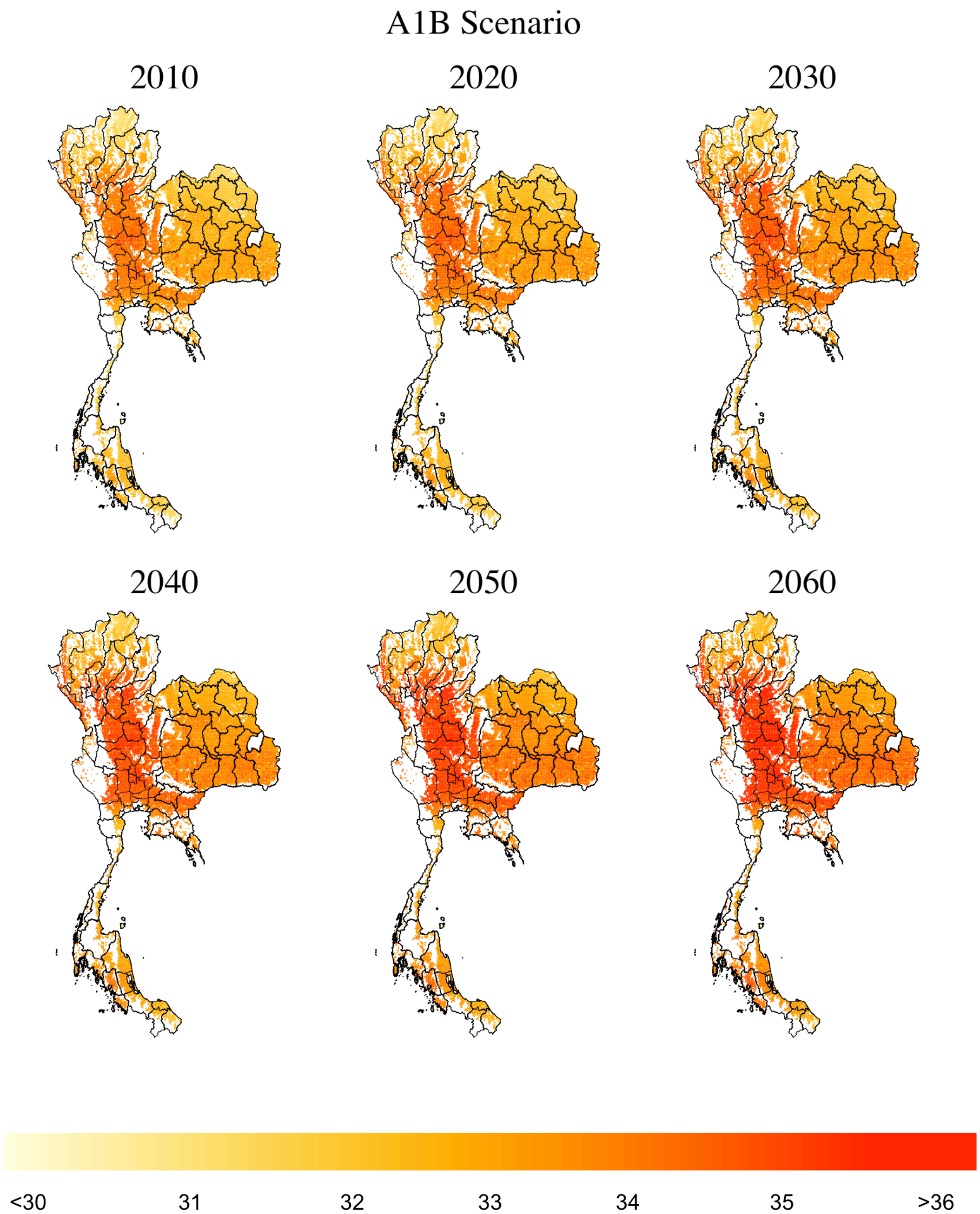
Notes: Figure shows the median predicted monthly changes in temperature and precipitation predicted across 18 Global Climate Models under the three SRES economic scenarios (A1B, A2, B1) described above. Changes are relative to the average GCM estimates of climate conditions over the study period (1980-2010).

Figure 9: Forecast Minimum Temperature During Growing Season



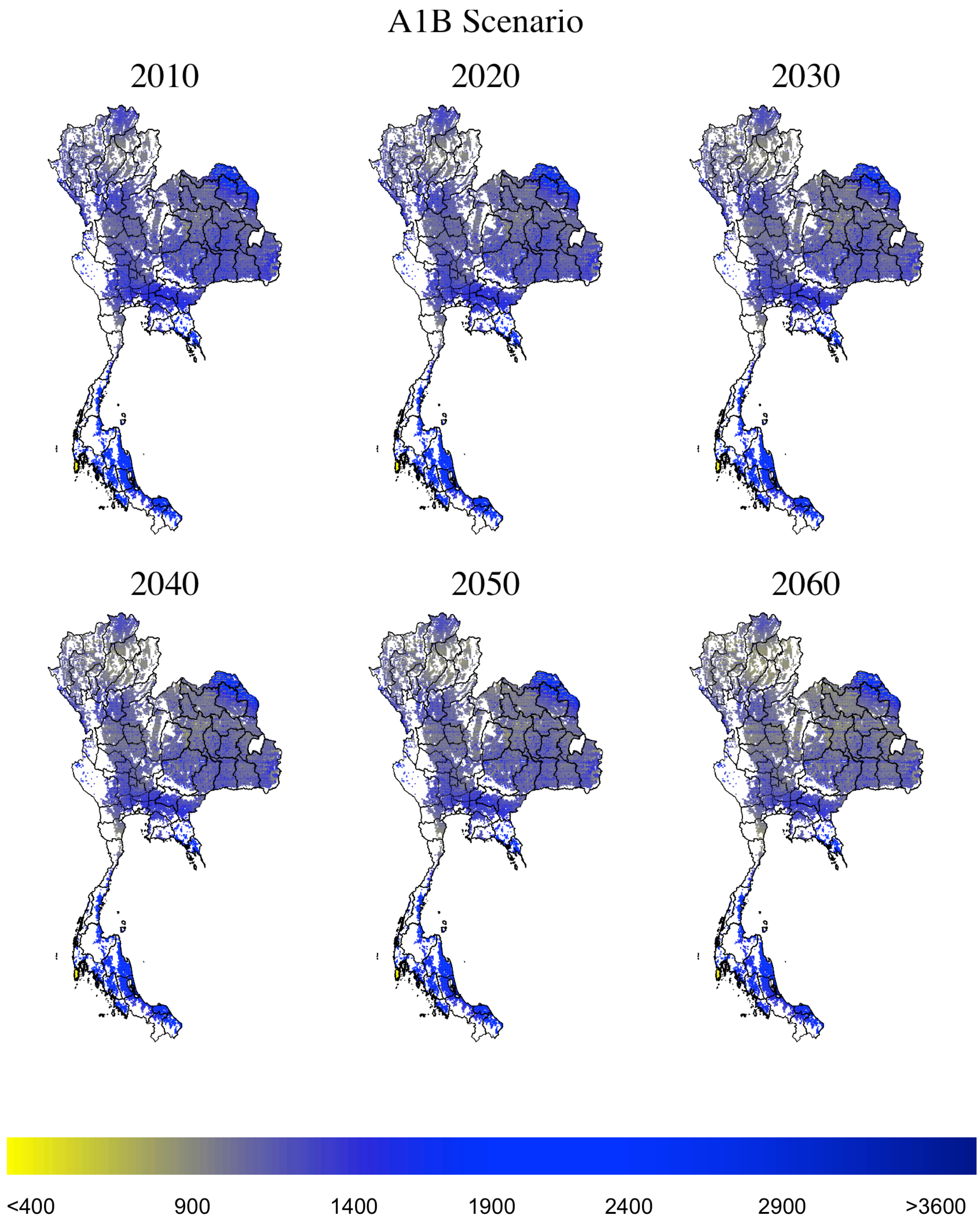
Notes: Projected average minimum temperature over the current growing season by decade under the A1B climate scenario. Temperature is in degrees Celsius.

Figure 10: Forecast Max Temperature During Growing Season



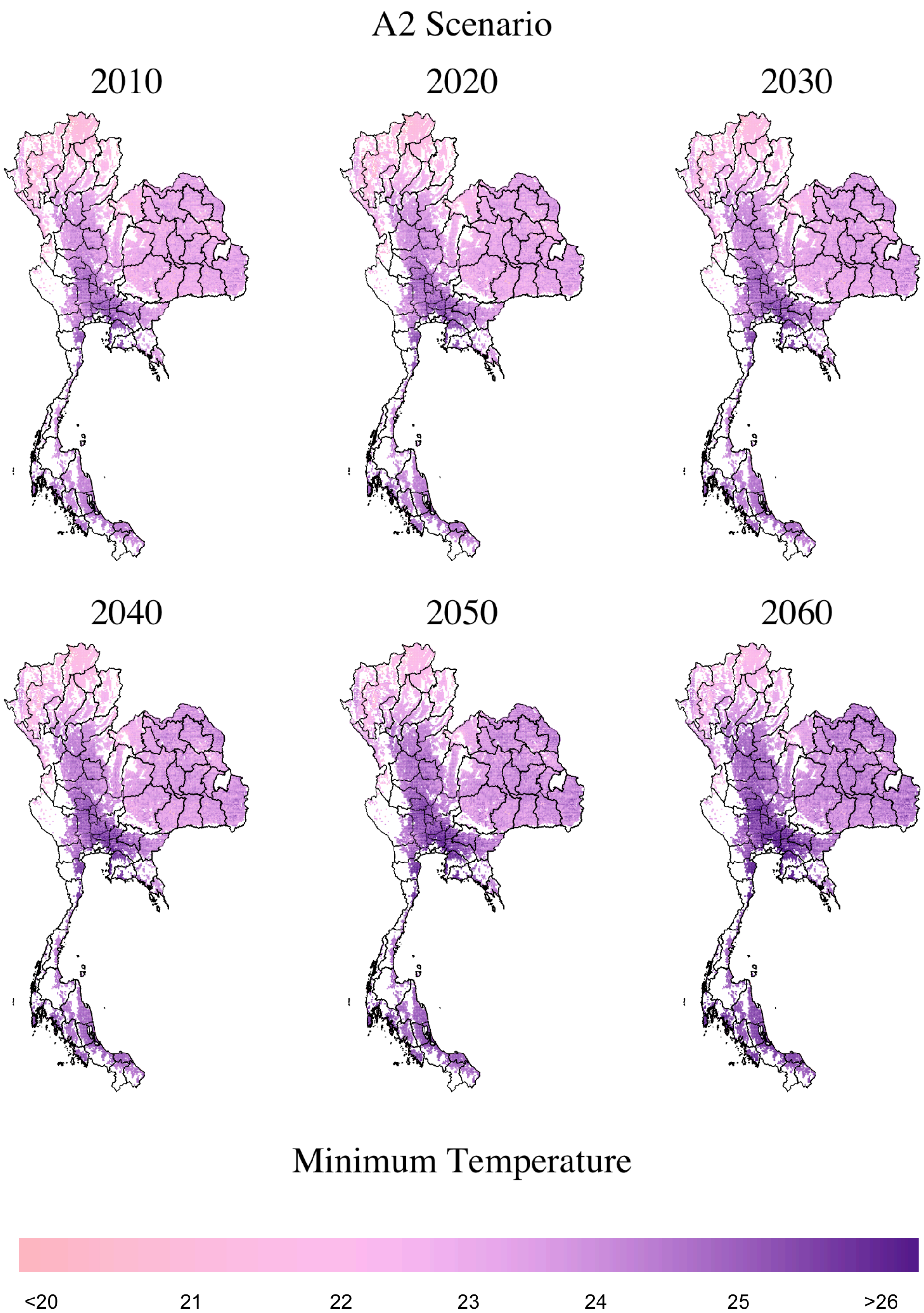
Notes: Projected average maximum temperature over the current growing season by decade under the A1B climate scenario. Temperature is in degrees Celsius.

Figure 11: Forecast Precipitation During Growing Season



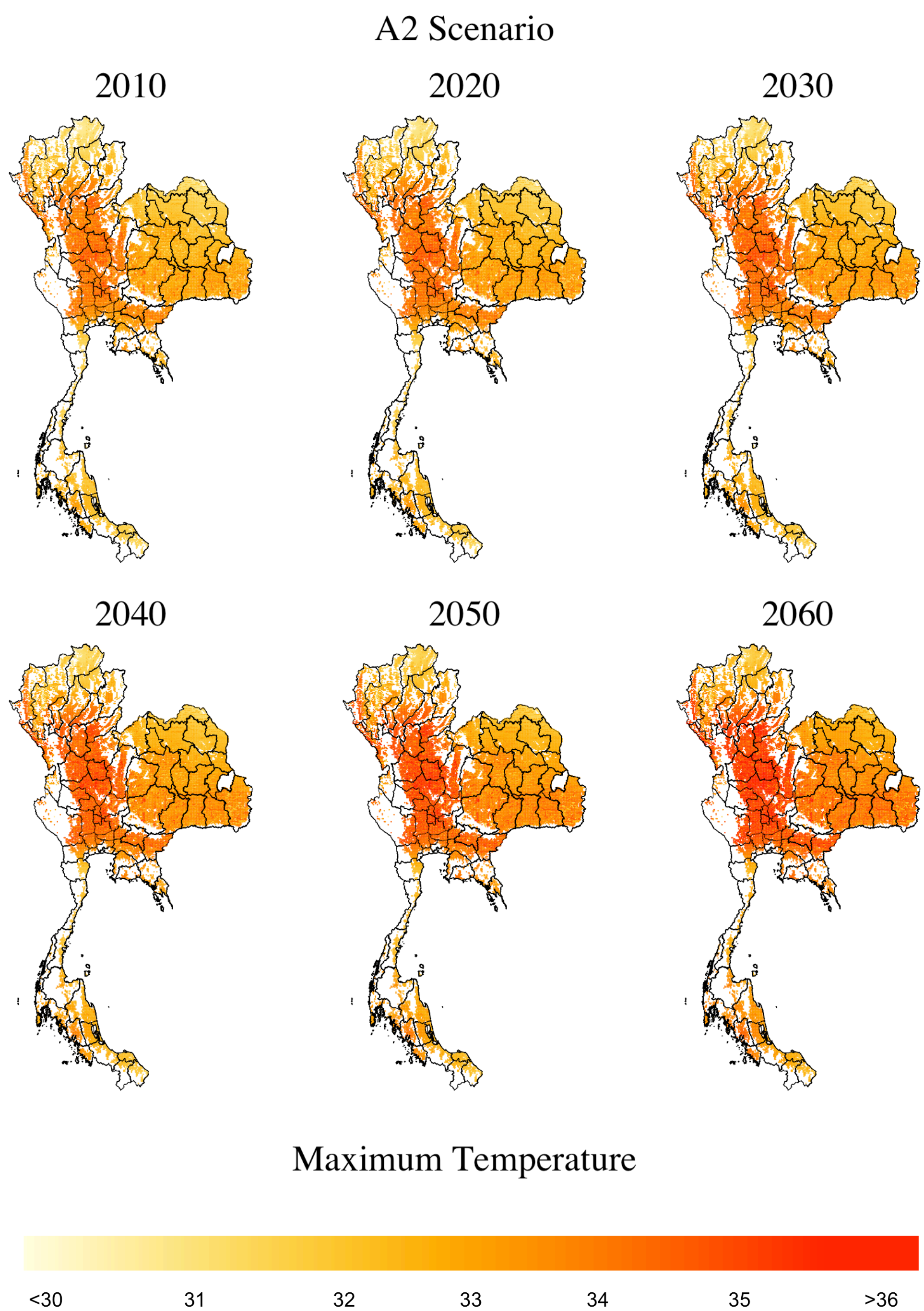
Notes: Projected total precipitation over the current growing season by decade under the A1B climate scenario. Precipitation is measured in millimeters.

Figure 12: Forecasted Minimum Temperature During Growing Season



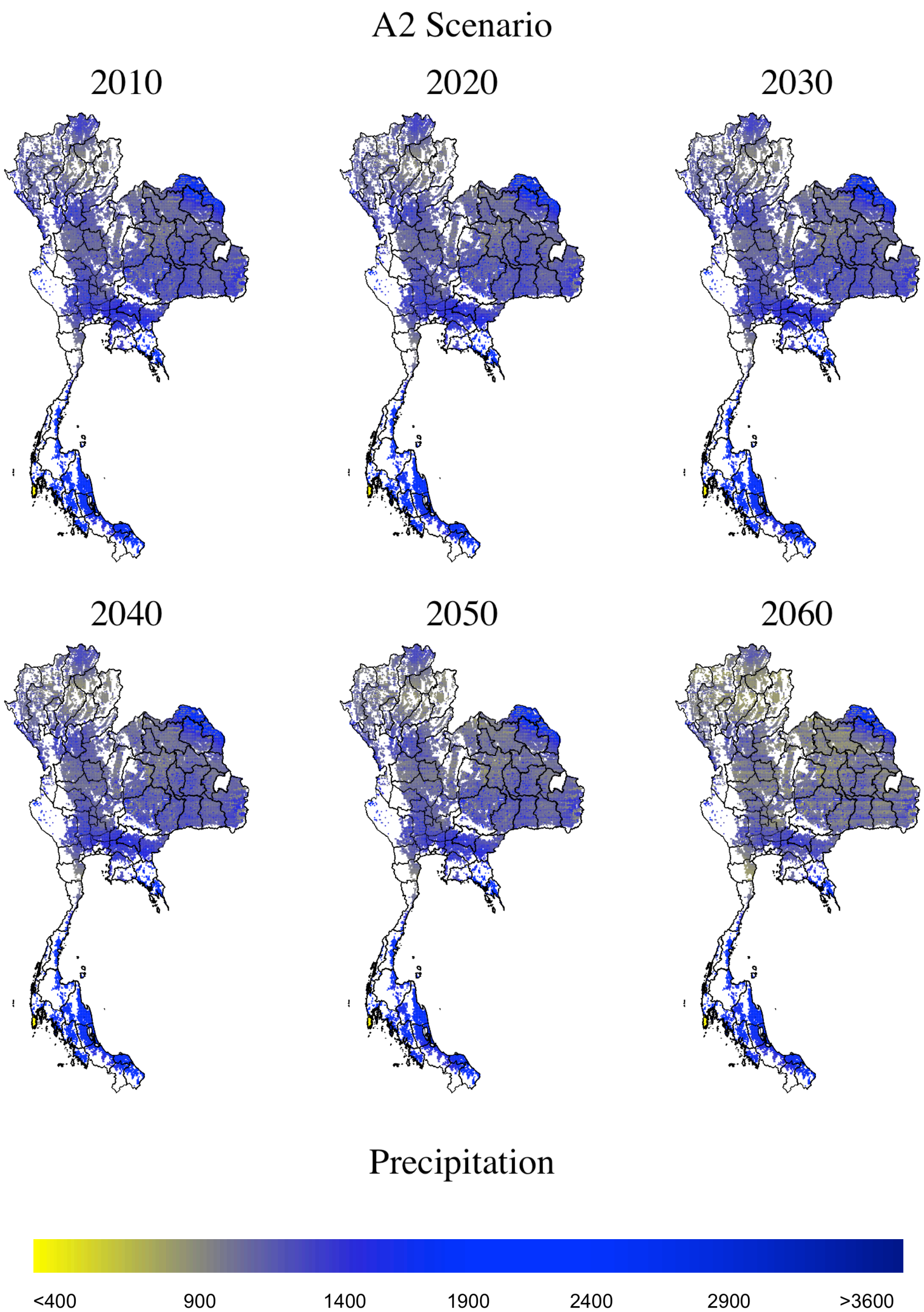
Notes: *Projected average minimum temperature over the* ***current*** *growing season by decade under the A2 climate scenario. Temperature is in degrees Celsius.*

Figure 13: Forecasted Max Temperature During Growing Season



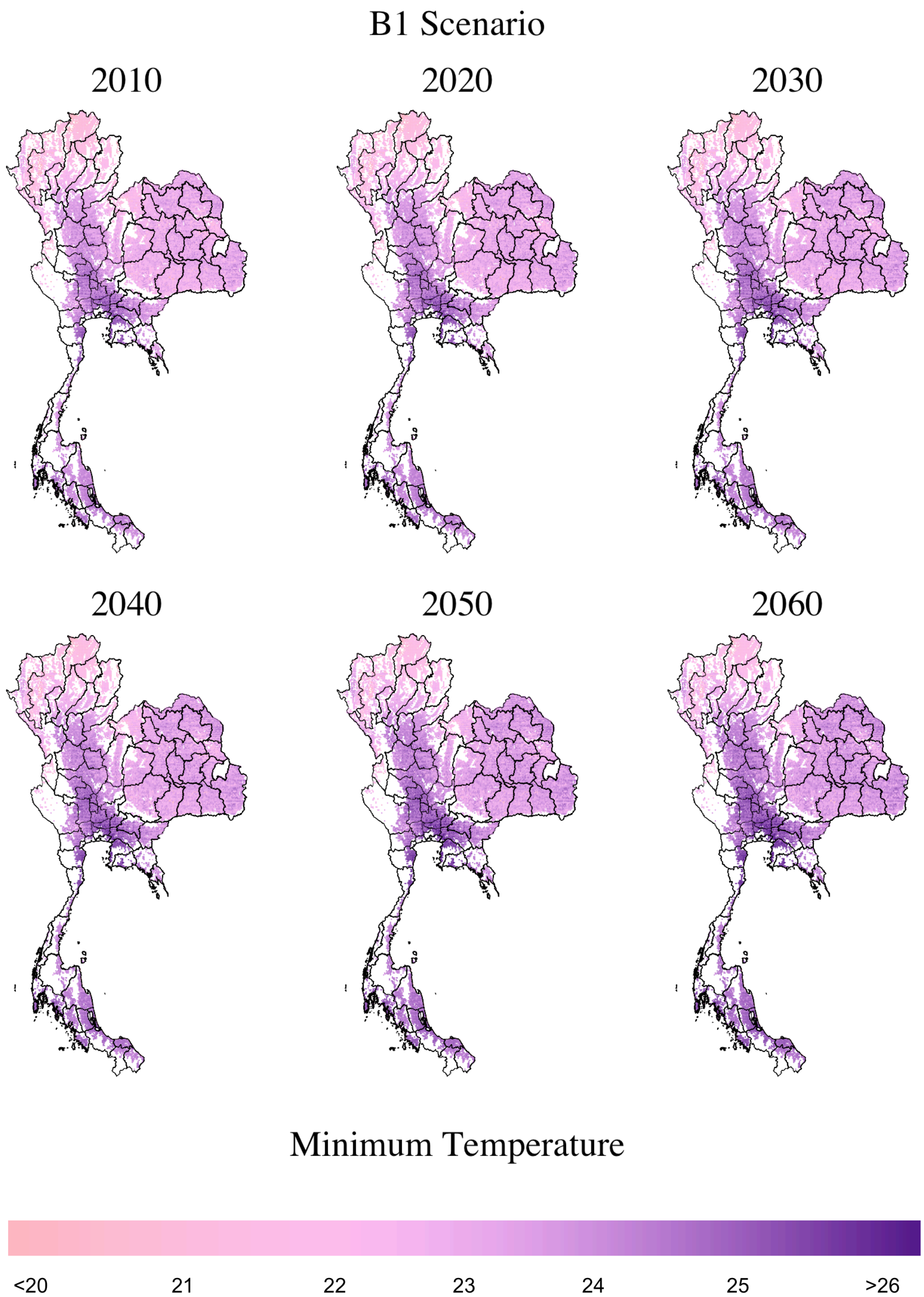
Notes: Projected average maximum temperature over the current growing season by decade under the A2 climate scenario. Temperature is in degrees Celsius.

Figure 14: Forecasted Precipitation During Growing Season



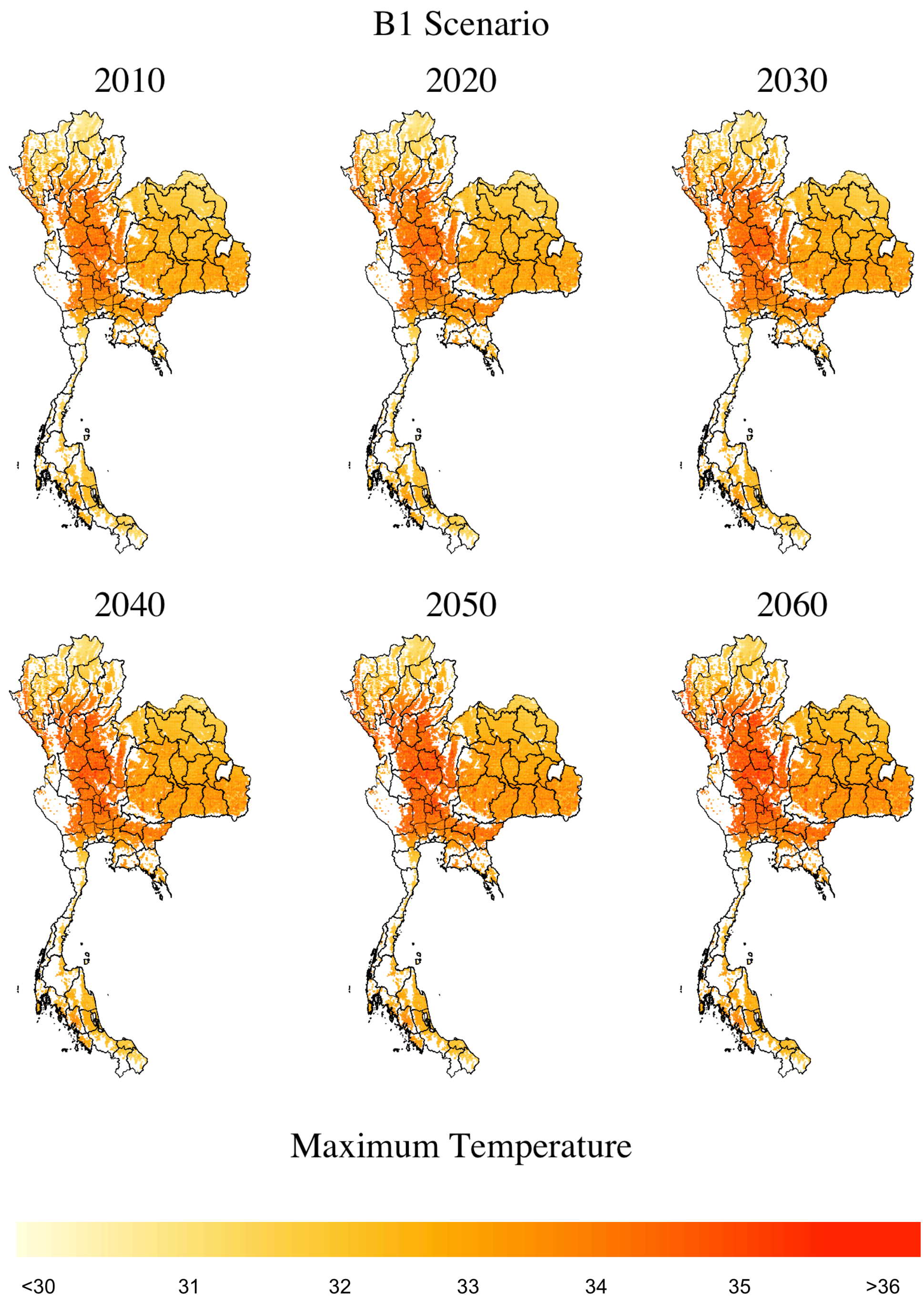
Notes: *Projected total precipitation over the* ***current*** *growing season by decade under the A2 climate scenario. Precipitation is measured in millimeters.*

Figure 15: Forecasted Minimum Temperature During Growing Season



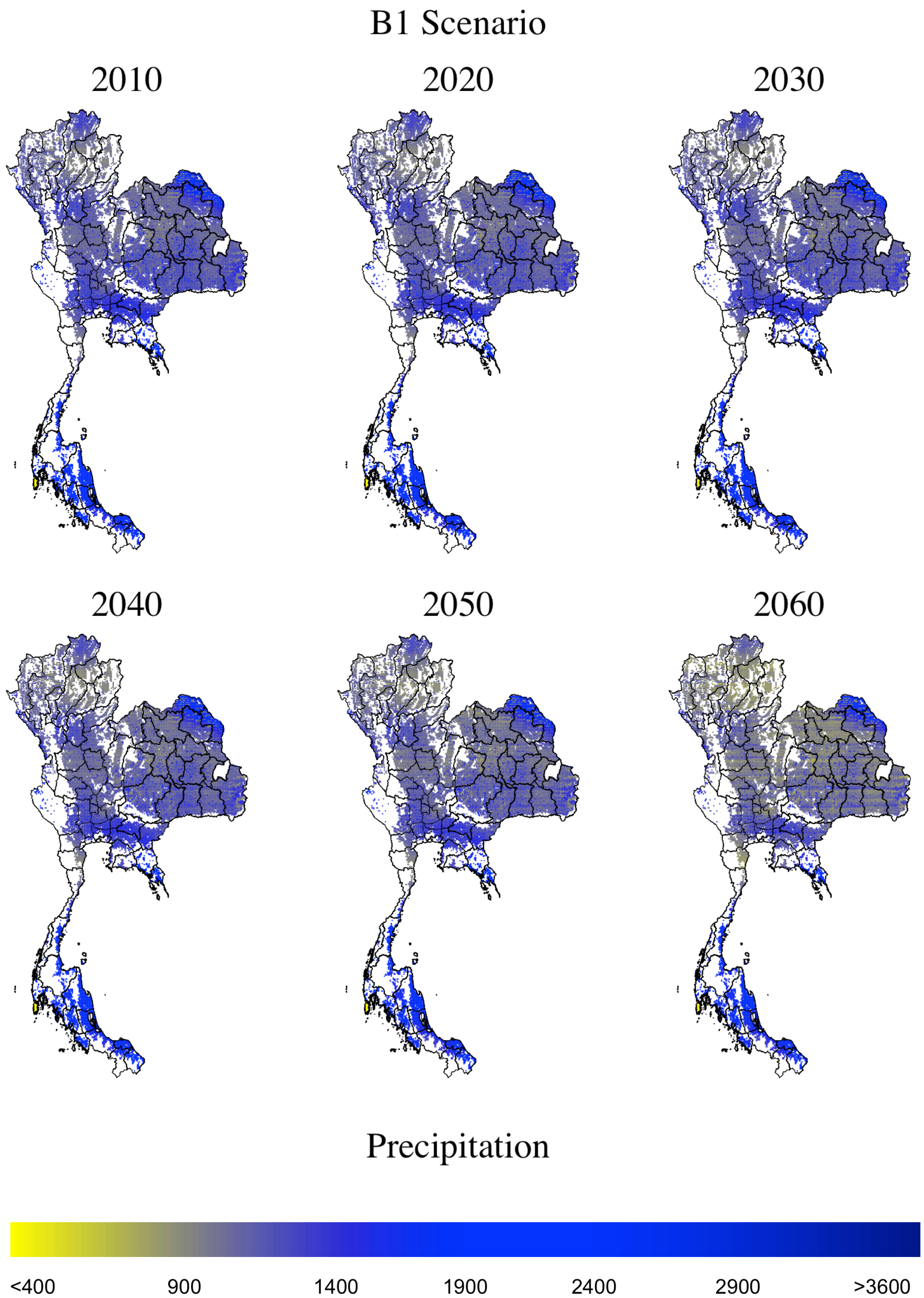
Notes: *Projected average minimum temperature over the* ***current*** *growing season by decade under the B1 climate scenario. Temperature is in degrees Celsius.*

Figure 16: Forecasted Max Temperature During Growing Season



Notes: *Projected average maximum temperature over the **current** growing season by decade under the B1 climate scenario. Temperature is in degrees Celsius.*

Figure 17: Forecasted Precipitation During Growing Season



Notes: *Projected total precipitation over the* ***current*** *growing season by decade under the B1 climate scenario. Precipitation is measured in millimeters.*

8 Yields Under Future Climate Scenarios

In order to evaluate the potential impacts of climate change on the rice sector in Thailand, we use the models developed in the previous section to predict yields under various climate scenarios. First, future conditions are estimated for each GCM under each of the three economic scenarios (A1B, A2, B1). Projected changes in temperature (precipitation) are added (multiplied) to historical 30-year averages in order to predict future climate conditions. These projections are then plugged into the statistical yield models to predict decadal yields up to 2060 under climate change. As a baseline, we estimate yield potential under no climate change. These estimates take the average weather conditions over the past 30 years and use them to forecast future yields assuming a constant rate of technological progress. The yield potential under no climate change is then subtracted out from the climate change yield forecasts in order to estimate relative losses. In other words, our estimates compare forecasted rice yields under the various climate change scenarios to rice yields forecast along the present trend. We take this approach to estimate potential climate impacts for each of our models, with predicted climate change conditions for each of the 18 GCM models, under each of the three economic scenarios. We then calculate the median yield predictions across GCM models to represent our estimates for each of the three climate scenarios.

Figures 9, 10 and 11 show the dispersion across climate models under the A1B economic scenario. The linear model predicts smaller yield losses of 1-5 percent through 2050. The piecewise linear model, however, predicts larger losses of 10-15 percent through 2050. This difference arises because much of the rice growing area presently experiences temperatures close to the upper threshold of optimal rice growing conditions. Sufficiently large increases in temperature would force more of the rice growing area out of the optimal temperature range.

From A1B climate change, however, most areas are projected to miss out on 10-15 percent of rice yields by 2050.

8.1 Putting Our Results in Context

Several other recent projects have investigated linkages between climate change and the Thai agriculture sector. ARCC (2012) review many of these types of studies carried out in the region and conclude that previous studies have come to a wide range of conclusions about potential impacts on agriculture in the region.

Several case studies have highlighted important facets of the issue. MWBP (2005) and Oxfam (2009) case studies highlights farmer perceptions of climate change. MWBP (2005) finds that farmers worry about both floods and droughts, but that droughts are considered less desirable due to increased fishing opporutnities associated with floods. Oxfam (2009) and Rattana, K., and Krawanchid, D. (2012) both found that farmers biggest worry was that rainfall would arrive too late in the season. Researchers in the study also carried out an intervention where they provided loans for constructing irrigation technologlies. They found that providing capital to assist in building these technologies allowed farmers to depend less on rainfall in order to plant at the desired time and improved yields overall. Suddhiyam et al found that farmers perceive an increase in the number of extreme weaterh events recently. This is in contrast to WMBP (2005) where farmers interviewed felt that neither droughts nor floods were more common that have been historrically.

A number of case studies have also examined what types of adaptations farmers have taken in the past. Suddhiyam et al observe that farmers alter their choice of crop, adjust planting season, and move some crops (partiuclarly those inteded for consumption) to locations less vulnerable to flooding or other damages. Chinvanno et al (2008) observed that seasonal and permanent migration to cities were common forms of adapation in their case study. Farmers also changed seeds to varieties that are more robust to extreme conditions.

Chivanno (2013) proposed a more broad framework for analyzing cliamate impacts that incoporates sectors outside of agriclture. The author conducts a case study of Krabi province and examines other sectors such as tourism and how they might be affected by climate change.

In addition to the exclusively Thai studies, several regional studies discuss parts of Thailand. START (2006) studies the impact of climate change on hydrological conditions and note that rainfed rice production is particularly vulnerable to water shortages.

Of all the studies, the recent study by CIAT (2012) is most similar to ours in scope and purpose. That study used crop models to predict changes in suitability of growing conditions for 15 crops out to 2050 under the IPCC A1B scenario climate change. That study provides useful comparison findings related to our research.

The CIAT report offers independent discussion of the progression of climate conditions in Thailand over the past 100 years, more detailed than our examination of weather changes over the past 30 years. CIAT uses a different data set and a different interpolation approach, however, it is reassuring that the climate trends they describe in recent decades closely mirror our own results.

Generally, our findings regarding the vulnerability of individual crops are also similar. For example, both reports identify longan as one of the most vulnerable crops and cassava as one of the most robust. Results are also comparable for maize, oil palm, and sugarcane. Our results for rubber and durian are slightly more optimistic, while our forecasts for soybeans are more pessimistic. Both reports acknowledge the inherent uncertainty associated with these crops in particular.

The crop forecast with the biggest discrepancy across reports is also the most important; rice. CIAT forecasts a 0-1.5% *increase* in rice yield by 2050 under the A1B climate change scenario while we forecast a 12-15% *decrease* in yields[2]. It should be noted that rice is divided into different groups in each report. The CIAT report divides rice into the KDML 105 strain and all others while we divide rice into primary crop and second season crop. There are several possible reasons for this discrepancy across studies. One issue is that the CIAT study identifies rice as one of the crops with the highest associated uncertainty as determined by range of forecasts across different climate models. However, the most notable difference, which is present across the results for most crops, is the mechanism identified as the driver of climate impacts. Their model identifies rainfall as the primary driving force while we rising minimum temperatures to be the salient risk factor. This difference is quite important and should be further elucidated as it would lead to very different predictions and adaptation responses.

The difference in rice results most likely arises from the contrasting methodologies

[2] *In our linear specification where we do not take into account differential effects of extreme heat, we find a 1-3% decrease in rice yields. However, once we account for the non-linear impacts of extreme temperatures, we find the much larger effect described above.*

applied. The CIAT study uses a model of crop growth (Ecocrop) that is parameterized to each crop in order to evaluate suitability based on climate conditions. Parameters used in the Ecocrop model include measures of both ideal and possible ranges of climate variables for crop growth. Essentially, an understanding of growing conditions suitable for each crop is applied to climate projections in order to evaluate how suitability will change. In contrast, our approach uses statistical models based on historical relationships between yields and climate variables, which are in turn projected to 2050 using climate model outputs. Therefore, our results are driven by historical observation. For example, in years where minimum temperatures were higher than normal in particular areas, we observe significantly lower yields in those areas. This suggests that rice yields respond negatively to rising minimum temperatures. We control flexibly for differences across provinces, trends over time, and irrigation extent.

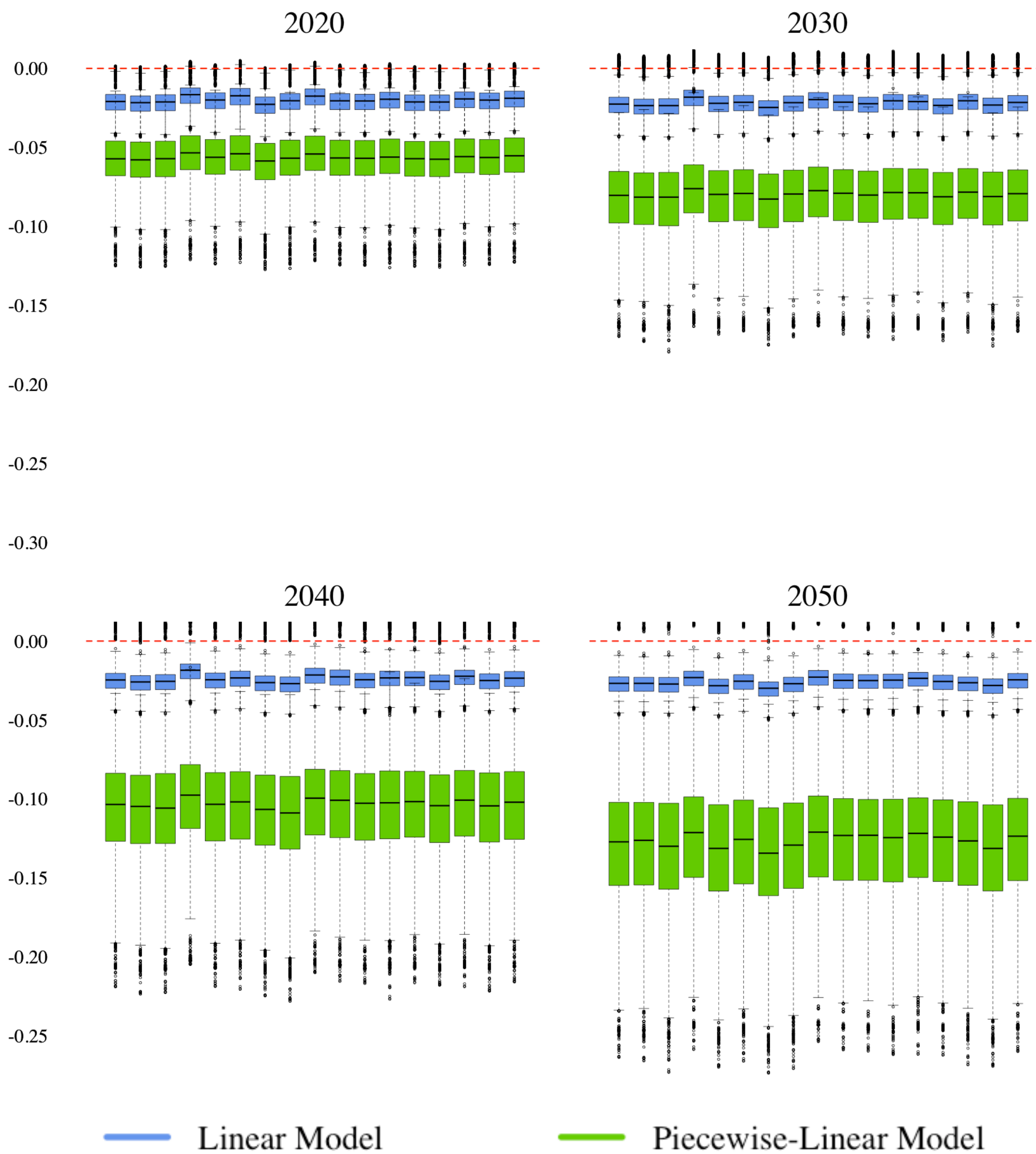
The result that minimum temperature is a driving factor of rice yields is supported by many studies using a wide variety of methodologies. While we use provincial-level panel data, similar results have been found in studies using statistical models with field-level panel data (e.g., Felkner: 2009, Welch: 2010), using controlled laboratory experiments (e.g., Yin et al: 1996), and using other crop models (e.g., ORYZAI and SIMRIW crop models in Mathews et al: 1997 and ORYZA2000 and EEQ crop models in Sheehy et al: 2006, Krishnan *et al.* (2007), Konn et al (2001) ; DSSAT in Jintrawet and Chinvanno 2009). Consequently, we are confident that our finding that minimum temperature is a driving factor for rice yields is not a product of our methodology or data. Admittedly, our model may fail to capture the full extent of rainfall's impact due to the difficulty of incorporating an annual measure of rainfall that accurately represents its effect on rice yields. That being said, underestimating rainfall's importance is unlikely to bias our results for minimum temperature and would not change our ultimate finding that rice yields are likely to decrease by 2050 absent adaptation.

At least one crop model study (Jintrawet and Chinvanno (2009)) found that rice yields would slightly increase in the future.

Aside from rice, a few studies have examined potential effects of cliamte change on other crops. Chinvanno (2004) and Chinvanno and Snidvongs (2005) tested the impact of climate change on maize, sugar, and cassava in various locations in Lao PDR and Northeast Thailand. They found that….

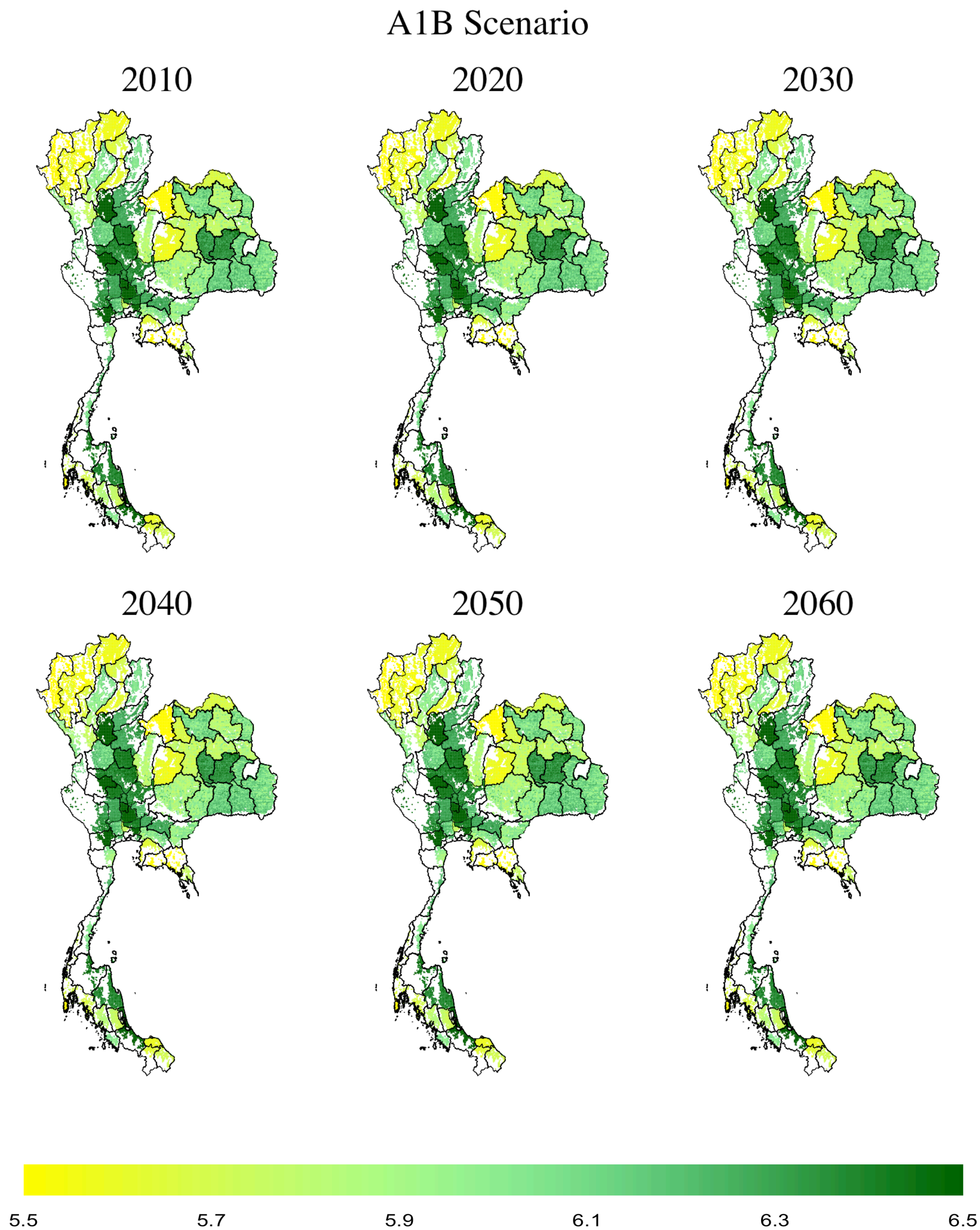
Herrera et al (2011) examine threats to cassava production. They find that…

Figure 18: Predicted Yield Change Across GCM and Statistical Models (A1B Scenario)



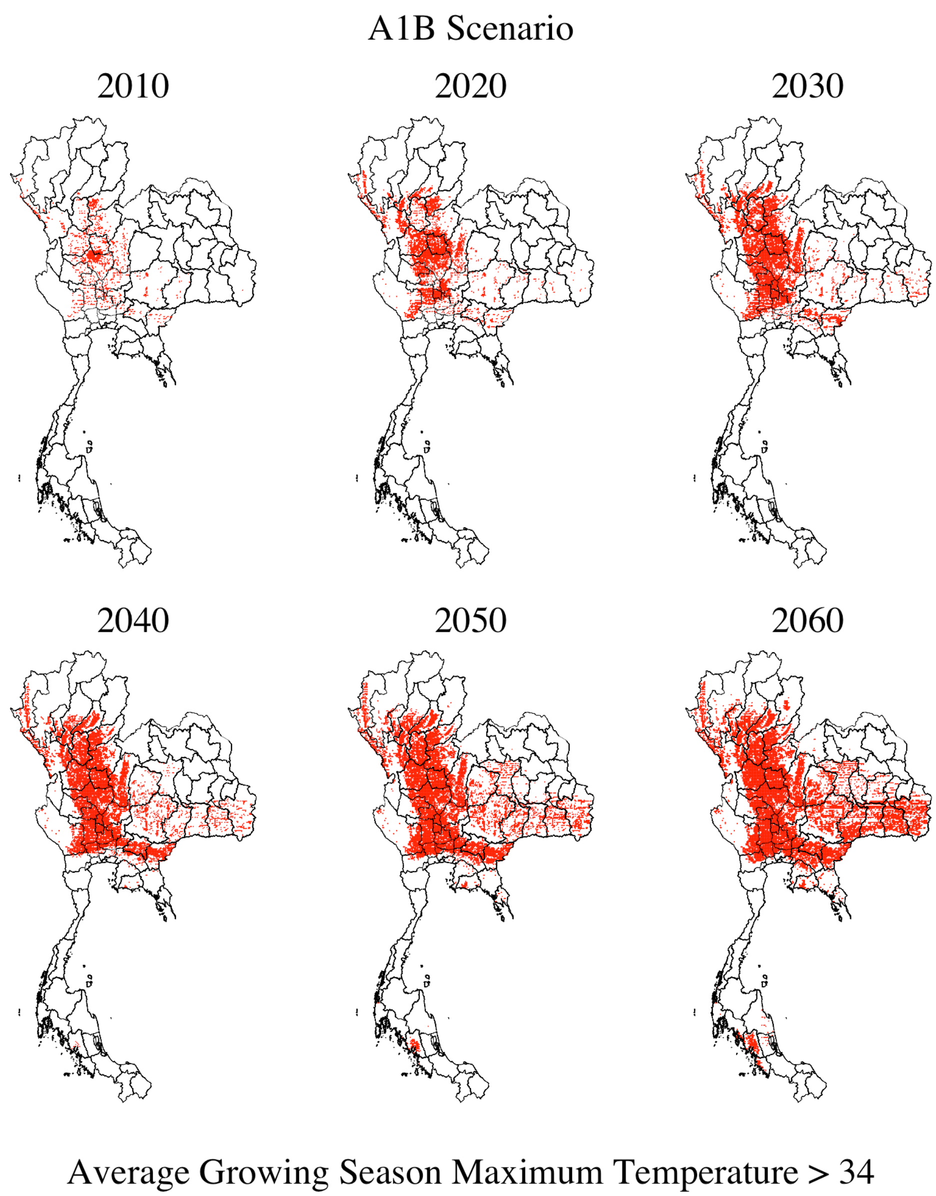
Notes: Statistical model predicted yield change across GCM models. Each box represents a different GCM and the dispersion is across rice growing areas. Under the linear model (blue) all areas are expected to lose potential yields from A1B climate change, however, even by 2050 most losses are projected to be less than 5% of potential rice yields. Under the piecewise-linear model (green), approximately 5% of areas are expected to benefit from A1B climate change, however, most areas are projected to lose 10-15% of potential rice yields by 2050.

Figure 19: Linear Model Yield Forecasts Under A1B Scenario



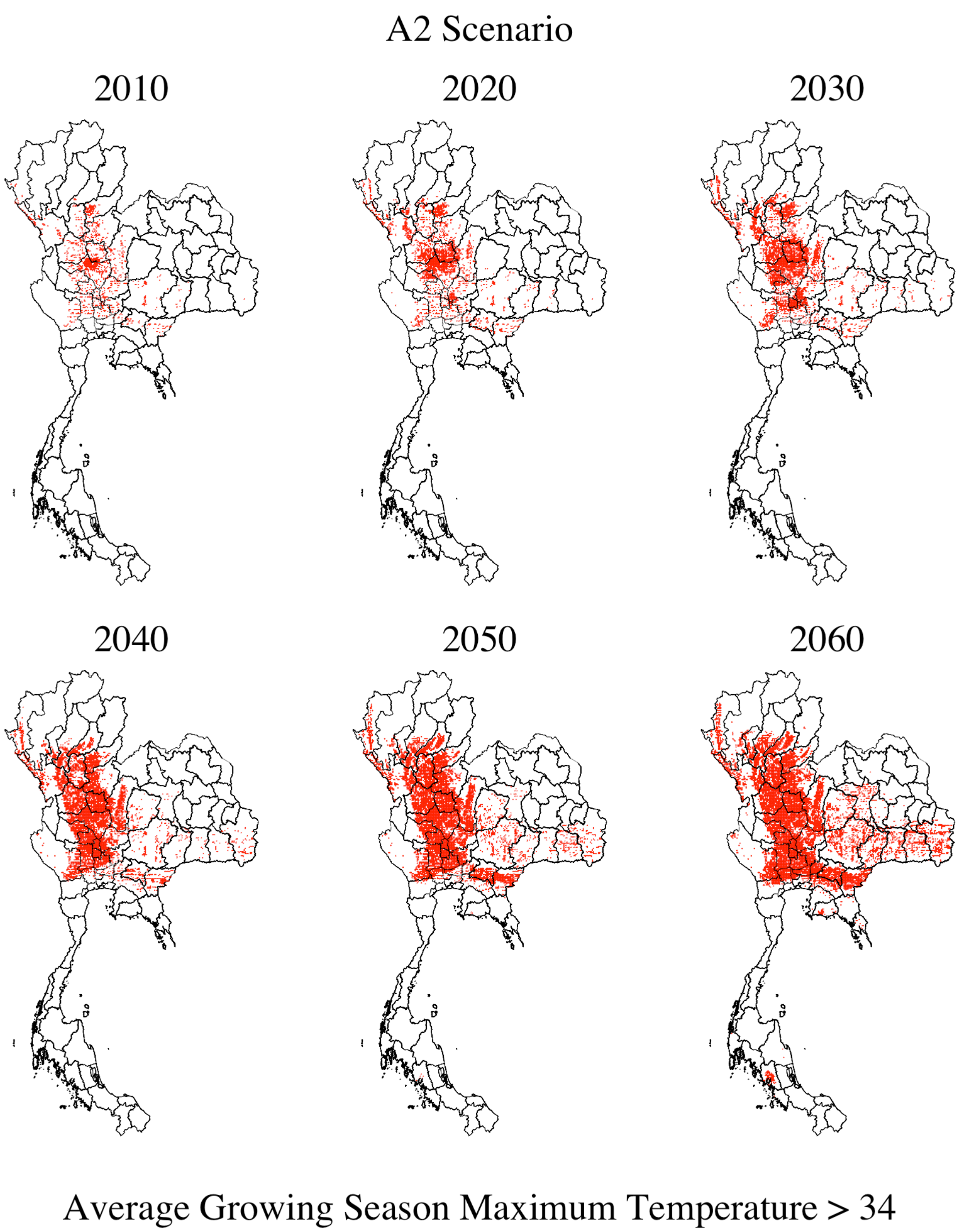
Notes: *Figure 19 shows yield predictions using the linear model under the A1B climate scenario. Units are log yield (kg/rai).*

Figure 20: Rice Growing Area Over the Negative Threshold for Maximum Temperature



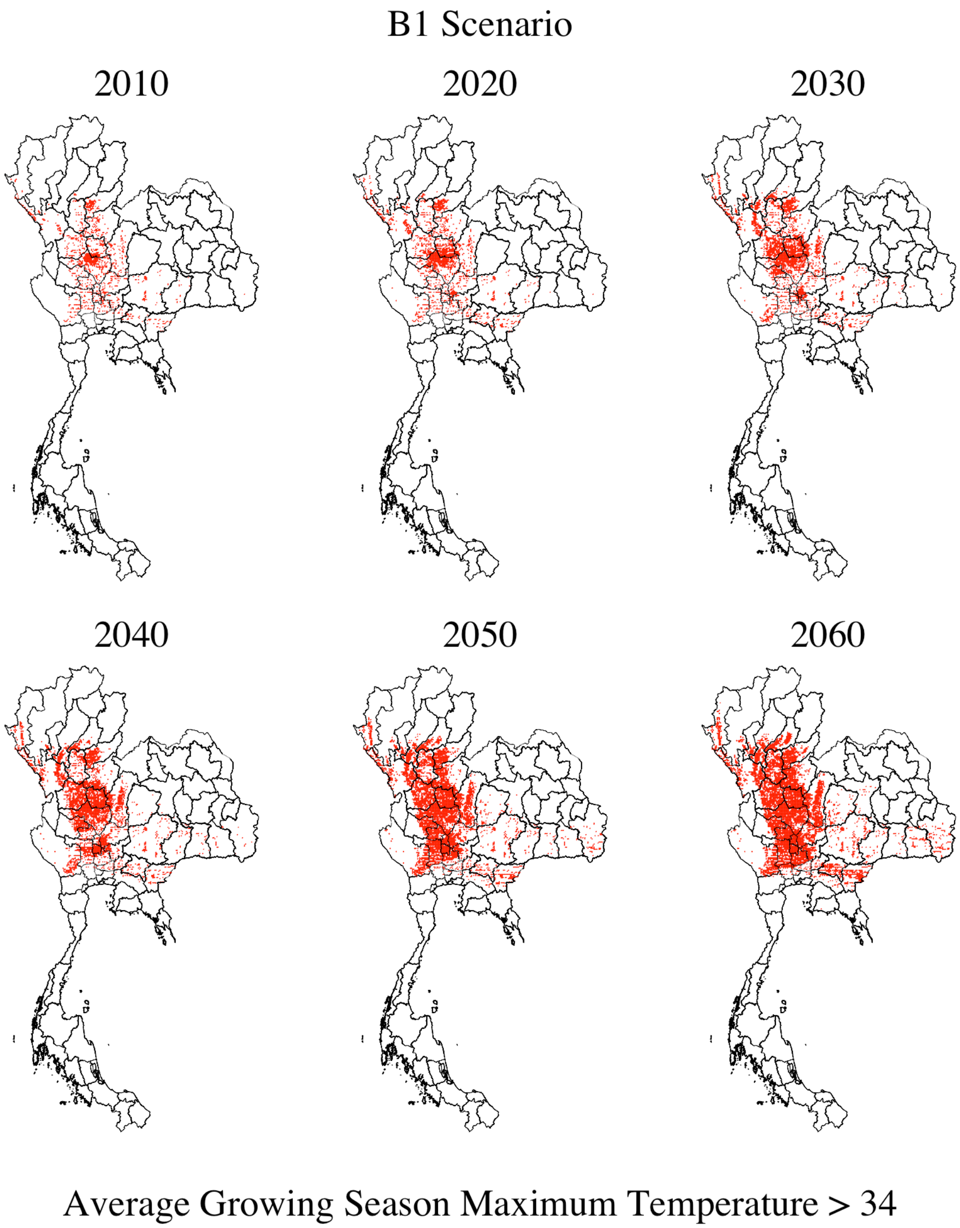
Notes: *Figure shows the rice growing area forecast to have an average growing season daily maximum temperature over 34 degrees under the A1B climate scenario. Forecasts used here are medians forecasts across 18 GCMs. The 34-degree threshold, estimated in the piece-wise linear model, is the temperature above which maximum temperature is expected to be strongly harmful to rice yields. Under the A1B climate scenario, the percent of rice growing area above the threshold rises from less than 5% in 2010 to more than 45% in 2060.*

Figure 21: Rice Growing Area Over the Negative Threshold for Maximum Temperature



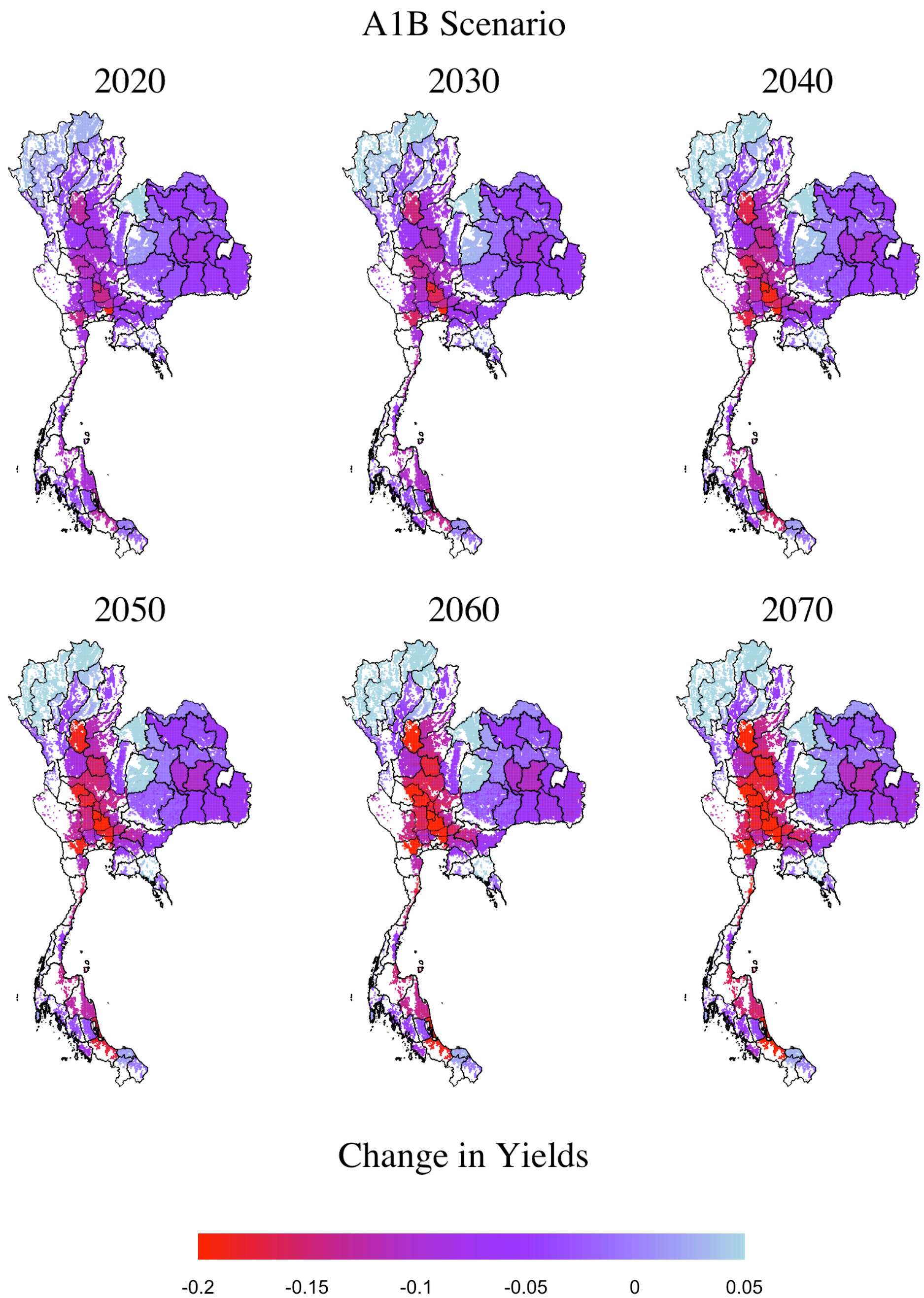
Notes: *Figure shows the rice growing area forecast to have an average growing season daily maximum temperature over 34 degrees under the A2 climate scenario. Forecasts applied here are median forecasts across 15 GCMs. The 34-degree threshold, estimated in the piece-wise linear model, is the temperature above which maximum temperature is expected to be highly harmful to rice yields. Under the A2 climate scenario, the percent of rice growing area above the threshold rises from less than 5% in 2010 to more than 35% in 2060.*

Figure 22: Rice Growing Area Over the Negative Threshold for Maximum Temperature



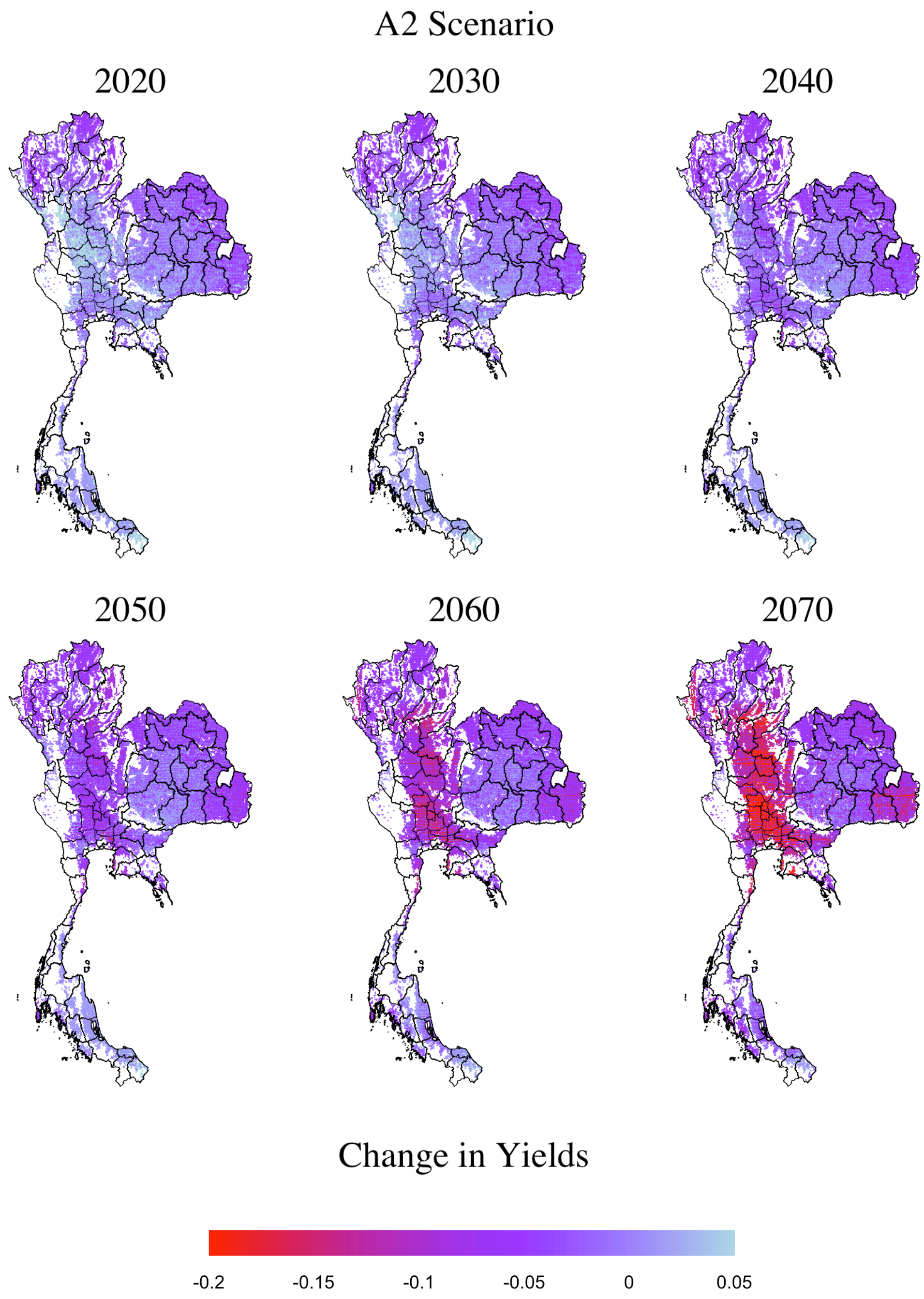
Notes: *Figure shows the rice growing area forecast to have an average growing season daily maximum temperature over 34 degrees under the B1 climate scenario. Forecasts applied here are the median forecasts across 21 GCMs. The 34-degree threshold, estimated in the piece-wise linear model, is the temperature above which maximum temperature is expected to be highly harmful to rice yields. Under the B1 climate scenario, the percent of rice growing area above the threshold rises from less than 5% in 2010 to approximately 25 % in 2060.*

Figure 23: Yield Gains and Losses Predicted by Piecewise-Linear Model



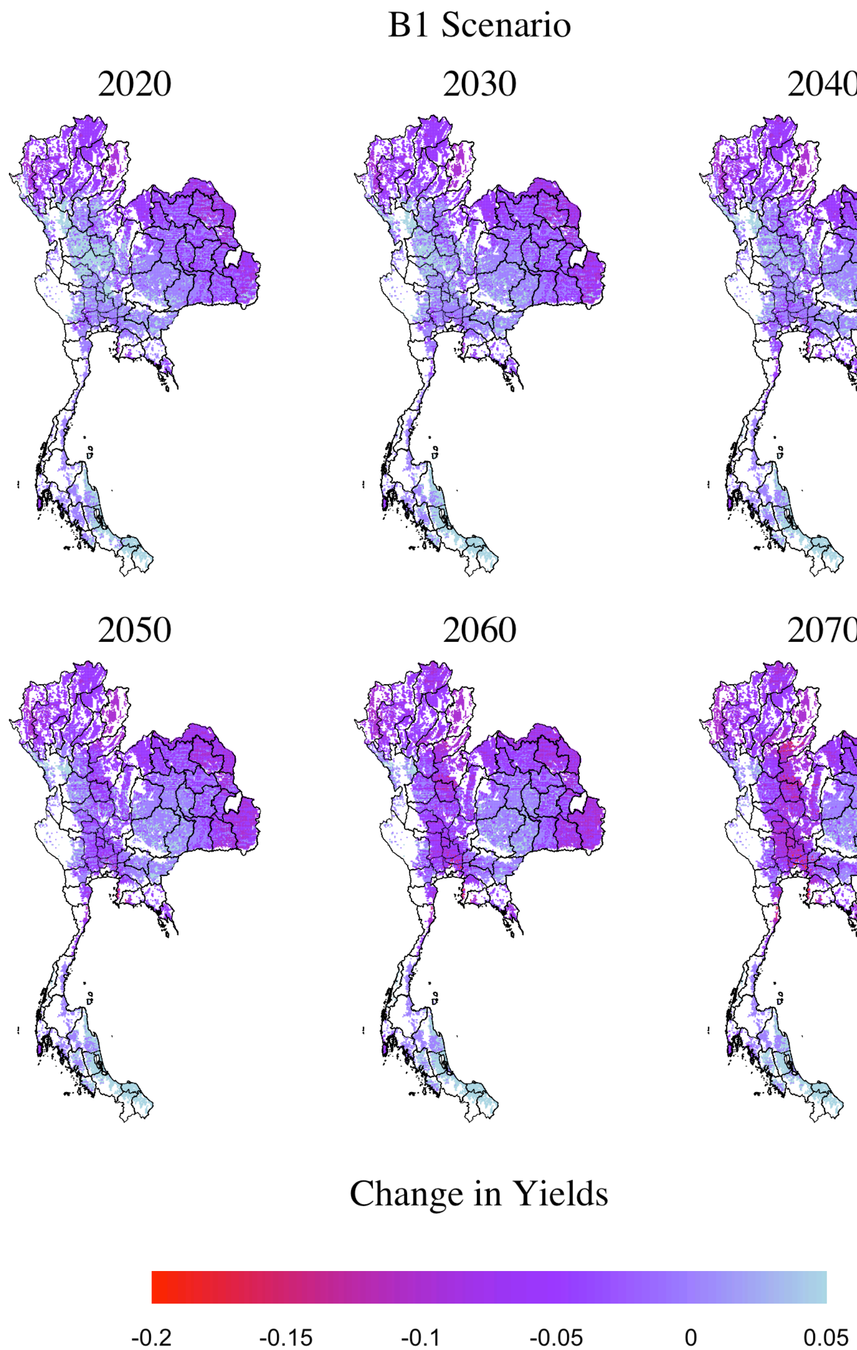
Notes: *Figure shows relative yield changes under A1B scenario climate change. Forecast yields under climate change are measured relative to baseline yield predictions, which are forecast along present trends under historical weather conditions. Under the A1B scenario, some provinces gain from weakly higher maximum temperatures and changing rainfall patterns. Yields in relatively hotter areas are negatively effected by both rising minimum and rising maximum temperatures.*

Figure 24: Yield Gains and Losses Predicted by Piecewise-Linear Model



Notes: *Figure shows relative yield changes under A2 scenario climate change. Forecast yields under climate change are measured relative to baseline yield predictions, which are forecast along present trends under historical weather conditions. Under the A2 scenario, several provinces initially gain from weakly higher maximum temperatures as well as shifting rainfall patterns. In the longer run, yields in relatively hotter areas are negatively effected by both rising minimum and rising maximum temperatures.*

Figure 25: Yield Gains and Losses Predicted by Piecewise-Linear Model



Notes: *Figure shows relative yield changes under B1 scenario climate change. Forecast yields under climate change are measured relative to baseline yield predictions, which are forecast along present trends under historical weather conditions. Under the B1 scenario, many provinces gain from weakly higher maximum temperatures as well as shifting rainfall patterns. In the longer run, only yields in the hottest areas suffer losses nearing 20%.*

9 Opportunities for Climate Adaptation in the Rice Sector

As the preceding results suggest, Thailand has already experienced sustained changes in national and local climate conditions and will continue to do so over at least the next century. The implications of this climate change for agriculture are complex, but for some parts of the country adaptation will be essential. Adaptation responses will happen spontaneously, as they have over the expanse of human history, but policy makers can reduce adjustment costs and improve outcomes by facilitating adaptation that protects national food security and local livelihoods. To do this effectively requires detailed information on consequences, like that developed in this project, but also a careful review and comparison of adaptation options. In this section we discuss the salient opportunities for climate adaptation in Thailand's rice sector.

Before reviewing the salient public policy responses, it is worth considering the main private agent's behavior. Farmers have a variety of potential responses to climate change, including but not limited to the following:

- Improve farming practices
- Adjust growing season
- Improve water management efficiency
- Diversify crops
- Diversify income sources with off-farm employment
- Leave agriculture

As climate conditions continue to shift, individual farm households will continuously review their options. The greater the shift in the enviroment, the more likely they will consider adopting some combination of the above responses. Since neither the farmer or the Government of Thailand can alter the underlying climate process, the task of the public sector should be to guide private responses in directions that are most likely to limit social costs and capture potential social benefits. We review these options below.

9.1 Extension Services

Thailand already has a wide array of services to promote farm-level productivity, and extension services will be the first line of defense for climate adaptation in rice and other agricultural activities. This is also the broadest and most diverse category of opportuntities to reduce adaptation costs and even promote investments that can improve livelihoods. The main extensions challenges, as usual, are the following :

1. Identify needs
2. Develop or source hard (technological) or soft (institutional) innovations to meet those needs
3. Provide the information required to promote adoption of the new technologies or institutional arrangements
4. Address financial needs for adaptation, including investment requirements, learning costs, etc.
5. Address market access issues related to new products and production practices.

Each of these components is essential to successful agrifood extension service, and the present research contributes only to the first of these. Clearly, climate change adaptation will be a complex agenda for public policy, but the nation's food security and the livelihoods of its rural majority must be protected from this systemic risk.

9.2 Public Information

One of the most effective ways for governments to enlist private agency in ways compatible with public interest initiatives is to improve the quantity and quality of information available to the public. To facilitate more effective climate adaptation in this way, this means committing more public resources to timely and detailed information about expected climate processes and their consequences. Several general categories of this kind of public information are of special importance.

Weather Forecasting

Weather forecasting is probably the oldest and best-established public information service to agriculture, but climate change gives it new significance and presents new challenges to forecasters. Our understanding of climate change science is evolving rapidly, and our forecasting methods need to take this into account with more intensive analysis of recent historical weather patterns. Combined with a shorter retrospective view, we need a longer prospective view for forecasting, in recogition of the fact that some changes once thought to be cyclical may in fact be trends (rising temperature, shifting rainfall patterns, etc.). In all these areas, weather forecasting can help private actors make the longer-term commitments needed to adapt to a changing environment.

Early Warning Systems

As part of its weather/climate forecasting services, the government should support public and private contingency planning by investing in early warning capacity. This would include, but not be limited to, enhanced capacity to detect high amplitude weather events such as severe storms, heat waves, cold spells, droughts and floods. General weather forecasting provides information about relatively smooth trends in averages for these environmental state variables. An early warning system would more intensively research variance around these trends. In addition to research capacity and dissemination standards, an effective early warning system should include infrastructure for communication, protocols for decentralization/localization of warnings, and contingency planning for civil responses. The response component would require determined coordination across public agencies at the national, provincial, and local levels.

Risk Mapping

A more passive information that could be part of the foundation for early warning services would be risk mapping. Using forecasting methods like those developed in this project, the government can produce standardized and regularly updated maps reflecting anticipated short-, medium- and longer-term climate conditions. With the government disseminating these over low-cost media like the internet, the public can update and harmonize their expectations as soon as new information becomes available, reducing adjustment costs and improving coordination between public and private adaptation response.

9.3 Water Infrastructure

Water management is critical to productive and sustainable agriculture, and changing climate conditions will present new challenges to existing soft and hard water infrastructure. Of special importance, as usual, will be water management adaptation that deals with extremes—water scarcity (drought) and excess (floods). In this context, climate science clearly reveals a new generation of challenges, with increased seasonal variability in rainfall combined with more frequent and severe storms. The methods used in this project can contribute to better identification of areas at risk of moderate and severe drought, as well as highlighting shifting patterns of natural water allocation. This kind of information can strengthen collabortion between agencies responsible for strategic planning in agriculture, public works, and hydropower.

9.4 Genetic Research and Development

There is already a robust global research industry dedicated to developing climate change-tolerant or adaptable genetic varieties of food crops, horticultural products, and livestock. Because of the yield risk patterns revealed in the present research, it is clear that Thailand should be an active participant in this research. National initiative in this areas makes sense not just to assert scientific leadership or promote fundamental agbiotech research, but because any innovations developed elsewhere will have to be localized to Thai conditions if they are to make optimal contributions to food security, livelihoods, and overall sustainability.

Fortunately, Thailand already has very advanced agrifood research capacity, both public and private. Climate change presents a new opportunity to capture returns from investment in this knowledge-intensive, high wage sector, includiing the prospect of global competitive advantage from discoveries and new, climate-resilient products. Given the country's size and geographic diversity, Thailand is also a good incubator of emerging agrifood innovations, making it an attractive partner for innovation research investment by foreign partners. Just as the Thai food processing sector leveraged foreign partnership in the early days of its emergence, agbiotech and advanced agronomy research in Thailand can be a platform for jointly financed new variety and technology development, the benefits of which will be reaped in both home and export markets. In this way, the challenge of climate adapation can become a golden opportunity for innovation.

9.5 Crop Diversification

For any existing stock of crop and livestock varieties, farmers will strive to produce combinations that maximize their welfare and economic security. Even in the unlikely event that today's production patterns are optimal, climate change will alter the conditions of production. Thus it is reasonable to expect that today's geographic patterns of cropping and animal production could be improved by adaptation. Given the uncertainties involved in this process, private agents will be at a disadvantage in making these adjustments, particularly the poor who have limited access to information about new varieties and limited capacity to invest in them.

In this context, better climate forecasting will only be partially helpful. It will be just as important to support farm responsiveness with information about new crop/animal yield performance, production practices, and even new credit mechanisms to facilitate adoption. As we have seen many times, in response to migration, land clearing, and land reclamation, farmers can establish new practices and adapt to widely varying conditions. The agriculture ministry can significantly facilitate this by reducing information costs, technology access, market uncertainty, investment barriers, and other systemic risks of structural change in agrifood production.

Special emphasis in this and other policy contexts should be placed on smallholders, who remain the majority of operators in Thai farming. Larger operators are better able to overcome adjustment hurdles at their own expense. While that lowers public adaptation costs, it also presents the possibility of excessive consolidation in the agrifood sector, with its attendant migration risks. A variety of market organization models can promote adaption/technology adoption without disrupting landholding patterns, includling contract farming, product certification, and cooperatives. The climate change agenda offers new opportunties to consider these kinds of institutional innovation, improving individual farm enterprise profitability and sustainablity at all scales of operation. This should be a high research priority for OAE and allied agencies.

9.6 Emergency Assistance

In situations where dramatic external shocks arise, assistance to rural poor and emergency measures to secure agrifood supplies are inevitable. For example, when global food markets experience sharp transitory price movements, governments may react defensively, increasing imports or limiting exports of essential products. Unfortunately, such policies often merely aggravate price volatility and increase adjustment costs, especially when the countries in question are large traders in their respective markets. More appropriate risk management in these circumstances usually takes the form of long-term buffer stocks.

In any case, emergency assistance is what the name implies: rapid response to dramatic unforeseen circumstances. We do not address this directly in the context of climate adaptation, which should be understood as a gradualist response to trend changes in environmental conditions. Having said this, however, a growing body of climate science suggests that with changing average temperature and precipitation levels will come increased variation in weather conditions, meaning more frequent and higher amplitude in weather shocks. This higher variability, including greater storm, drought, and flood severity, suggests that public investments in emergency response should be increased over time.

9.7 Crop Insurance

There is a large body of evidence suggesting that farmers (particularly smallholders) may underinvest in their production systems because of high systemic risks, especially those arising from weather and market prices. This risk aversion leads to lower long-term production because other factors of farm production are less productive, and farm enterprises generally are less resilient to transitory adverse shocks like flooding, drought, price swings, etc. In the aggregate, society then faces higher food security risk as the national food supply is reduced. To the extent that individual farmer risk could be pooled, regionally or nationally, this could increase farm-specific returns and promote individual investment.

Crop insurance schemes are designed to increase risk-adjusted smallholder returns in way, but private financial markets rarely offer these products becasue of high transactions and monitoring costs. Because food security and poverty alleviation are national priorities, however, some countries have supported public crop insurance. These programs can certainly be effective in terms of higher agrifood output, but they have complex incentive characteristics, and must be designed and implemented with care to avoid resource misallocation and inefficiency.

In Thailand, natural disasters, especially floods and droughts, have become increasingly common. In response, the Bank for Agriculture and Cooperatives (BAAC), in cooperation with Japan Bank for International Cooperation (JBIC), and Sompoh Japan Insurances (Thailand) signed the MOU to implement a crop insurance program for the rice smallholders, based on a standardized weather index. Thailand's first-ever crop insurance program aims to improve production risk management and enhance economic security for small farm families.

In 2011, the area coverage of the insurance effort comprised five provinces : Khon Kaen, Maha Sarakam, Roi-et, Kalasin and Nakhon Ratchasima in the northeastern region. This phase covered 6,713 farmers, with cultivated rice area of 35,775 rai, total insurance fees of 3,319,920 baht and the insurance coverage of 71,550,000 baht. To date, compensation of 141,000 baht has been paid to 90 farmers participating the program who suffered drought damages. In addition, insurance premiums of 1,404,498 baht were paid to 6,083 participating farmers who did not face such a disaster.

The program has since been extended to four more provinces : Burirum, Surin, Si-saket and Ubol Ratchathani. Those project participants are required to be BAAC clients who are borrowers for rice production. The insurance rate is 4.64 percent of the crop value to be insured. For example, a rice producer who makes request for a loan of 200,000 baht and who wants to insure his rice crop for 10,000 baht needs to pay an insurance fee of 464 baht. The policy began August 1, 2012. The growing period of 92 days is divided into two stages, the first of which ran from July 1 to July 31, 2012; the second stage started on August 1 and ended on September 30, 2012.

The compensation receivable is in case that the cumulative precipitation is equal to or less than the upper bound of the cumulative precipitation designated for each and every type of drought as described in the insurance policy; the farmer will be paid a rate of 10 percent compensation for drought occurring during the first stage, 15 percent for the disaster in the second stage, or 40 percent of the loan amount to be insured for a severe, season-wide drought event.

10 Conclusions and Recommendations

Expected long-term climate changes are expected to have far-reaching impacts on Thailand's agricultural sector, and effective adaptation will be essential to make those changes beneficial to rural livelihoods and food security. Increases in temperature average and variation, combined with greater seasonal variation in water resources, will change growing conditions around the country. More frequent and severe storm activity can be expected to pose threats to rural and urban populations alike, with special damage risks for crops and livestock that secure the nation's food supply. Effective public policy can mitigate these risks, and in some cases even turn them into opportunities for more sustainable improvements in Thai living standards.

This report is part of a larger research effort to identify patterns of climate change risk for the agricultural sector in Thailand. Using the most up-to-date and detailed weather and agronomic data avaiable, we have applied methods of statistical and spatial analysis to identify climate risk arising from long-term changes in patterns of temperature and rainfall. Our results suggest that crop yields are threatened by these trends, and that the degree of risk varies significantly around the country. Risk levels generally do not appear to be catastrophic, and we believe the Government of Thailand and its private partners can meet these challenges. Timely and targeted responses, however, can dramatically reduce adaptation costs, however, and we strongly support an evidence-based, forward-looking activist approach.

The current study is dedicated to Thailand's primary staple crop, rice. While rice production remains nearly unbiquitous in the Kingdom, climate change will affect rice yeilds quite differently in different areas. This is one of the most fundamental lessons of agricultural adaptation policy—one size will not fit all situations. For this reason, adaptation policies need to be targeted with detailed spatial information like that used in this study. For areas at highest risk, the public sector can facilitate adjustment by promoting new production techniques, alternative crops, and the extension and credit services needed to adopt them. In areas with lower risk, the government can deploy a different package of policies to promote higher rice yields to compensate for declines eleswhere. In addition to direct public adaptation assistance, public information and other policies can help the private sector bear the costs of these adjustments without undue hardship, or even profit through induced innovation.

Simply put, climate change is a gradual but inevitable process. The Government of Thailand has the capacity to adapt effectively, but this requires foresight and determination. The former will come from more intensive use of information resources and related technologies, of which this project is an example. Determination is already apparent in the support for the project, but many challenges lie ahead for commitment to real investment and institutional evolution.

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Appendix : Second Season Rice Results

In addition to our results for wet-season rice, we also estimate the same models for dry-season rice production. For the linear, model, all of our results are extremely similar to our results for wet-season rice production. Find that minimum temperature and radiation are negatively associated with higher rice yields, while higher maximum temperatures are positively associated with rice production. For rainfall, since dry season rice production requires irrigation, we only include a single rainfall term for rainfall over irrigated area. Again, our rainfall results are similar in both rice seasons. We find that the rainfall term is negatively associated with higher rice yields while the squared terms if positive. These results are again consistent with the idea that irrigated rice farmland is hurt by the introduction of additional unplanned water through rainfall.

For the piecewise-linear model, the thresholds for min temperature, max temperature, and radiation that minimize in-sample RMSE are identical to the optimal thresholds estimated for wet-season rice production. This is reassuring in that our results are consistent across data sets (and planting season) which suggests that our results may be capturing physiological aspects of rice production. The coefficients measuring the effect of average minimum and maximum temperatures above the cutoffs are both strongly negative, also consistent with our findings for wet-season rice. However, the signs of our estimated effects for minimum and maximum temperature in the dry-season are opposite of what we found in the wet-season. In the dry-season, we find that minimum temperatures below the cutoff are *positively* associated with rice production, while maximum temperatures below the cutoff are *negatively* associated with production (above the threshold the effect size nearly doubles). For rainfall, we find that additional rainfall below the cutoff has a *positive* effect, while additional rainfall above the cutoff has no effect.

Forecasted Yields

Under all three climate scenarios, the piecewise-linear model forecasts significant losses for dry-season rice production. Because it is typically hotter in the dry-season, many of the temperatures are already close the cutoffs, above which we find strongly negative effects on yields. Consequently, as temperatures rise, many of the dry-season areas in production will cross the thresholds and thereby incur significant losses. Overall, we estimate 5-10% losses in dry-season yields, relative to the no climate change scenario. Figures A1-A3 maps the areas that are forecast to incur losses of 5% or greater by year. Most of the losses are occurred in the hottest area of the central region, as well as in some areas of the northeast. The losses are driven by minimum and maximum temperatures crossing the negative thresholds.

Table A.1: Linear Seasonal Average Panel Model Results

	(1)	(2)	(3)
Min Temperature	-0.080***	-0.109***	-0.052**
(deg C)	(0.019)	(0.020)	(0.020)
Max Temperature	0.055***	0.067***	0.010
(deg C)	(0.019)	(0.020)	(0.039)
Radiation	-0.047***	-0.049***	0.020
(mjd^{-1})	(0.013)	(0.014)	(0.013)
Rainfall	-0.011**	-0.013***	-0.011
(10 cm irrigated)	(0.004)	(0.004)	(0.014)
$Rainfall^2$	0.000	0.000**	0.001*
(10 cm irrigated)	(0.000)	(0.000)	(0.000)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**6.459**	**6.459**	**6.459**
No Obs	**1203**	**1203**	**1203**

Table A.2: Piecewise-linear Seasonal Average Panel Model Results

	(1)	(2)	(3)
Min Temp (< 24)	0.002**	0.001	0.000
(deg C)	(0.001)	(0.001)	(0.001)
Min Temp (>24)	-0.134***	-0.169***	-0.093***
(deg C)	(0.030)	(0.033)	(0.029)
Max Temp (<34)	-0.003***	-0.003***	-0.002***
(deg C)	(0.001)	(0.001)	(0.001)
Max Temp (>34)	-0.054***	-0.054***	0.017
(deg C)	(0.014)	(0.015)	(0.015)
Radiation (<17)	0.045**	0.049**	0.035
(mjd^{-1})	(0.022)	(0.024)	(0.028)
Rainfall (<20)	0.006*	0.006*	0.005
(10 cm irrigated)	(0.003)	(0.003)	(0.003)
Rainfall (>20)	0.001	0.001	0.013***
(10 cm irrigated)	(0.004)	(0.004)	(0.005)

Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**6.459**	**6.459**	**6.459**
No Obs	**1203**	**1203**	**1203**
R^2	**0.214**	**0.289**	**0.415**

Figure A.1: Yield Gains and Losses Predicted by Piecewise-Linear Model (A1B Scenario)

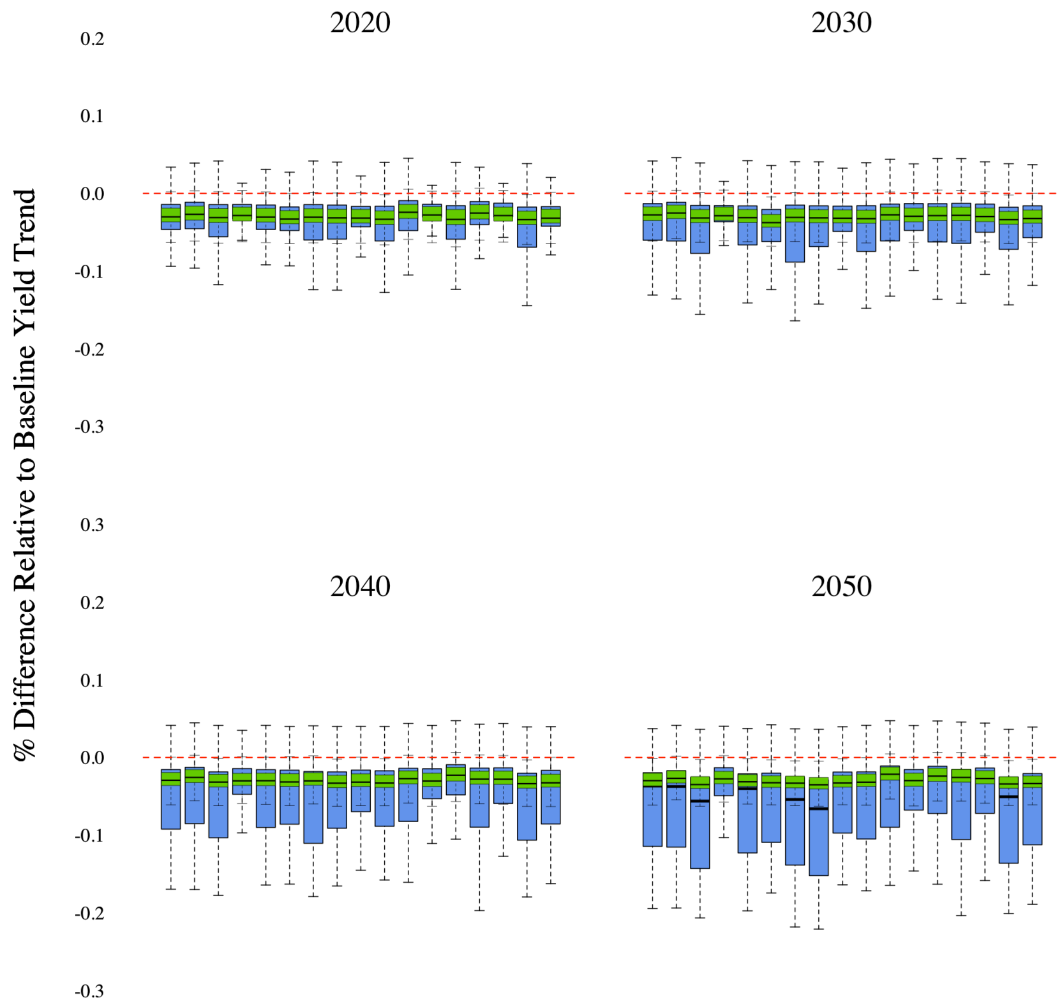

Figure A.2: Yield Gains and Losses Predicted by Piecewise-Linear Model (A2 Scenario)

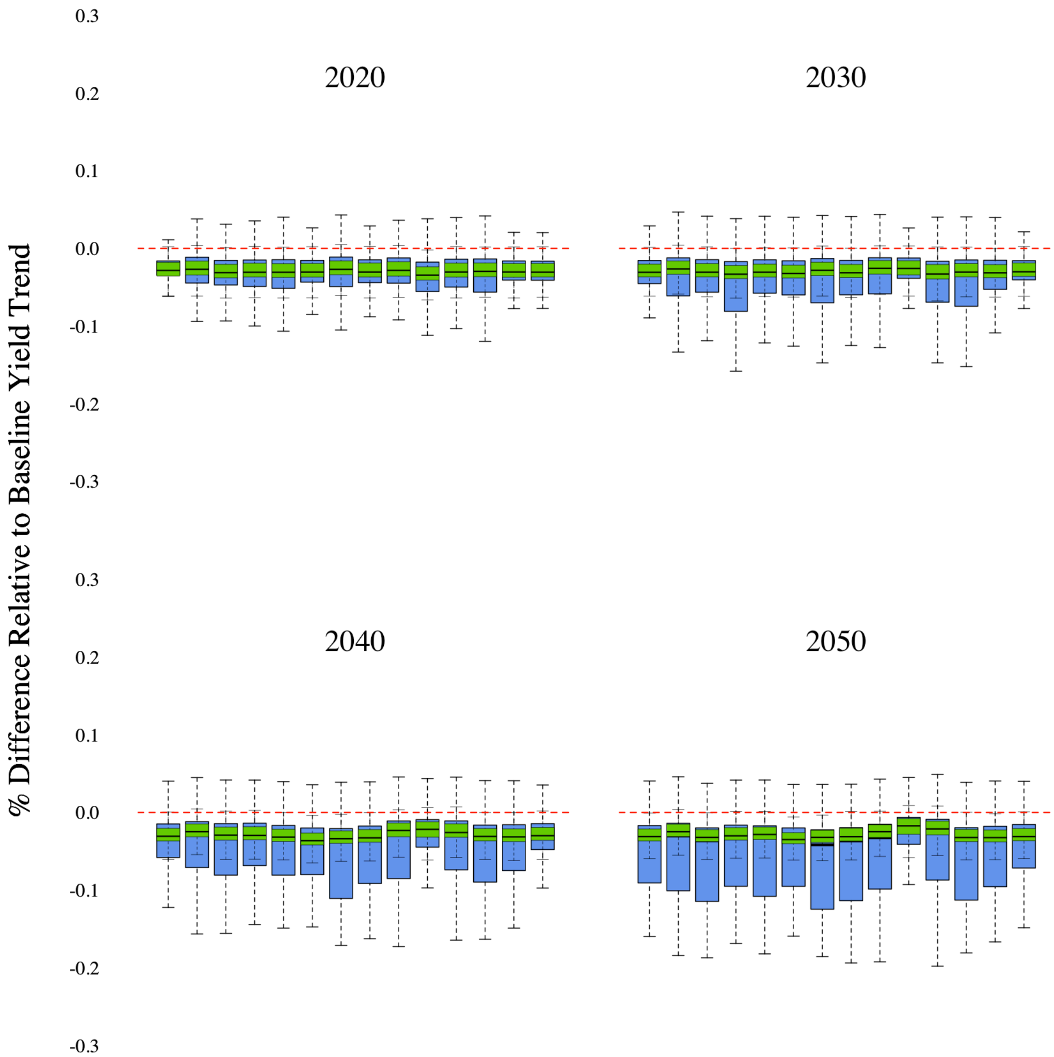

Figure A.3: Yield Gains and Losses Predicted by Piecewise-Linear Model (B1 Scenario)