Challenges and Opportunities for Climate Adaptation in Thailand Agriculture:

Tree Crops

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.

This research was performed in a collaboration between Thailand's Office of Agricultural Economics (OAE) and the United Nations Food and Agriculture Organization (FAO). We wish to thank the OAE and FAO staff for their inputs of staff expertise, data, insights, and advice. Authors of the report were Sam Heft-Neal and David Roland-Holst of UC Berkeley, Beau Damon of FAO, and the following OAE staff and independent researchers:

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Sukhon Khongklom
Suprama Rojanaburanon
Wirawan Jasmin
Kajonwan Itharattana
Aree Somwadee
Panida Paibunjitt-Aree
Manoj Potapohn
Anaspree Chaiwan

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Tree Crop Production Systems

Rubber

Rubber production is tied closely to the world automobile industry. As automobile production has expanded in Thailand, so has its rubber industry. Presently, more than 99% of the world's rubber comes from one species of tree (*Hevea brasiliensis*), which happens to be well suited to the climate of Thailand. Because of these developments, Thailand has become a major exporter of rubber. While rubber trees do not produce rubber for approximately 5-7 years after planting, once they begin production, they can be tapped periodically (every 1-2 months), depending on the weather conditions. Yields are highest in the rainy season (October through December), and lowest in the dry season (February through April). However, yields are highly sensitive to water availability, and tapping may be delayed if the conditions are either too wet or too dry (Mak, 2006) [Figure 1].

Oil palm

Palm oil is the leading vegetable oil, and Thailand is the world's third-largest producer. Oil palm production is located primarily in the south[1], but recently expansion has been taking place into the northeastern and eastern regions (Preechajarn et al, 2007). Oil palm largely uses marginal land (e.g., former rubber fields and unused fruit orchards), and is expected to expand in the future (Colchester and Chao, 2011). While harvesting takes place throughout the year, about half of all palm oil harvested annually is harvested between November and January [Figure 1]. Over the past 20 years, palm oil yields have been increasing slowly but steadily. However, significant year-to-year variability remains [Figure 2].

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[1] In 2008, three provinces accounted for 72% of total oil palm planted area: Krabi, Surat Thani, and Chumphorn (Jongskul, 2010)

Longan

Longan fruit are harvested primarily in May and June in the northeast, and May through November in other regions. Longan trees prefer temperate climates, and thus may be susceptible to yield losses from heat waves as well as rises in average temperatures. Since 1996, longan yields have been steadily declining [Figure 2], losing more than 1% of yields per year nationally.

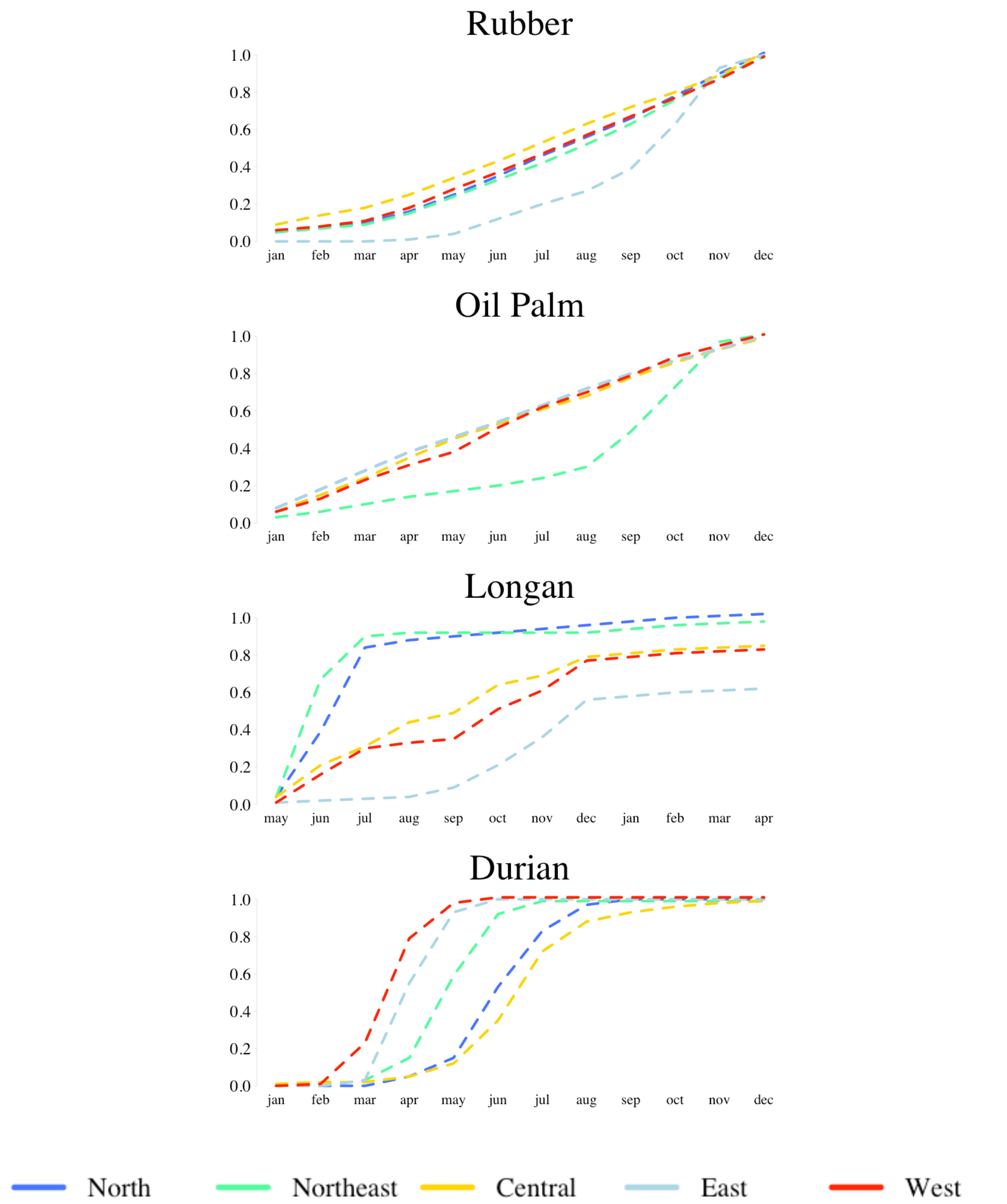
Coconut

Coconut yields have been relatively stable over the course of the past 20 years. In fact, 2010 national average yields were only slightly below 1995 levels.

Durian

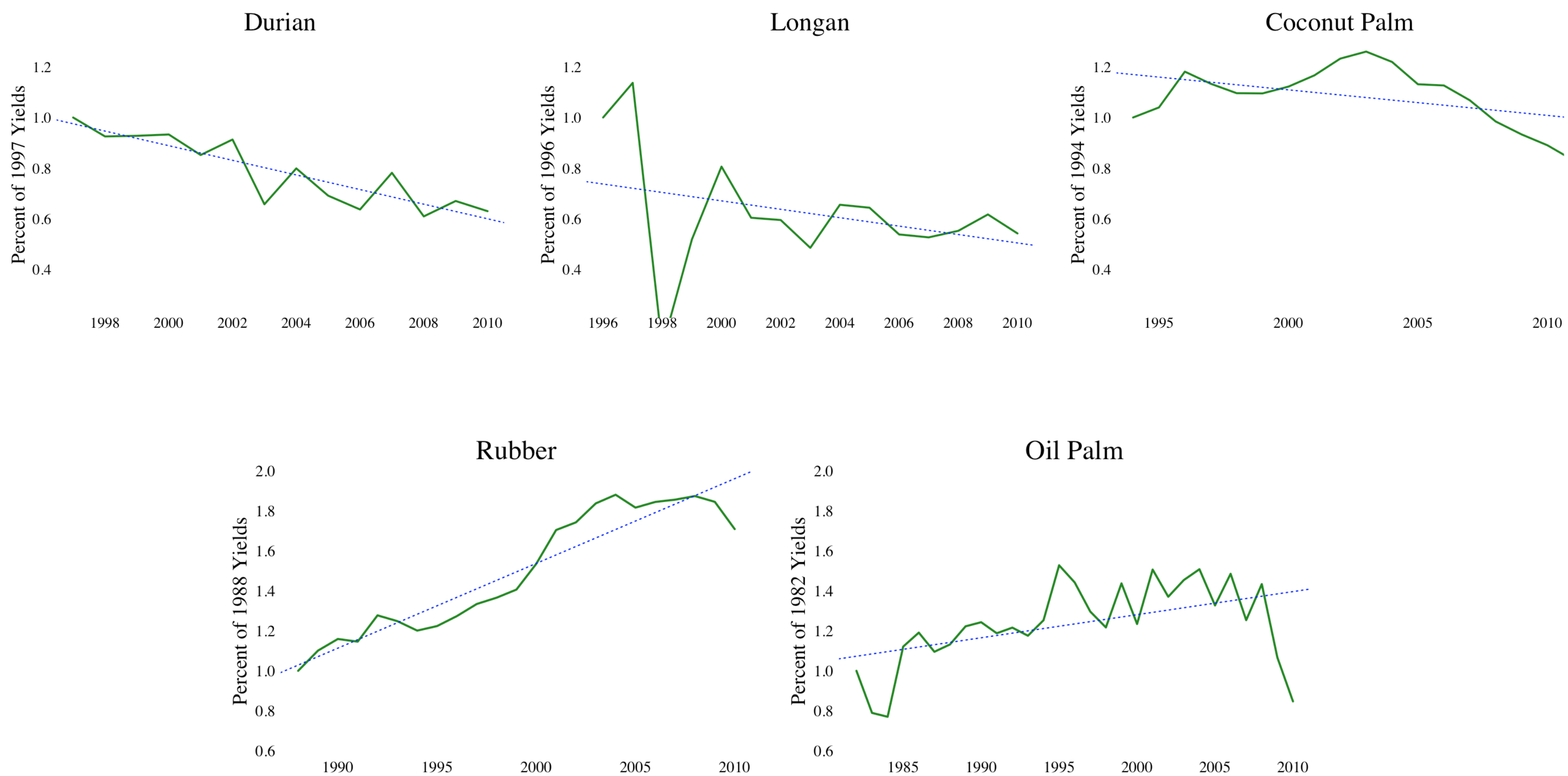
Durian production is located primarily in the central, east, and southern regions of Thailand. Fruit is harvested March through July [Figure 1], and yields are typically highest in April (Pokterng S. and Kengpol, 2010). Floods and heat waves are considered significant obstacles to durian production.

Figure 1: Distribution of Harvest by Month



Notes: *Distribution of monthly harvesting for perennial crops. Note that all crops do not begin in January; Longan figure begins in May and sugar in March. Rubber and oil palm are all harvested relatively evenly over harvest months. Harvest data are not available for coconuts.*

Figure 2: Long-Run Tree Crop Yield Trends



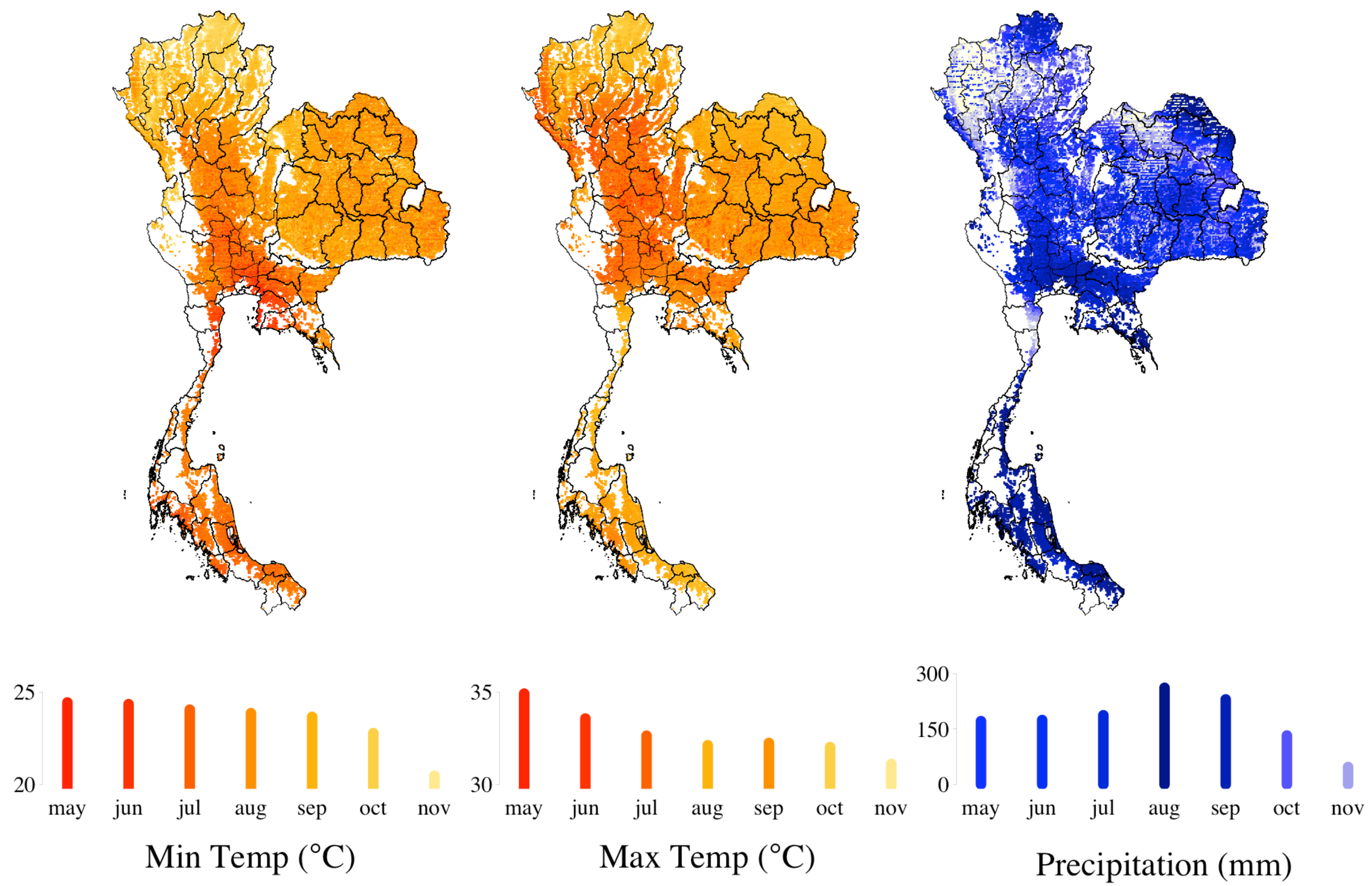
Notes: *Yield trends in crops. Yields are normalized to the first year observation so that all series begin at 1. In percentage terms, maize and rubber yields have increased the fastest, nearly doubling over the past 30 years. Oil palm yields exhibit the most year-to-year variation. All fruit crops exhibit downward yield trends over the study period. In percentage terms, durian yields have had the fastest decline, averaging nearly 2% lower yields per year.*

Table 1: Mean Weather Conditions in Tree Crop Growing Area
1980-2010

	MIN	MAX	RAD	RAINF
Longan	22.4	32.6	17.2	41.5
Durian	23.8	32.6	17.4	51.9
Coconut	23.8	33.0	17.8	26.5
Oil Palm	23.0	32.3	17.5	51.4
Rubber	22.7	32.5	17.5	43.4

Notes: *Table shows mean growing conditions throughout the year in growing areas for each tr Measurement units are degrees Celsius (Min, Max), mega-joules per day (Radiation), and cm Conditions are measured interpolated from daily weather station observations and averaged year. For oil palm and rubber, weather data were extrapolated over the spatial extent of planted a*

Figure 4: Average Annual Weather Conditions (1980 - 2010)



Estimation Approach

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. For some crops, (maize, cassava, soy, rubber, sugar, oil palm) we use GIS data[2] in order to interpolate weather over planted areas and divide rainfall into two variables: rainfall over rain-fed cropland, and rainfall over irrigated cropland. For other crops (longan, coconut, durian), we interpolate weather over the entire provinces with production data available and use a single rainfall variable in our analysis.

I. Average Growing Season Conditions

(i) Linear Fixed-Effects Panel Model

The first approach that we take is to estimate linear panel regression fixed-effects models for log yields as a function of weather metrics (estimation equations described in Technical Appendix). Minimum temperature, maximum temperature, and radiation are all averaged, while the rainfall terms are summed. 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. Including year fixed effects is the most flexible approach, but it requires the most data, as much of the year-to-year variation required to estimate panel models is absorbed by the fixed effects. Consequently, the third specification requires larger data sets in order to have the power to detect an effect. For some crops, we do not have large data sets,

[2] Shapfile data was provided by the Department of Land Use

so it is unsurprising that we generally do not find statistically significant results in those settings. Nonetheless, we estimate all three specifications for all crops.

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 results included in the discussion, and displayed in the appendix, are estimated with average total production weights.

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 different weather-yield relationships across different ranges of weather covariates.

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 temperature, radiation, and precipitation, we relax the assumption that a single yield-covariate relationship holds across the range of covariate values. This approach relies on selecting cutoff points, or thresholds, that separate differential effects of a given weather input. Here we select thresholds by minimizing the in-sample RMSE. Specifically, the thresholds are chosen by looping over the range of observed values for each variable and selecting the threshold that best fits the data. This approach allows for differential effects of weather over various ranges, and typically represents a better fit for the data. In general, the piecewise-linear models have higher R^2 and lower RMSE values. A similar piecewise-linear modeling approach has previously been used to estimate the effect of extreme temperatures on wheat and maize yields in the United States (Schlenker 2010). The same regression weights system is also included for the piecewise-linear models.

III. Results

Oil Palm

In the linear model, none of our estimates is statistically significant with the exception of radiation, in one of three specifications, which is found to be negatively correlated with oil palm yields. However, in the piecewise-linear specification for oil palm, temperature as well as radiation covariates are found to be statistically significant. The endogenously selected thresholds are 24 degrees for minimum temperature, 32 degrees for maximum temperature, and 110 cm for rainfall. Average maximum temperature above the threshold is the only temperature covariate that is significant in more than one specification. We find that higher temperatures above the 32-degree threshold are associated with 3-4% higher yields. Our precipitation results are not significant in any of the specifications, suggesting that we are poorly measuring rainfall as it affects oil palm production.

Rubber

For rubber, the linear model finds that a one-degree rise in average minimum temperature *increases* yields by 6%, while a one-unit increase in average radiation *reduces* rubber yields by 8%. However, in the piecewise-linear specification, these results vary across different ranges of the covariates.

The piecewise thresholds selected to minimize in-sample RMSE are 24 degrees for minimum temperature, 33 degrees for maximum temperature, 16 mjd^{-1} for radiation, and 60cm for rainfall. The results for minimum temperature, although only significant in the second specification, suggest that, over the range of observed values, higher temperatures are associated with higher rubber yields up to 33 degrees, at which point rising temperatures are associated with lower rubber yields.

Our results for maximum temperature, radiation, and rainfall are consistent across most specifications and suggest that a 1-degree increase in average maximum temperature up to 33 degrees *increases* rubber yields by 4-7%. However, above 33 degrees, a one-degree increase in average maximum temperature is associated with 3-7% *lower* rubber yields. The results for radiation are similar. In all three specifications we find that higher levels of radiation are associated with higher rubber yields (11-20%) up to 16mjd^{-1}, above which one unit increases in radiation are associated with yield reductions of 3-10%.

For rainfall we find that additional rainfall below the cutoff point does not have a significant impact on rubber yields, while additional rainfall above the threshold is associated with 2% lower yields in two of three specifications, and insignificant in the third.

Overall, we find evidence that rubber yields are likely to benefit from rising average temperatures and radiation up to an average daily maximum of 33 degrees and 16 mj per day of radiation. Above those thresholds we estimate 5-10% reduction in yields for each additional unit rise in temperature or radiation. We also not find some evidence that decreased levels of rainfall would help rubber yields in areas where rainfall levels are presently high.

Fruit Production

Longan

In the linear model for longan yields, we find that rises in minimum temperature, maximum temperature, and radiation are all associated with lower longan yields, suggesting that longan production is best suited to a temperate climate and may be harmed by future changes predicted by climate models. The magnitude of our estimated coefficients is large, with yield reductions from rising minimum and maximum temperatures greater than 50%, however, it should be noted that our longan data contains only 350 observations. Piecewise-linear models require that data be divided into subsets along the ranges of the independent variables, and separate regressions slopes are estimated for each sub-range. Consequently, the low number of observations in our longan data set make drawing inference on non-linear models even more questionable. Consequently, we restrict radiation, the weather covariate with the smallest range in our data, to a linear specification.

We find that rising temperatures hurt longan yields. In fact, when we control for linear trends (specifications 1 and 2) we find that rising average maximum temperature reduces longan yields by more than 15% until average maximum temperature reaches 33 degrees. At that point, a one-degree increase in average maximum temperature reduces yields by 75%. However, in our third, more flexible specification, we do not find any significant results for temperature. In reality, the true relationship is likely to lie somewhere in between these estimates, where rising temperatures hurt longan yields, but by smaller amounts than we find in our first two models.

Unlike our results regarding temperatures, our results for radiation and precipitation are robust across all specifications. We find that higher levels of radiation reduce yields; a 1-mjd^{-1} increase in average radiation levels reduce yields by 17-20%. Precipitation was found not to have a significant effect on longan yields at low levels, but rainfall above 80 cm increased yields by 15-25%. This suggests that low levels of rainfall are insufficient for growing longan, but that once there is enough rainfall to grow, additional rainfall increases yields[3].

Collectively, these results suggest that longan production is likely to be hurt by future changes in climate, since radiation and temperature levels are forecast to increase while rainfall is expected to decrease (IPCC, 2007).

Durian

The linear model for durian yields finds that a one-degree increase in average minimum temperature reduces durian yields by more than 10-20%. However, a 1-unit increase in average radiation is found to *increase* durian yields by 6-9%. Rainfall is found to be negatively associated with durian yields, with a positive square term. This suggests that durian production is likely to be affected by future changes in rainfall patterns and more likely to be affected by temperature changes.

The data available for durian are insufficient to estimate non-linearities in all of our weather covariates. Consequently, we restrict radiation to a linear specification because it has the smallest range[4]. In specifications 1 and 2, where we use linear controls for long-run trends, we find average minimum temperatures below 24 degrees do not have a strong effect on durian yields, but that average minimum temperatures above 24 degrees reduce durian yields by about 25%. However, in the third specification we find a yield reduction above 24 degrees of only 8%, and the result is not statistically significant. Over the range of observed average maximum temperatures, we do not find any strong relationship with durian yields in any of the specifications. We find that radiation is positively associated with higher durian yields in the all three specifications, but our results are only significant in the two specifications with linear trends.

[3] At some extreme of high rainfall levels we would expect additional rainfall to begin reducing yields, however, we do not have power in our data to detect the second non-linearity in rainfall.

[4] Therefore, we argue that it is the most likely to have a linear relationship with yields over the observed range of values.

Our results for rainfall are the consistent across all of our specifications. We find that at low levels of rainfall (below 90 cm), additional rainfall is associated with *lower* yields (-1.5% yield for each additional 10cm of rainfall). At higher levels of rainfall (above 90cm) we find that additional rainfall is associated with *higher* durian yields (+4% yield for each 10cm of rainfall). While we do not have irrigation data for durian production, and thus cannot separate our sample, our rainfall results are consistent with the idea that farmers in areas with low levels of annual rainfall use irrigation while farmers in areas with higher levels of rainfall do not. In that case, our sample below the cutoff would be made up of more farmers with irrigation, for whom additional rainfall may hurt yields since it disrupts the planned water introduction into the production system. Similarly, observations in our sample above the rainfall cutoff may be farmers who rely on rainfall to irrigate their crops and thus are helped by additional rainfall.

In the context of climate change, our results suggest that, so long as irrigation resources remain available, farmers with pre-existing irrigation would not be hurt by forecast reductions in rainfall (and may even benefit) while farmers without irrigation would lose potential yields from insufficient water availability. Increases in radiation could potentially raise durian yields (although above some cutoff radiation is likely to be harmful). We do not find a strong relationship between maximum temperature and durian yields, but our results suggest that higher minimum temperatures may reduce yields in the future.

Coconut Palm

For coconut production, in both the linear and non-linear models we find that higher average temperatures (min and max) are generally associated with *higher* yields. For the linear model, a one-unit increase in min temperature raises yields by 1-5% and a one-unit rise in maximum temperature raises yields by 7-12%. In the piecewise-linear model, for average maximum temperatures below 35 degrees, a one-degree increase in average temperature raise yields by 7-12%, depending on the specification. Above the estimated threshold, we find that coconut yields increase by even more. We find that higher minimum temperatures are associated with *lower* coconut yields, however, the results are not significant in most of the specifications.

We find that, below 19 mjd^{-1}, a one mjd^{-1} increase in radiation reduces coconut yields by 8-12%. However, above 19 mjd^{-1} we find no effect. This suggests that radiation is harmful up to the cutoff, but above the cutoff no additional damage in incurred.
Our results for rainfall are inconclusive, however, we find marginally significant results that suggest additional rainfall below 40cm is positively associated with 3-4% higher yields.

In summary, our findings suggest that coconut production may not be hurt by rising temperatures but may be hurt by rising radiation, up to a point. Coconut production areas with presently low levels of rainfall may be hurt by less future rainfall.

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 (IPCC, 2007).

On a global scale, researchers estimate that minimum temperatures have risen faster than maximum temperatures over the last century. Easterling (1997) dissects the trend of increasing diurnal temperatures and attributes it to increased CO_2 concentration in the atmosphere. However, in our data set we observe maximum temperatures *rising faster* than minimum temperatures in the last 30 years. For more detailed predictions of future conditions we turn to the Global Climate Models published by the IPCC.

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. They take into account the physical components of weather systems and use these relationships to model future climate conditions. While there are high levels of uncertainty involved in GCMs, these models can help provide insights into future climate scenarios.

The IPCC serves as a central organization for research groups around the world to submit their models. Each research group must choose an approach to modeling physical climate interactions, spatial and time resolutions, and future economic conditions, among other things. Variation in model choice can result in a wide variety of predictions. Fortunately, the IPCC has attempted to standardize economic/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 result in a still wide variation in predictions across models, even within 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 changes toward a service and information economy with a population rising to 9 billion in 2050 and then declining thereafter. Clean and resource efficient technologies are introduced limiting future emissions. This scenario imagines an increase in global mean temperatures of 1.1 - 2.9°C 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 a decline in global birth rates. This scenario predicts, on average, a 2-6°C warming of global temperatures by 2100.

The A2 scenario describes a more heterogeneous world with uneven global economic develop and an 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°C by 2100.

Table 2: Average Forecast Weather Conditions in Tree Crop Growing Areas 2050 (A1B)

	MIN	MAX	RAINFALL
Longan	**23.7**	**33.9**	**38.9**
	(22.4)	*(32.6)*	*(41.5)*
Durian	**24.7**	**33.5**	**51.3**
	(23.8)	*(32.6)*	*(51.9)*
Coconut	**24.4**	**33.9**	**25.3**
	(23.8)	*(33.0)*	*(26.5)*
Oil Palm	**23.7**	**33.2**	**50.0**
	(23.0)	*(32.3)*	*(51.4)*
Rubber	**23.3**	**33.3**	**43.4**
	(22.7)	*(32.5)*	*(41.8)*

Notes: *Table shows mean forecast growing conditions for each tree crop. Forecasts are medians of 18 model predictions under A1B climate scenario. Measurement units are degrees Celsius (Min, Max), mega-joules per day (Radiation), and cm (PRCP). Bold numbers on top are predicted averages. Italic number below are historical averages over the period 1980 – 2010. GCMs predict rising min and max temperatures and slightly lower overall rainfall for every crop.*

Figure 5: GCM Forecasted Monthly Changes in Precipitation and Temperature

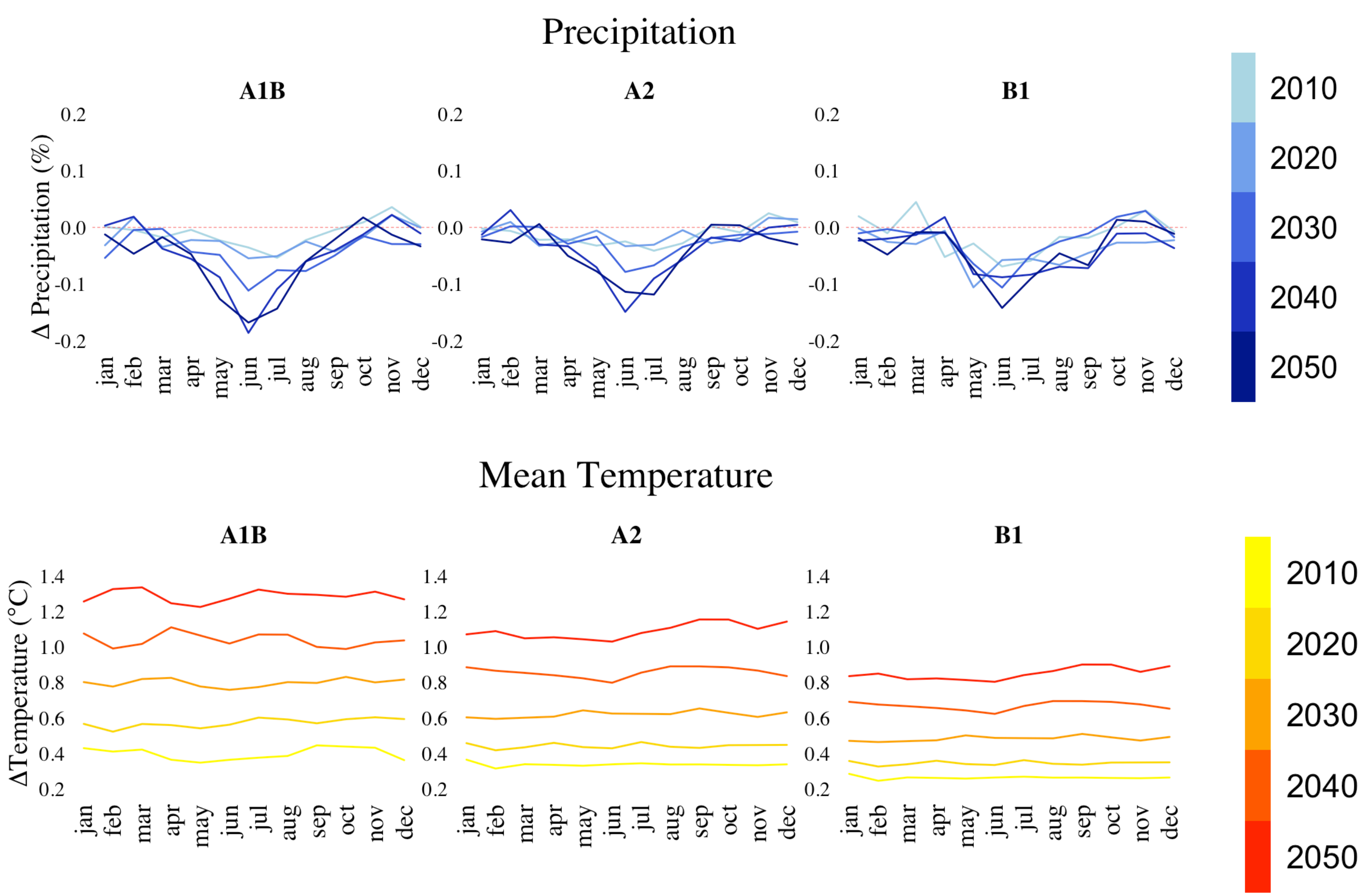


Table 3: Mean Weather Conditions in Tree Crop Growing Ar
1980 - 2010

	MIN	MAX	RAD	RAINF
Longan	22.4	32.6	17.2	41.
Durian	23.8	32.6	17.4	51.
Coconut	23.8	33.0	17.8	26.
Oil Palm	23.0	32.3	17.5	51.
Rubber	22.7	32.5	17.5	43.

Notes: Table shows mean growing conditions throughout the year in growing area each tree crop. Measurement units are degrees Celsius (Min, Max), mega-joules day (Radiation), and cm (PRCP). Conditions are measured interpolated from daily weather station observations and averaged over the year. For oil palm and rubber weather spatial extent of planted area data were use to extrapolate weather over.

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 2050 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 along current trends. Climate change yield forecasts are then compared to the yield potential under no climate change in order to estimate relative losses.

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.

Tree Crops

Longan

Longan production takes place primarily in the more temperate regions of Thailand, consequently, rising temperatures are potentially very dangerous to the longan sector. In our linear models, we found that rising minimum temperatures, maximum temperatures, and radiation levels are all extremely harmful to longan yields, although the results are not statistically significant in the most flexible model. When we estimated the piecewise-linear model, the results were similar with a sharp reduction in yields for maximum temperatures above 33 degrees in all models. Excessive radiation was also found to be highly harmful, and rainfall was found to be negatively associated with yields at low levels but positively associated at high levels (>40cm).

Driven largely by rising temperatures and higher expected radiation levels, long yields are forecast to decrease by 10-25% by 2050. These results hold for both the linear and non-linear models and under all three climate scenarios. The most extreme predictions, made by several models in the A1B scenario, predicted a greater than 25% reduction in yields by 2050. None of the models forecast increased yields in the future.

It should be noted that our longan projections rely on only 350 observations, consequently, we are making forecasting yields based on models with a small number of observations, and this small range of historical values for calibration. Moreover, the most flexible model specification (3) found that a one-degree increase in maximum temperature below 33 degrees only reduced longan yields by 3% (not statistically significant), although that specification did find significant results that a one-degree rise in maximum temperature *above* 33-degrees reduces yields by 20%.

Durian

Our models suggest that high minimum temperatures (>25 degrees) reduce durian yields, but that increases in radiation and maximum temperatures increase yields. Precipitation is found to be bad at low levels but good at high levels. Consequently, model forecasts predict that durian yields benefit from higher temperatures and radiation and are thus higher under all three climate change scenarios, relative to the baseline scenario with historical conditions. Median gains are nearly 5% by 2050 under the linear model and slightly lower under the piece-wise linear model. Overall gains are predicted under all three scenarios, however, they are largest under the lowest climate change scenario (A2). This is because we do find that durian yields decline with rises in maximum temperature above 33 degrees and minimum temperatures above 25 degrees. Less durian production areas cross these cutoffs under the A2 scenario than other the more drastic scenarios.

Coconut

The model median yield forecasts for coconut are, on average, higher than the baseline forecasts. In fact, we find that more provinces gain from changing conditions than lose [Figure 23]. However, average losses in those provinces predicted to experience lower yields, are greater in magnitude than the corresponding gains. Consequently, net production-weighted changes in forecast yields are expected to be roughly zero.

In our models, coconut yields are found to benefit from rising temperatures (over the range of historically observed values) and so many of the hottest coconut producing provinces in the central region are found to benefit from climate change [Figure 23]. Coconut yields are also found to benefit from low levels of rainfall, but hurt by excessive moisture levels. Consequently, predicted reductions in rainfall in some areas (the south) are found to be beneficial while predicted reductions in rainfall in other areas (northeast) are found to be harmful. Overall, we do not expect that the coconut production sector will be heavily impacted by climate change in the next 50 years.

Oil Palm

Median oil palm forecasts predict gains for the next twenty years and then slightly decreasing after 2040. However, by 2050, the median predicted change in yield is slightly negative. Results for both models (linear, non-linear) are similar, however, the range of predictions vary more for the non-linear model.

Rubber

Our non-linear models find that increases in temperature and radiation are beneficial for rubber yields , up to a point (33 degrees, 16mjd^{-1}), but that above these thresholds rubber yields decline with warming. We found the opposite effect for minimum temperature. Collectively, these predicted relationships imply that rubber yields will gain from incremental warming over the next few decades. However, if warming continues as predicted by GCMs, the weather covariates will cross the harmful thresholds, and rubber yields will begin to decrease. By 2050, the median predicted yield change (relative to baseline) is almost zero. By 2080, the median predicted change is -2.5%.

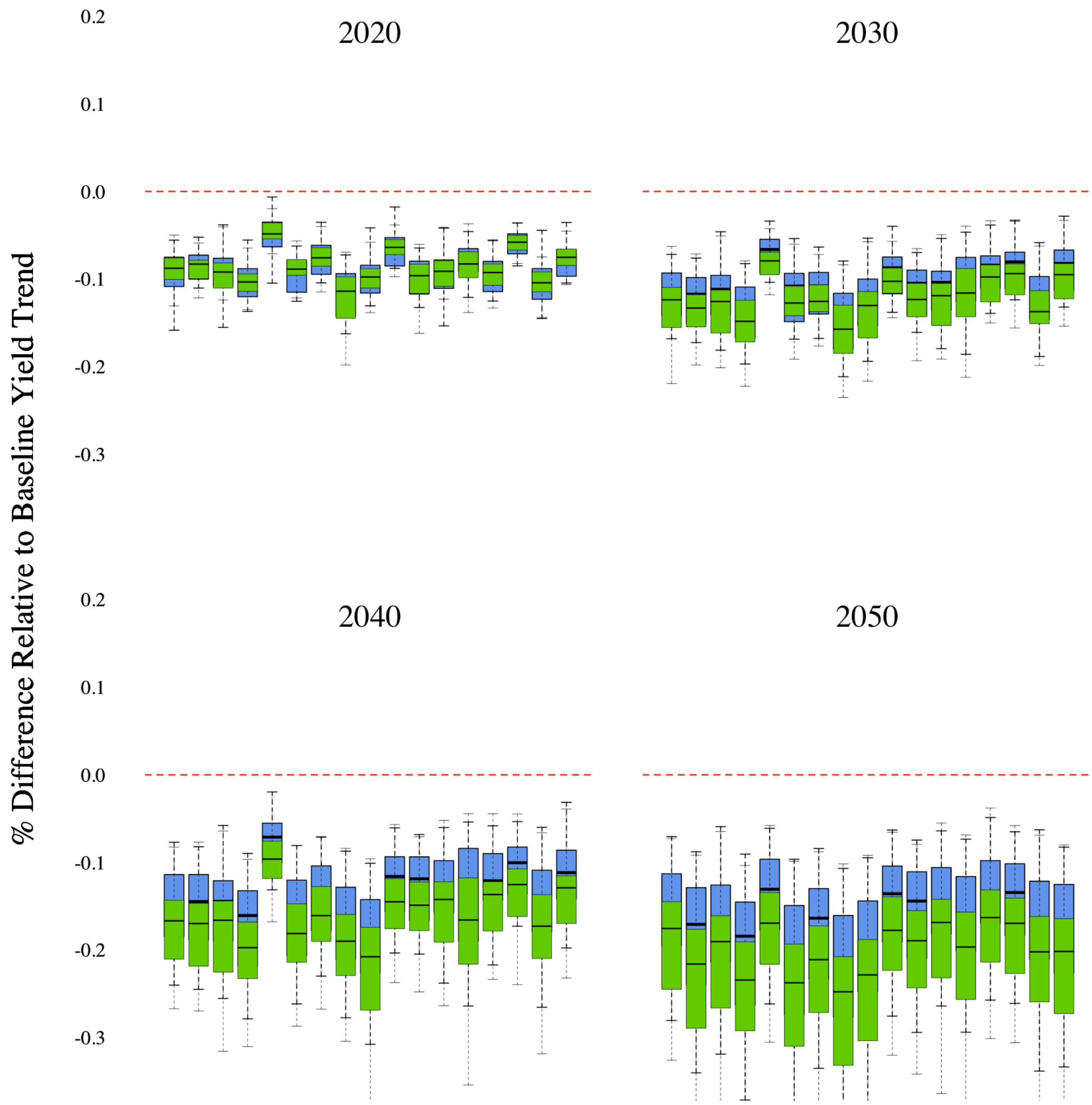
Across models and specifications, yield effects for rubber are predicted to vary across the country with approximately 40% of provinces experiences slight losses by 2040 (1-3%).

Discussion

Among the fruit crops, durian is found to be the most robust to climate change with gains from rising temperatures predicted under all models. Coconut is also found to be relatively robust to changing conditions while longan yields are expected to be reduced in all climate scenarios.

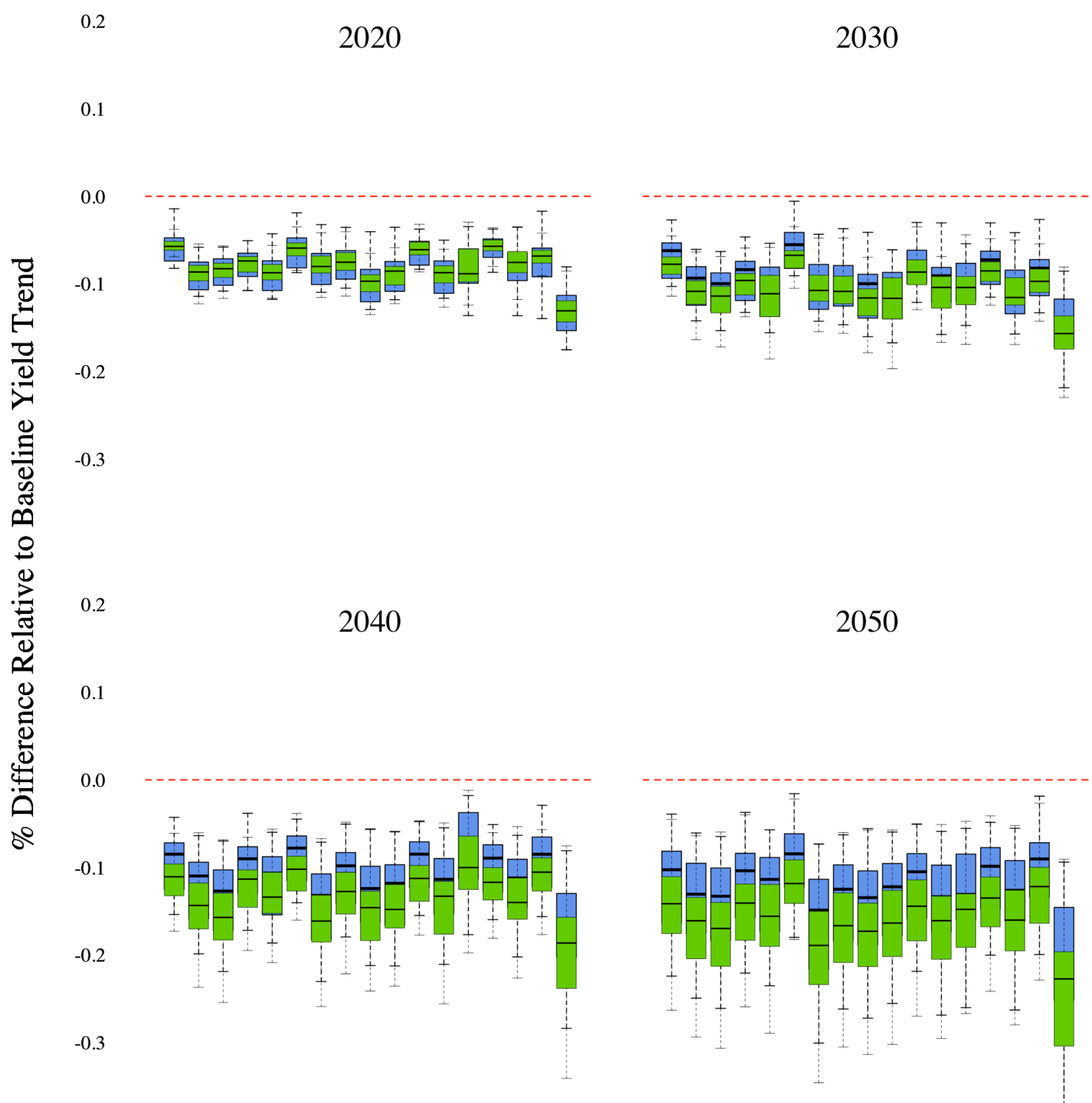
For both longan and durian we find highly significant results in both the linear and non-linear models that suggest that additional rainfall at lower initial levels if harmful to fruit yields, while additional rainfall at higher initial levels is beneficial. This result is counterintuitive since we typically expect rainfall to initially be helpful, until it reaches critical levels and become detrimental. One possible explanation is that, since we do not have irrigation data for these crops, we are picking up differential effects. This could be the case if many of our limited observations at low levels of rainfall were in locations with irrigation (because farmers are more likely to have irrigation if average rainfall levels are low) and observations at high levels of rainfall were rain-fed. If this is the case, then these results are consistent with our findings for rice where irrigated areas are hurt by additional water introduced to the system through rainfall while rain-fed areas depend on rainfall for water inputs into crop production.

Figure 6: Forecasted Change in Longan Yields Under A1B Climate Scenario



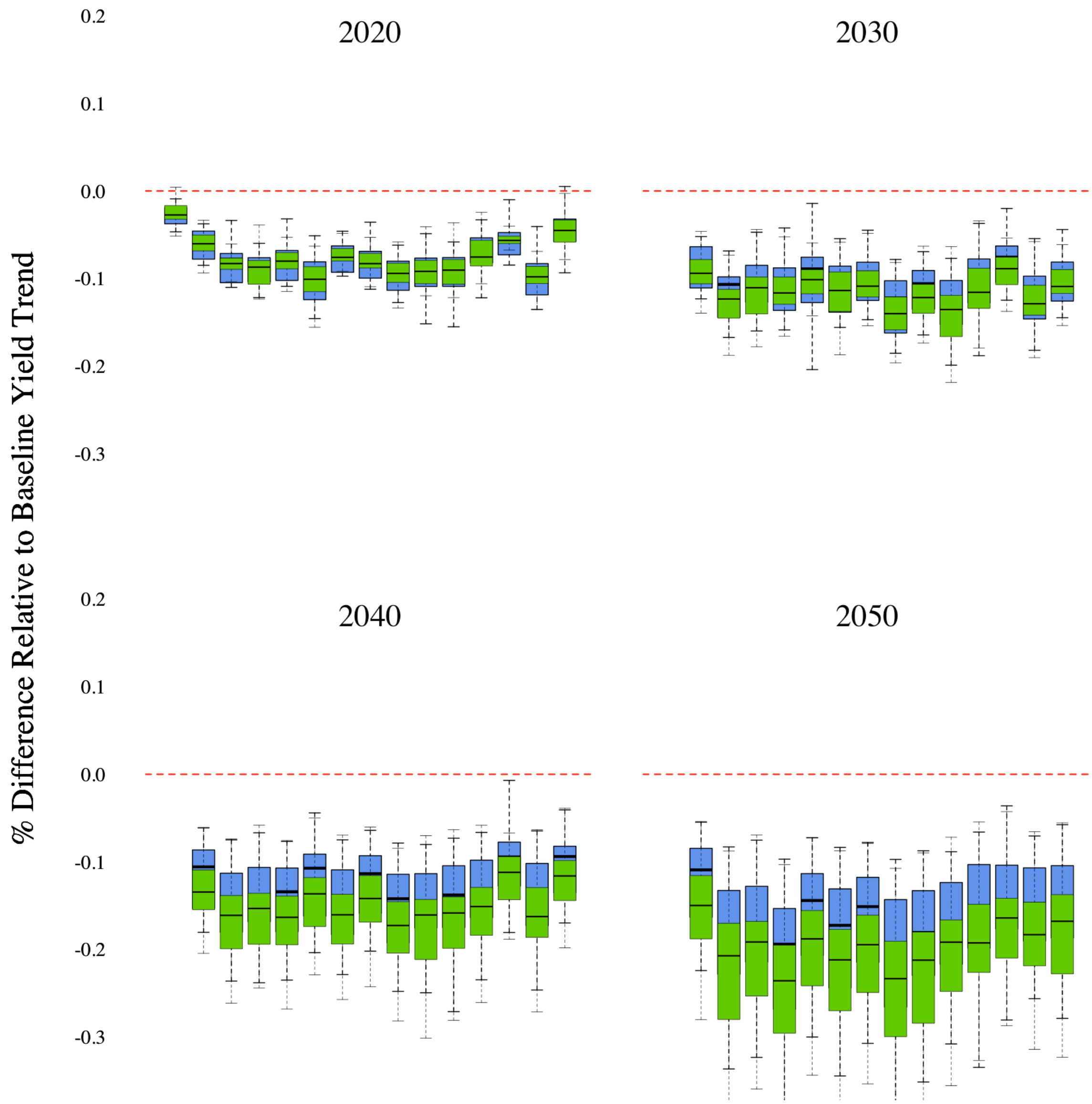
Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

Figure 7: Forecasted Change in Longan Yields Under B1 Climate Scenario



Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

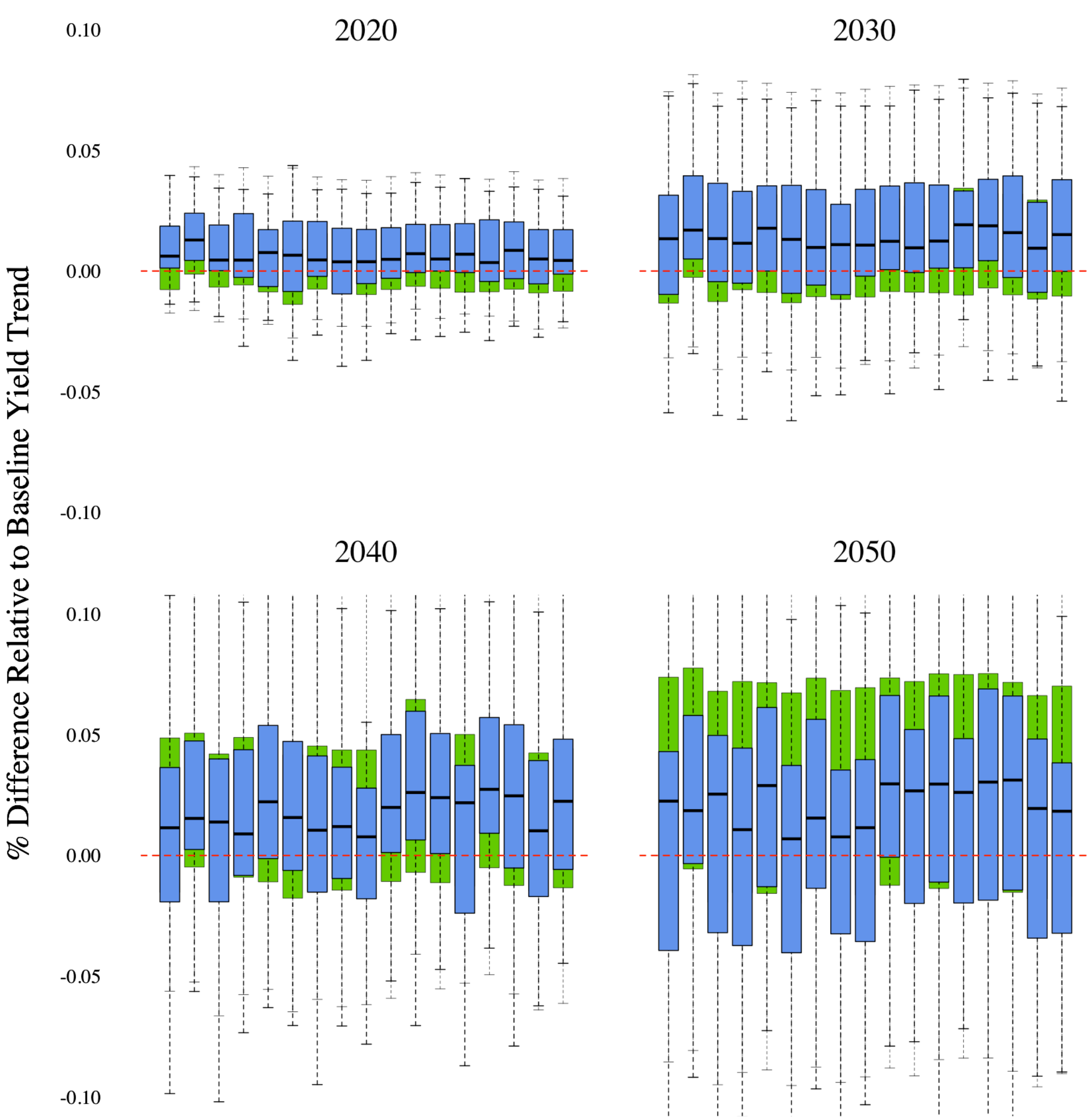
Figure 8: Forecasted Change in Longan Yields Under A2 Climate Scenario



Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces.*

The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.

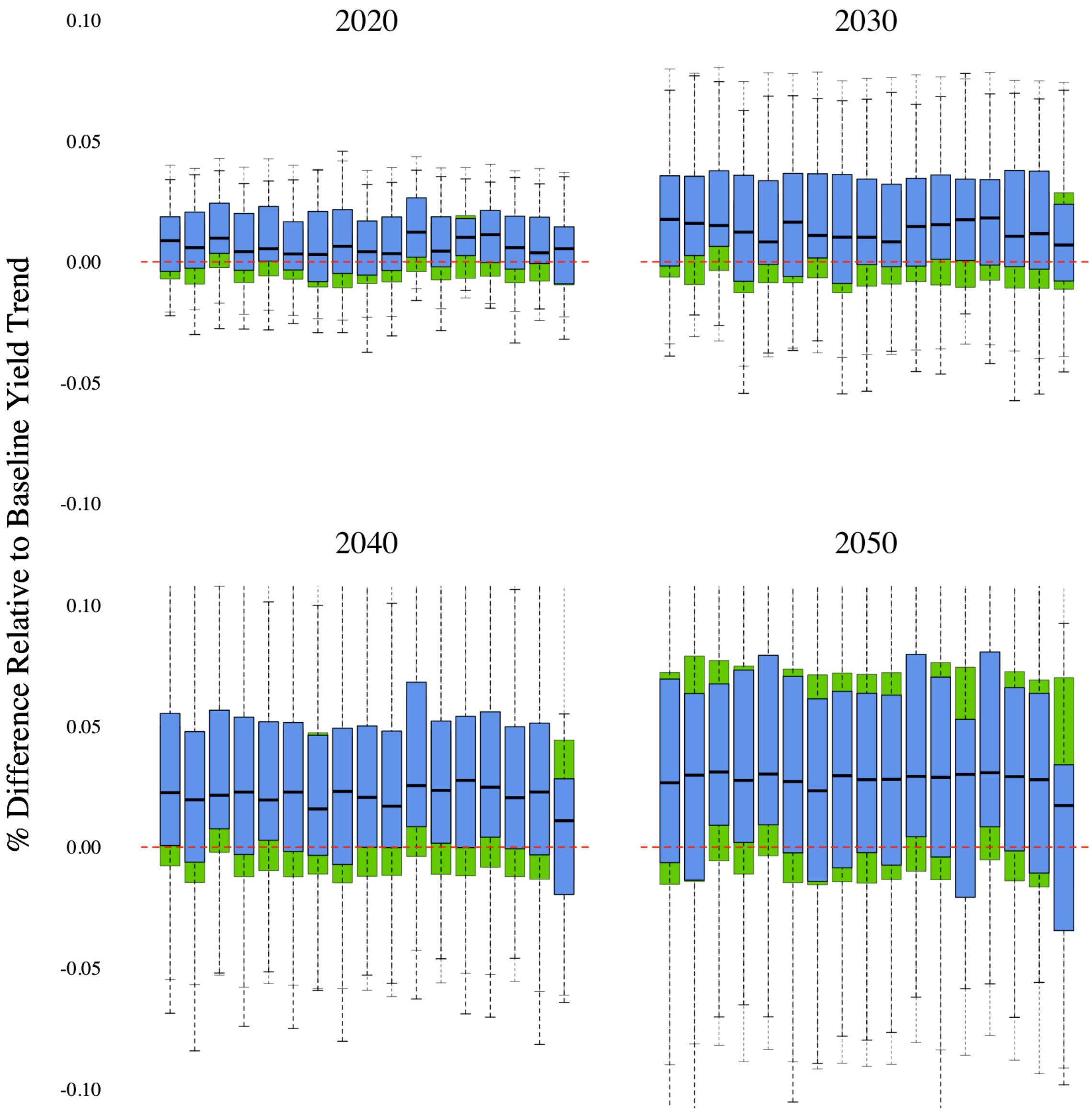
Figure 9: Forecasted Change in Durian Yields Under A1B Climate Scenario



Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces.*

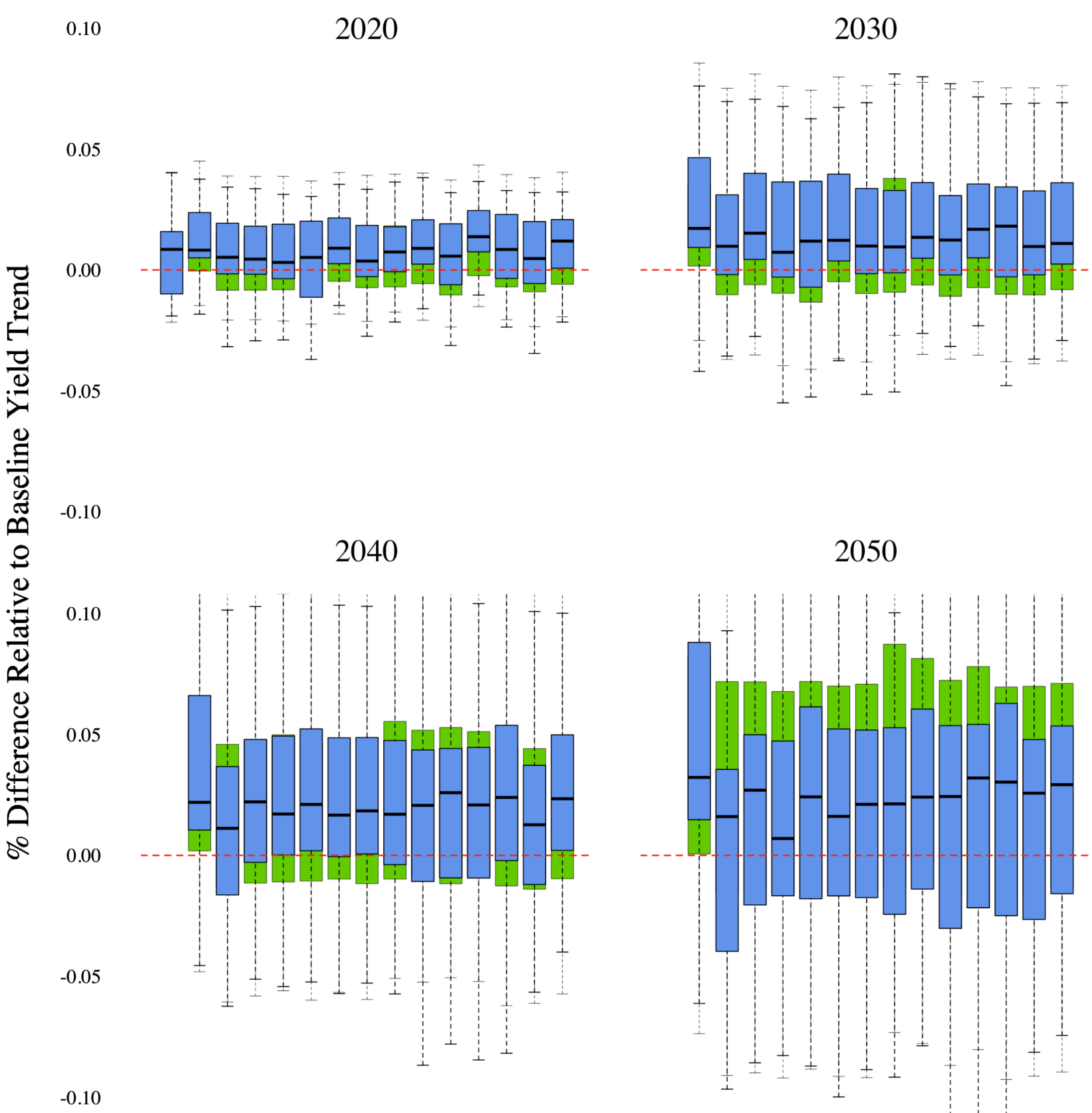
The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.

Figure 10: Forecasted Change in Durian Yields Under B1 Climate Scenario



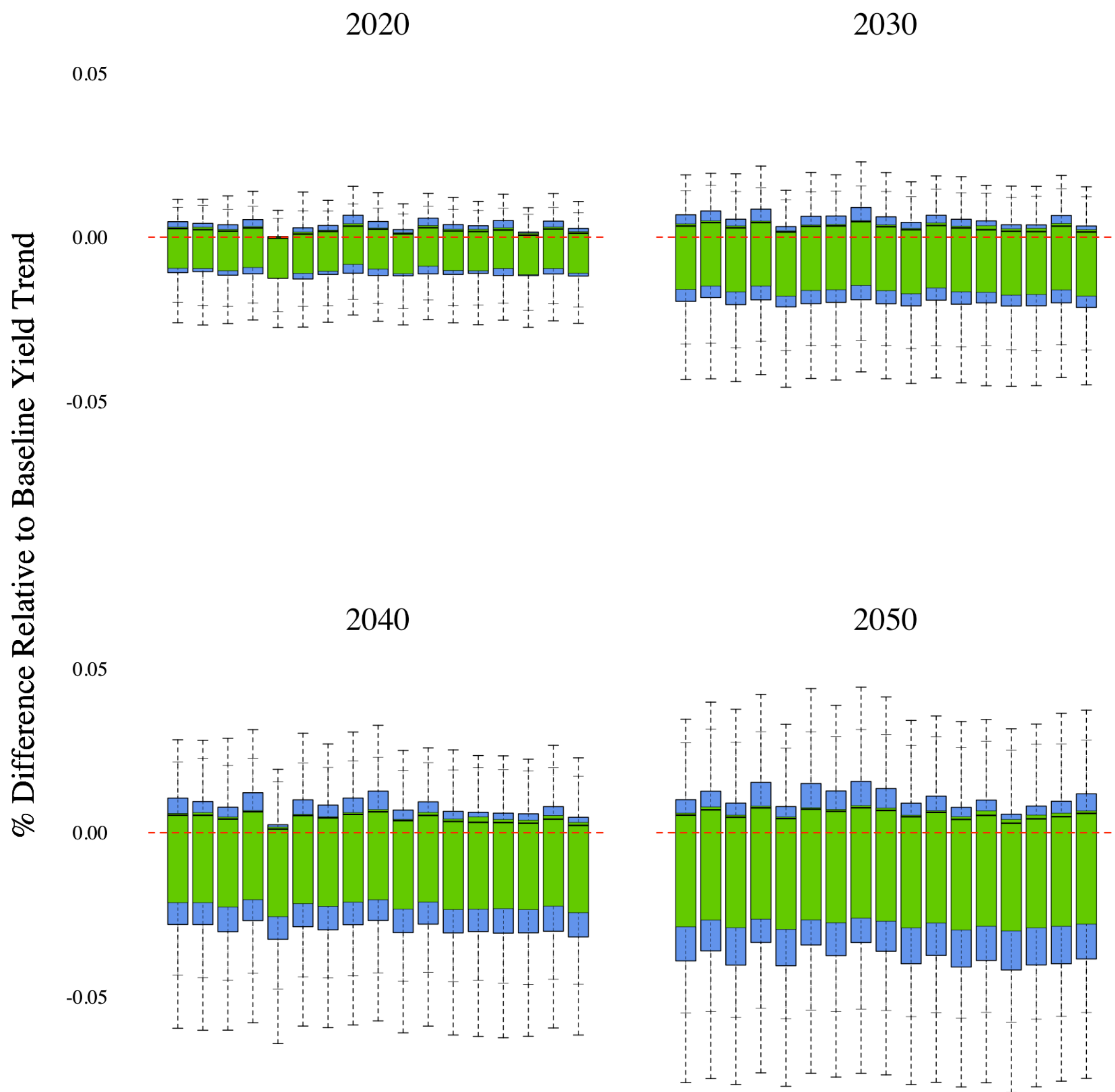
Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured* *relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

Figure 11: Forecasted Change in Durian Yields Under A2 Climate Scenario



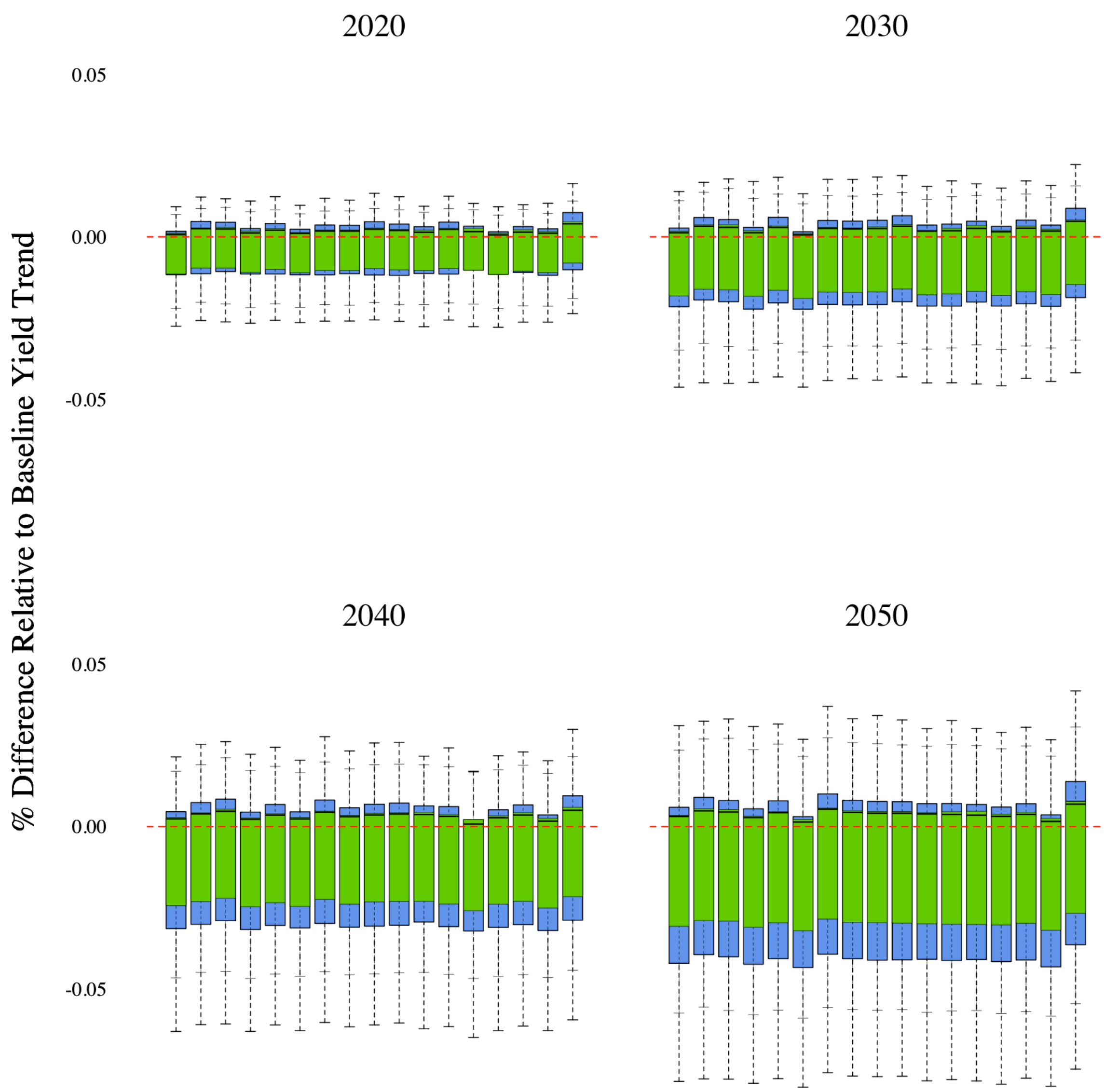
Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

Figure 12: Forecasted Change in Coconut Yields Under A1B Climate Scenario



Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

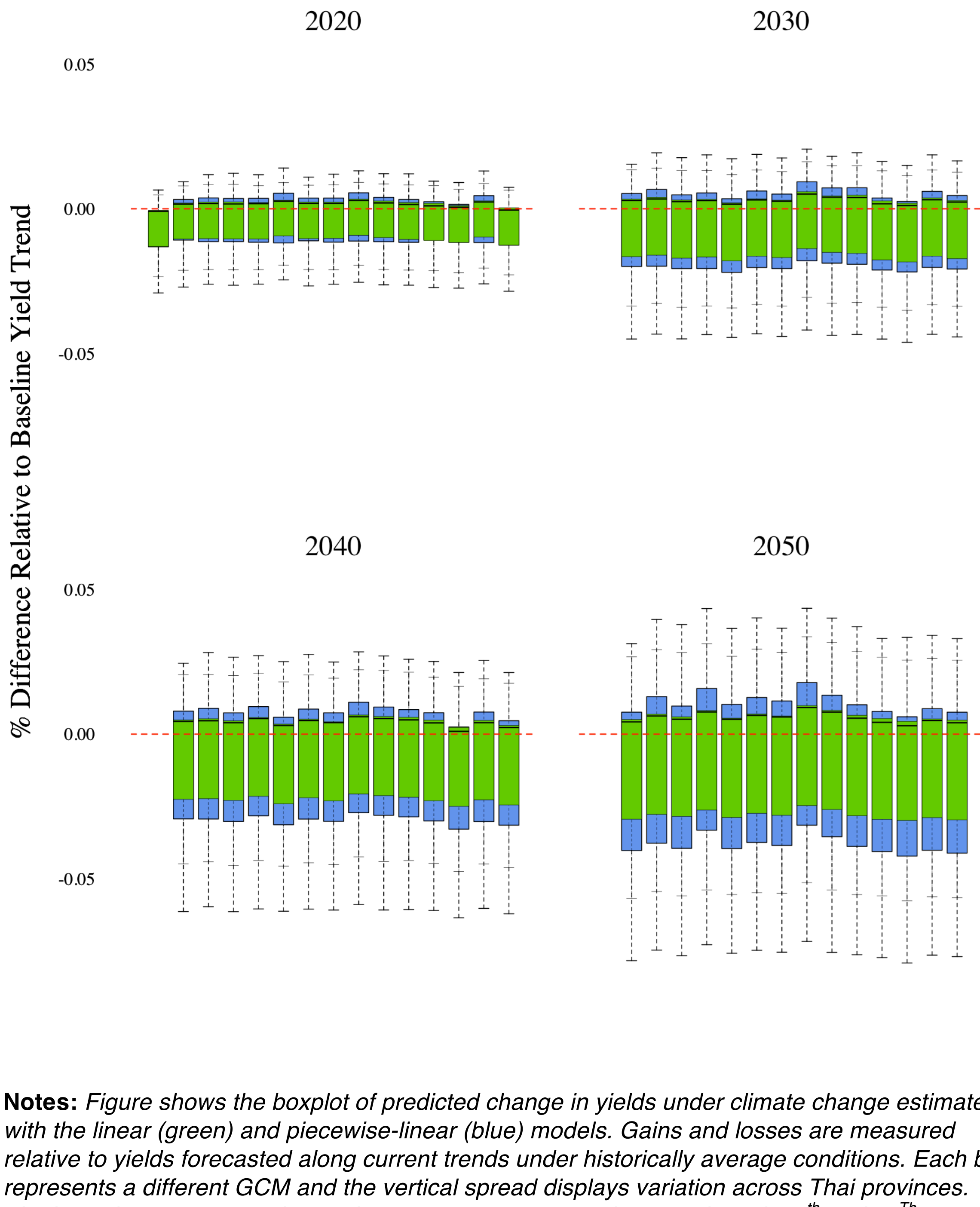
Figure 13: Forecasted Change in Coconut Yields Under B1 Climate Scenario



Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces.*

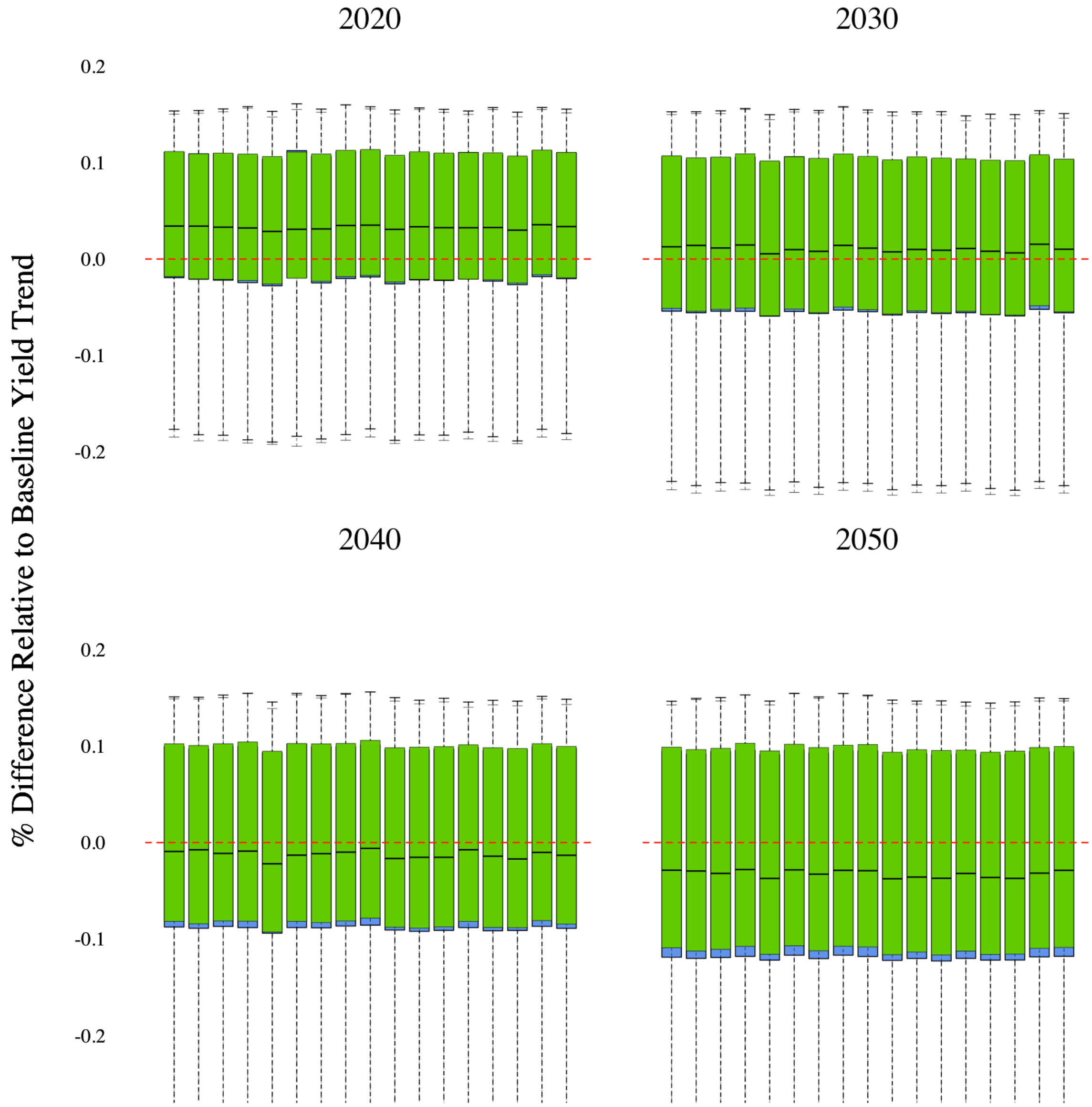
The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.

Figure 14: Forecasted Change in Coconut Yields Under A2 Climate Scenario



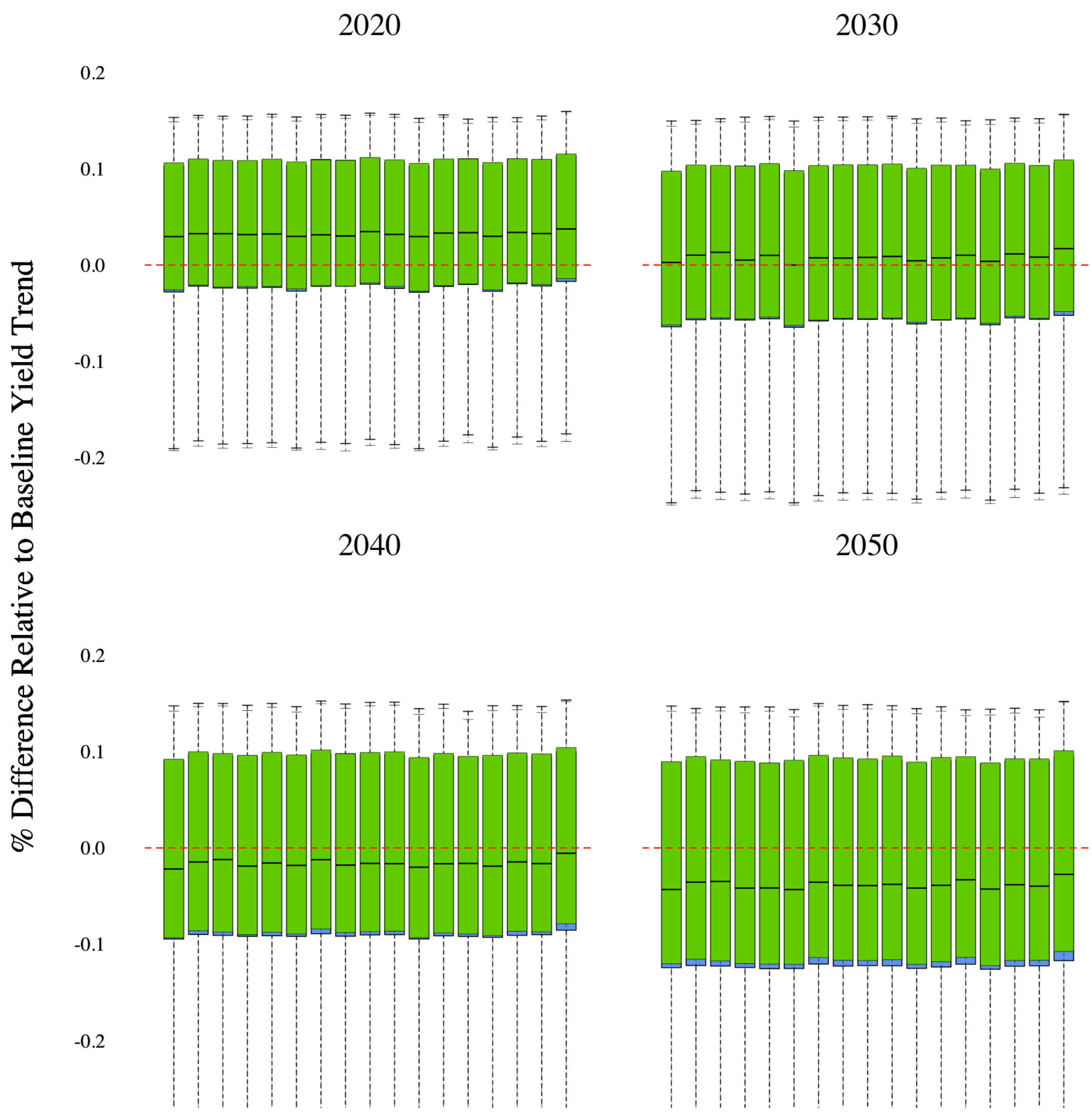
Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

Figure 15: Forecasted Change in Oil Palm Yields Under A1B Climate Scenario



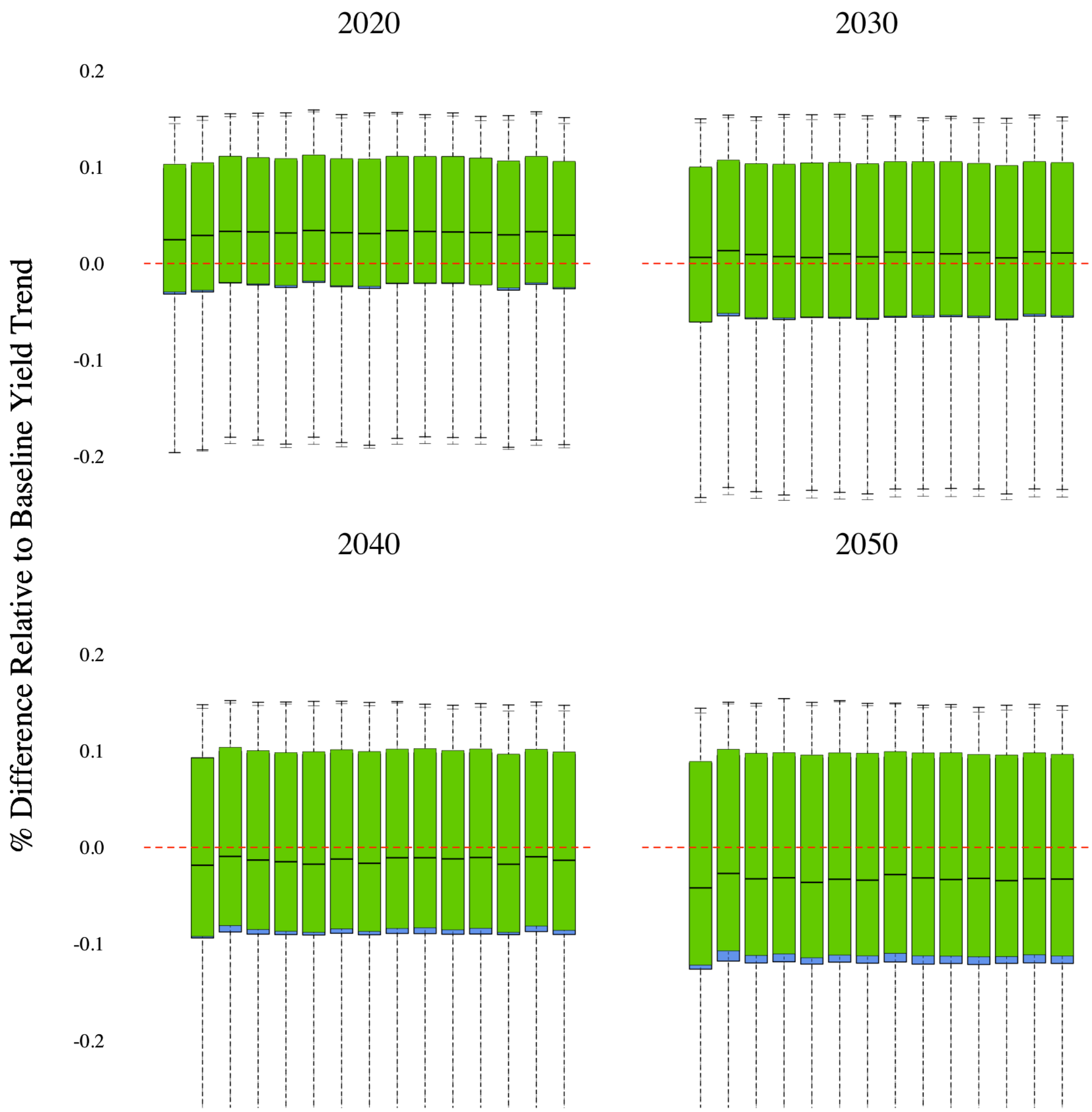
Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5^{th} and 95^{Th} percentile observations.*

Figure 16: Forecasted Change in Oil Palm Yields Under B1 Climate Scenario



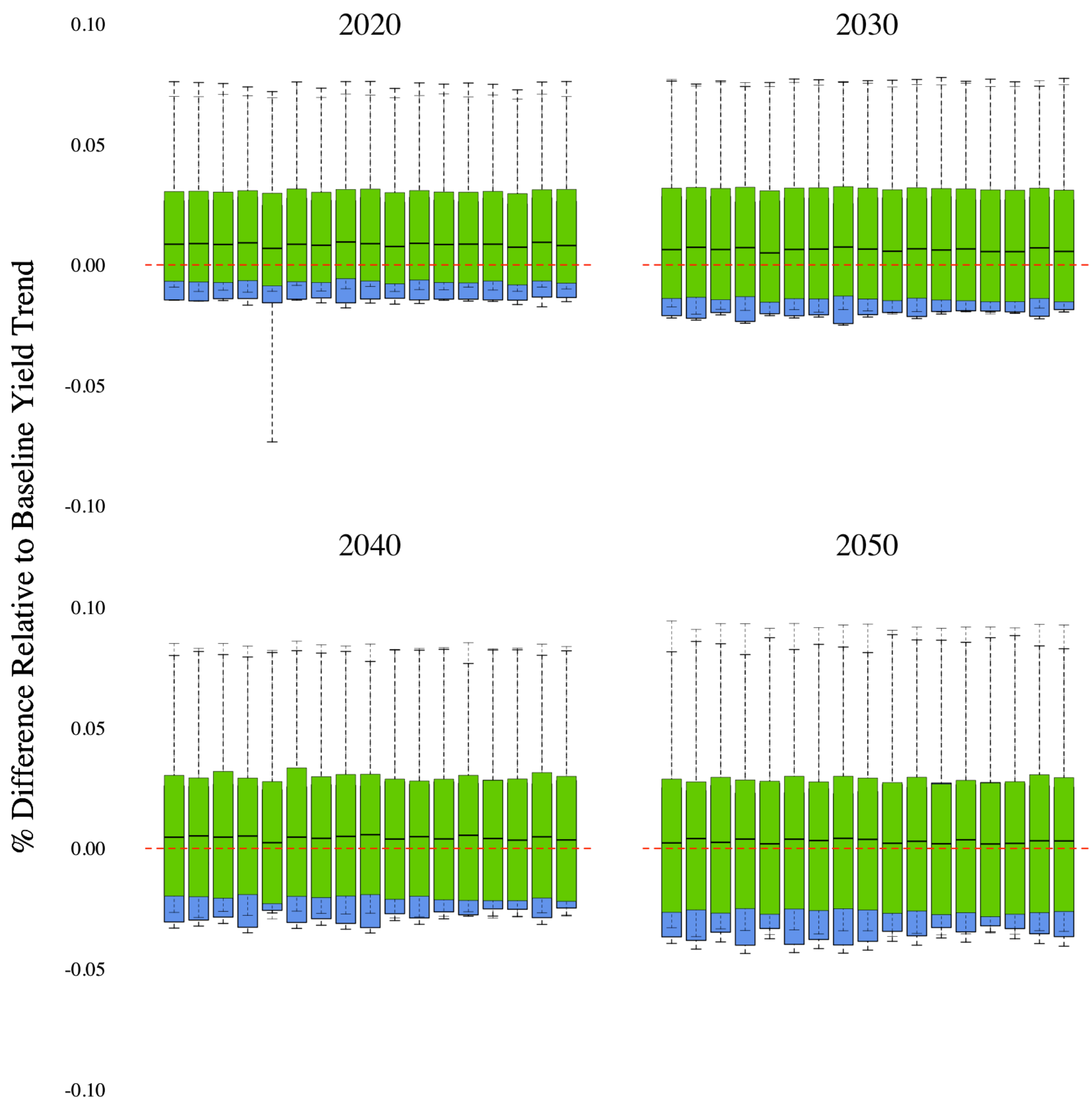
Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

Figure 17: Forecasted Change in Oil Palm Yields Under A2 Climate Scenario



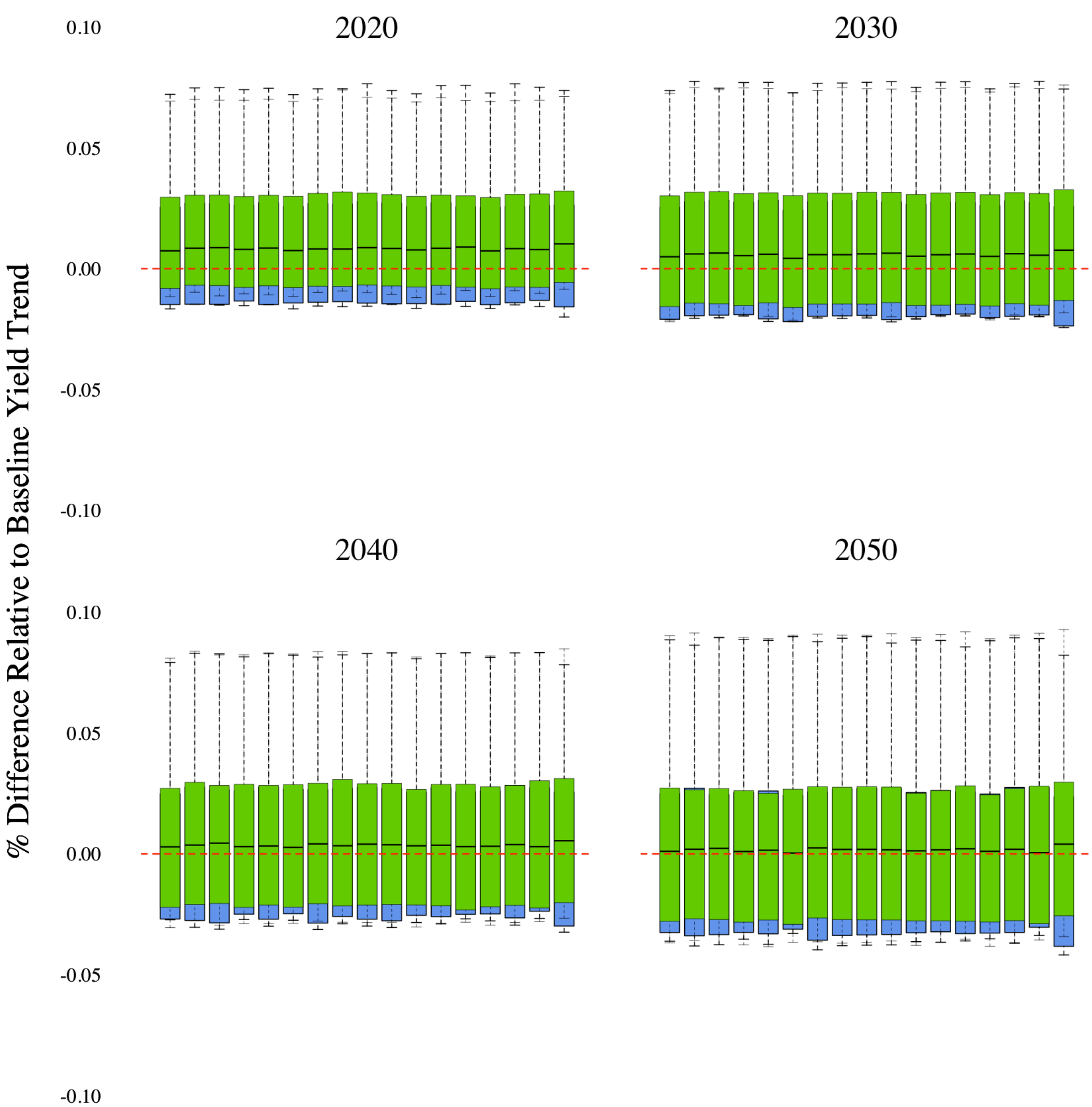
Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

Figure 18: Forecasted Change in Rubber Yields Under A1B Climate Scenario



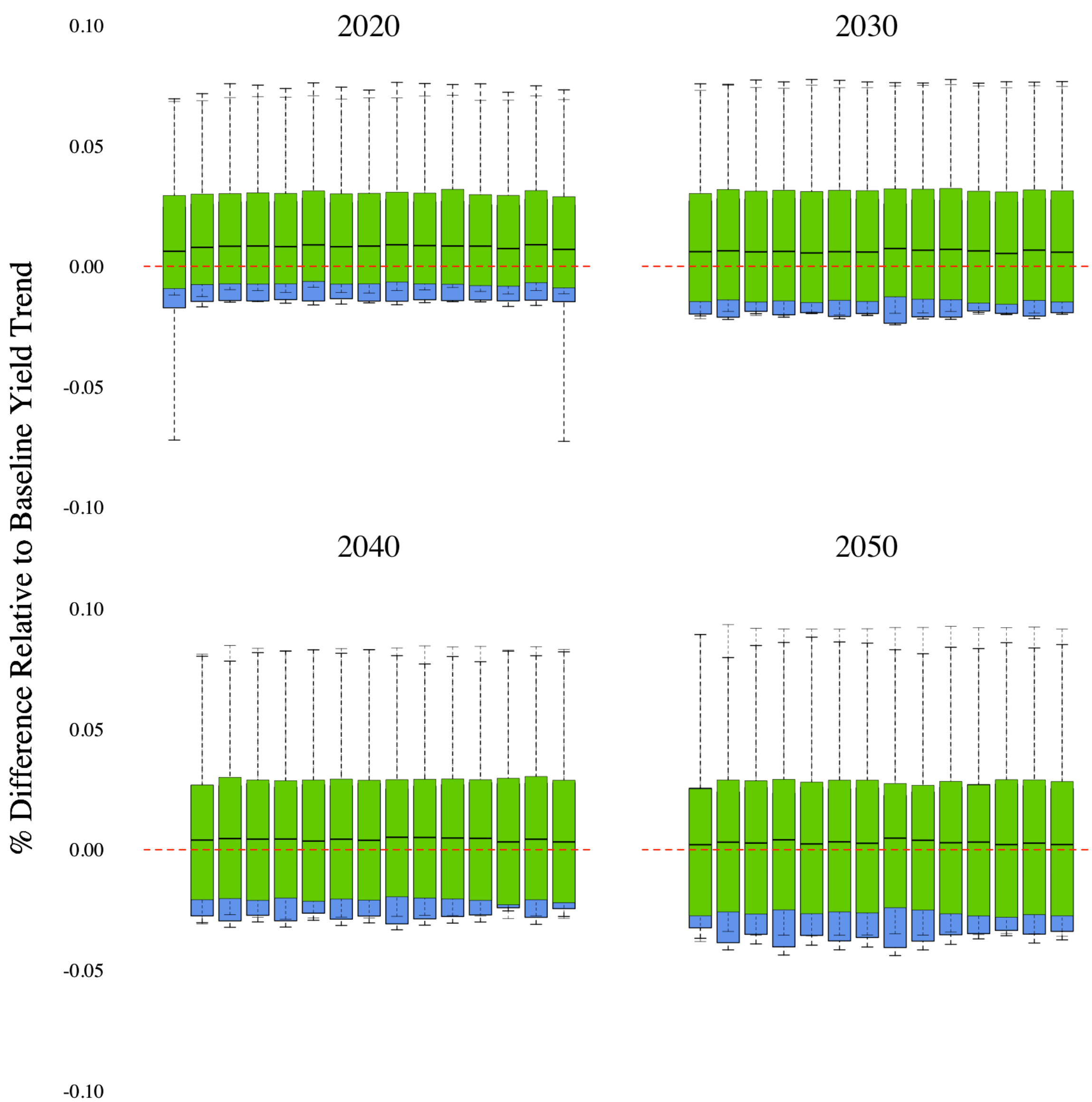
Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

Figure 19: Forecasted Change in Rubber Yields Under B1 Climate Scenario



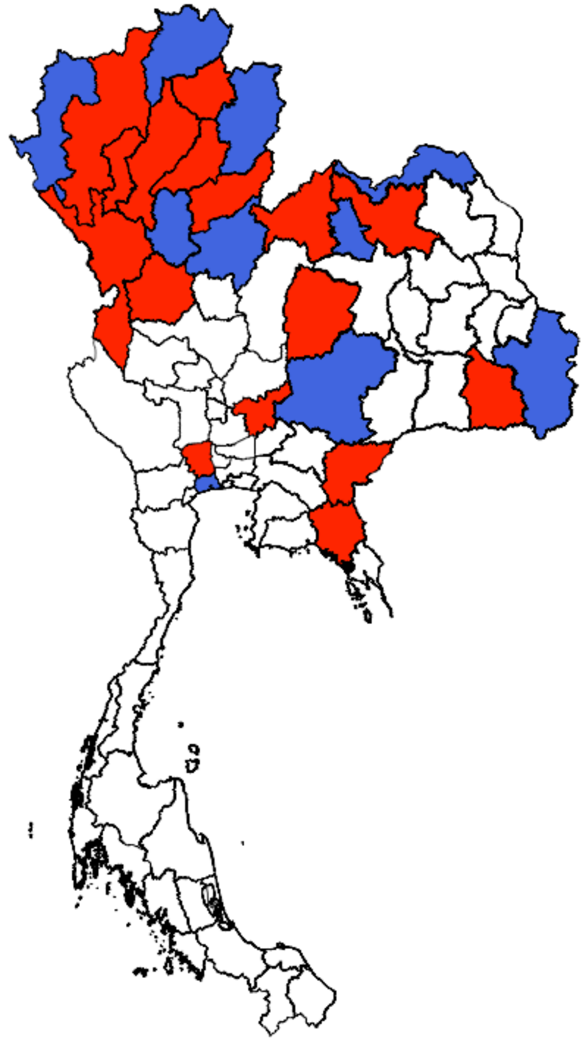
Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

Figure 20: Forecasted Change in Rubber Yields Under A2 Climate Scenario



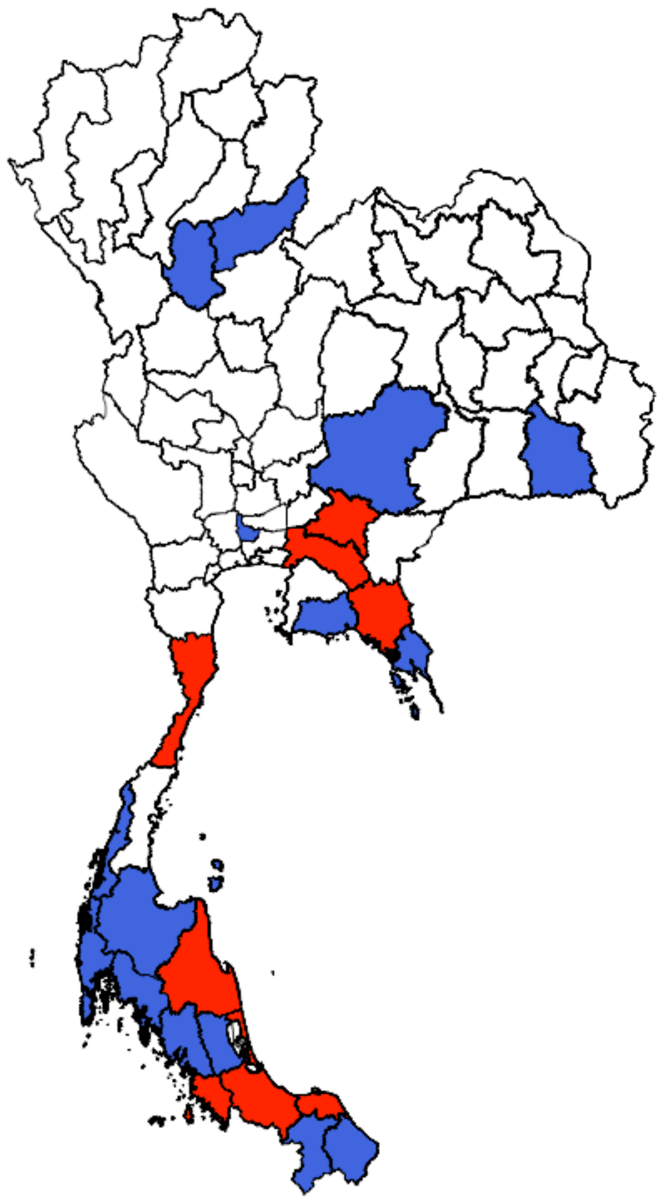
Notes: *Figure shows the boxplot of predicted change in yields under climate change estimated with the linear (green) and piecewise-linear (blue) models. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Each bar represents a different GCM and the vertical spread displays variation across Thai provinces. The black bar represents the median across provinces. Whiskers show the 5th and 95Th percentile observations.*

Figure 21: Longan Yield Gains and Losses from Climate Change in 2050 (A1B)



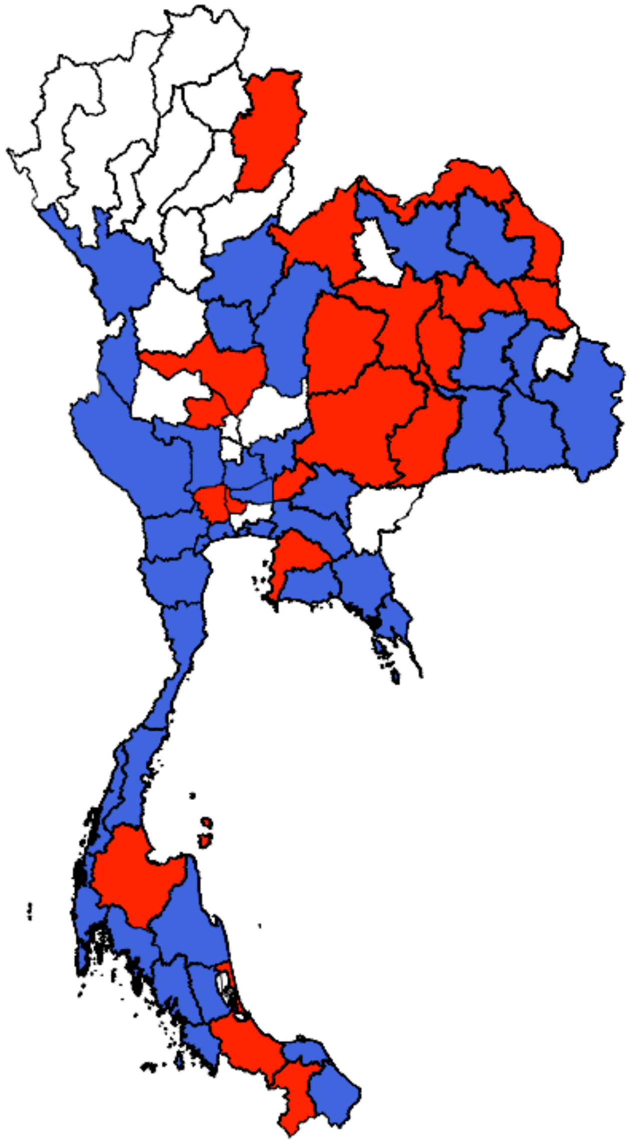
Notes: *Figure shows the provinces gaining (blue) and losing (red) from climate change under non-linear model by 2050. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Results in this figure pertain to the A1B climate scenario, however, the provinces predicted to gain and lose in our piecewise-linear model are nearly the same under all climate scenarios and for most of the decades up to 2070.*

Figure 22: Durian Yield Gains and Losses from Climate Change in 2050 (A1B)



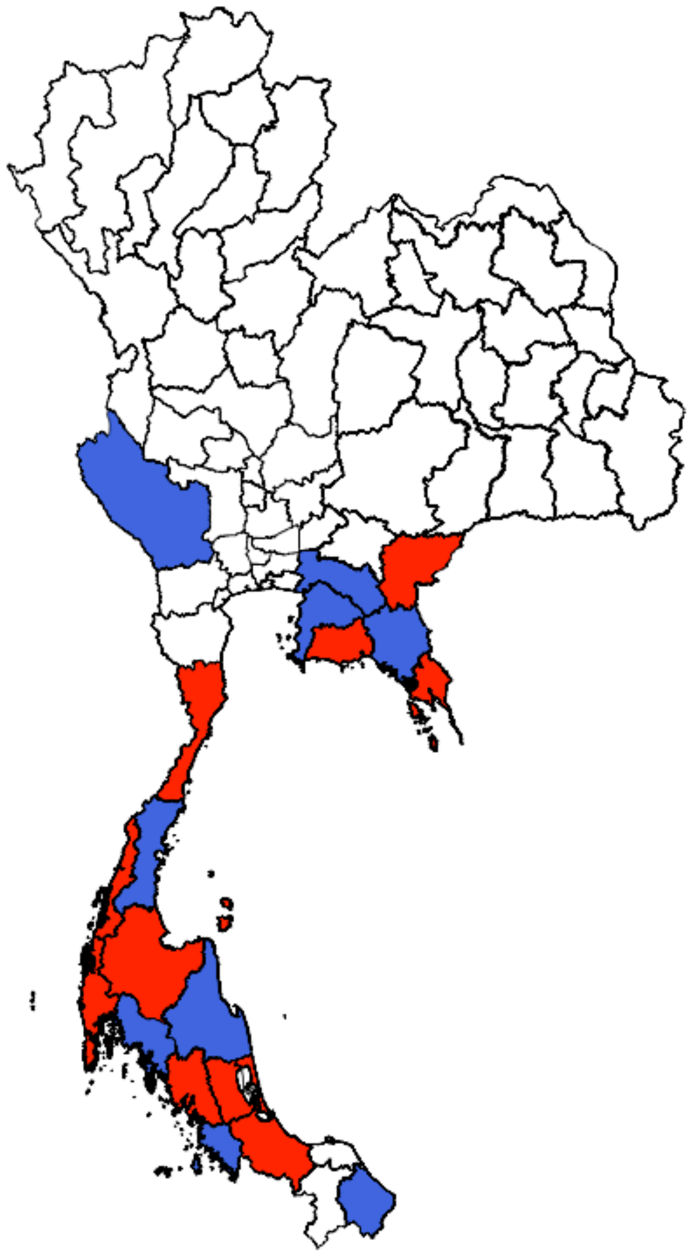
Notes: *Figure shows the provinces gaining (blue) and losing (red) from climate change under non-linear model by 2050. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Results in this figure pertain to the A1B climate scenario, however, the provinces predicted to gain and lose in our piecewise-linear model are nearly the same under all climate scenarios and for most of the decades up to 2070.*

Figure 23: Coconut Yield Gains and Losses from Climate Change in 2050 (A1B)



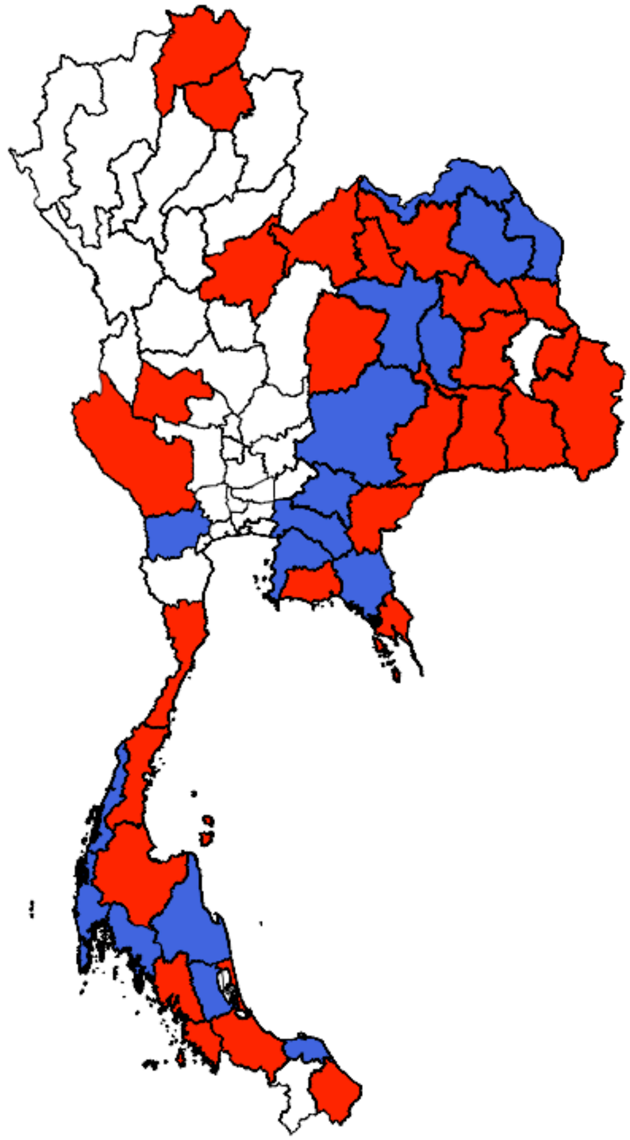
Notes: *Figure shows the provinces gaining (blue) and losing (red) from climate change under non-linear model by 2050. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Results in this figure pertain to the A1B climate scenario, however, the provinces predicted to gain and lose in our piecewise-linear model are nearly the same under all climate scenarios and for most of the decades up to 2070.*

Figure 24: Oil Palm Yield Gains and Losses from Climate Change in 2050 (A1B)



Notes: *Figure shows the provinces gaining (blue) and losing (red) from climate change under non-linear model by 2050. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Results in this figure pertain to the A1B climate scenario, however, the provinces predicted to gain and lose in our piecewise-linear model are nearly the same under all climate scenarios and for most of the decades up to 2070.*

Figure 25: Rubber Yield Gains and Losses from Climate Change in 2050 (A1B)



Notes: *Figure shows the provinces gaining (blue) and losing (red) from climate change under non-linear model by 2050. Gains and losses are measured relative to yields forecasted along current trends under historically average conditions. Results in this figure pertain to the A1B climate scenario, however, the provinces predicted to gain and lose in our piecewise-linear model are nearly the same under all climate scenarios and for most of the decades up to 2070.*

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Annex 1: Tables

Table A1.1: Linear Seasonal Average Panel Model Results:

Longan

	Model (1)	Model (2)	Model (3)
Min Temp (deg C)	-0.530***	-0.663***	-0.070
	(0.106)	(0.103)	(0.136)
Max Temp (deg C)	-0.531***	-0.542***	0.051
	(0.076)	(0.081)	(0.097)
Radiation (mjd^{-1})	-0.201***	-0.172***	-0.248**
	(0.040)	(0.043)	(0.098)
Rainfall (10 cm)	-0.021	0.019	-0.149***
	(0.054)	(0.049)	(0.036)
$Rainfall^2$ (10 cm)	0.006	0.001	0.016***
	(0.006)	(0.005)	(0.003)
Fixed Effects	**Prov**	**Prov**	**Prov, Year**
Time Trend	**National**	**Prov**	**--**
Mean Log Yield	**6.395**	**6.395**	**6.395**
No Obs	**350**	**350**	**350**
R2	**0.473**	**0.537**	**0.878**

Significance levels indicated by ***0.01, **0.05, *0.1
Regressions are weighted by average production over the study period.

Table A1.2: Linear Seasonal Average Panel Model Results:

Durian

	Model (1)	Model (2)	Model (3)
Min Temp (deg C)	-0.144**	-0.191***	-0.009
	(0.055)	(0.048)	(0.058)
Max Temp (deg C)	-0.012	0.012	-0.021
	(0.026)	(0.026)	(0.028)
Radiation (mjd^{-1})	0.093***	0.086***	0.067*
	(0.026)	(0.028)	(0.035)
Rainfall (10 cm)	-0.060***	-0.052***	-0.045***
	(0.012)	(0.010)	(0.012)
Rainfall^2 (10 cm)	0.004***	0.003***	0.002***
	(0.001)	(0.000)	(0.001)
Fixed Effects	**Prov**	**Prov**	**Prov, Year**
Time Trend	**National**	**Prov**	**--**
Mean Log Yield	**7.078**	**7.078**	**7.078**
No Obs	**333**	**333**	**333**
R2	**0.483**	**0.573**	**0.620**

Significance levels indicated by ***0.01, **0.05, *0.1
Regressions are weighted by average production over the study period.

Table A1.6: Linear Seasonal Average Panel Model Results:

Coconut Palm

	Model (1)	Model (2)	Model (3)
Min Temp (deg C)	0.014 (0.032)	0.045* (0.026)	0.069** (0.028)
Max Temp (deg C)	0.123*** (0.043)	0.070** (0.031)	0.098** (0.040)
Radiation (mjd^{-1})	-0.119*** (0.025)	-0.111*** (0.022)	-0.080** (0.030)
Rainfall (10 cm)	0.055* (0.029)	0.078*** (0.027)	0.027 (0.026)
$Rainfall^2$ (10 cm)	-0.004 (0.003)	-0.008*** (0.003)	0.001 (0.003)
Fixed Effects	**Prov**	**Prov**	**Prov, Year**
Time Trend	**National**	**Prov**	**--**
Mean Log Yield	**6.972**	**6.972**	**6.972**
No Obs	**754**	**754**	**754**
R2	**0.238**	**0.450**	**0.446**

*Significance levels indicated by ***0.01, **0.05, *0.1*
Regressions are weighted by average production over the study period.

Table A1.3: Linear Seasonal Average Panel Model Results:

Oil Palm

	Model (1)	Model (2)	Model (3)
Min Temp (deg C)	-0.008 (0.042)	0.004 (0.044)	-0.025 (0.023)
Max Temp (deg C)	0.003 (0.010)	0.011 (0.011)	0.015 (0.019)
Radiation (mjd^{-1})	-0.018 (0.011)	-0.031** (0.014)	0.002 (0.015)
Rainfall (10 cm)	0.004 (0.008)	0.000 (0.007)	-0.003 (0.012)
$Rainfall^2$ (10 cm)	-0.000 (0.000)	-0.000 (0.001)	0.000 (0.001)
Fixed Effects	**Prov**	**Prov**	**Prov, Year**
Time Trend	**National**	**Prov**	**--**
Mean Log Yield	**7.678**	**7.678**	**7.678**
No Obs	**462**	**462**	**462**
R2	**0.636**	**0.686**	**0.811**

*Significance levels indicated by ***0.01, **0.05, *0.1*
Regressions are weighted by average production over the study period.

Table A1.5: Linear Seasonal Average Panel Model Results:

Rubber

	Model (1)	Model (2)	Model (3)
Min Temp (deg C)	0.000 (0.018)	0.008 (0.022)	0.012 (0.008)
Max Temp (deg C)	-0.073*** (0.013)	-0.079*** (0.015)	0.002 (0.007)
Radiation (mjd^{-1})	0.025*** (0.007)	0.029*** (0.006)	-0.035** (0.016)
Rainfall (10 cm)	-0.023 (0.018)	-0.023 (0.017)	0.011 (0.015)
Rainfall^2 (10 cm)	0.004* (0.002)	0.004* (0.002)	-0.000 (0.002)
Fixed Effects	**Prov**	**Prov**	**Prov, Year**
Time Trend	**National**	**Prov**	**--**
Mean Log Yield	**5.421**	**5.421**	**5.421**
No Obs	**921**	**921**	**921**
R2	**0.786**	**0.817**	**0.894**

*Significance levels indicated by ***0.01, **0.05, *0.1*
Regressions are weighted by average production over the study period.

Table A2: Summary of Thresholds Selected for Piecewise-Linear Model

Crop	Minimum Temp			Maximum Temp			Radiation			Precipitation			Nonlinear Model in-sample RMSE Reduction
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	
Longan	21	21	22	33	33	33	18	18	18	9	8	8	**13%**
Durian	24	24	24	33	33	33	16	16	19	9	9	9	**5%**
Coconut Palm	25	25	26	32	32	32	17	17	17	5	5	3	**2%**
Oil Palm	24	24	22	31	32	32	16	16	17	11	11	9	**2%**
Rubber	24	24	22	33	33	33	16	16	16	6	5	11	**4%**

Notes: Table shows summary of selected thresholds for each weather covariate. The thresholds are selected by looping over possible values and selecting the thresholds that minimizes in-sample RMSE. The relationship between crop yields and the weather covariates are then estimated separately over the ranges above and below the endogenously selected thresholds. The final column compares the average RMSE for the piece-wise linear specifications relative to the RMSE for the corresponding linear models with the same trend controls. Trend controls vary across specifications. In specification (1) we include a single linear national trend. In specification (2) we include separate linear trends for each province. In specification (3), we estimate a more flexible form where we control for trends by including year fixed-effects.

Table A2.1: Piecewise-linear Seasonal Average Panel Model Res

Longan

	(1)	(2)	(3)
Min Temp (< 21) (deg C)	-0.392*** (0.192)	-0.391*** (0.167)	-0.206 (0.151)
Min Temp (>21) (deg C)	-0.137 (0.200)	-0.301 (0.242)	-0.005 (0.104)
Max Temp (<33) (deg C)	-0.195*** (0.066)	-0.170** (0.070)	0.056 (0.093)
Max Temp (>33) (deg C)	-0.746*** (0.041)	-0.722*** (0.055)	-0.031 (0.084)
Radiation (mjd^{-1})	-0.186*** (0.035)	-0.177*** (0.046)	-0.201** (0.092)
Rainfall (< 8) (10 cm rain-fed)	-0.011 (0.014)	-0.008 (0.015)	-0.031** (0.012)
Rainfall (>8) (10 cm rain-fed)	0.180*** (0.038)	0.149*** (0.013)	0.276*** (0.013)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**6.395**	**6.395**	**6.395**
No Obs	**350**	**350**	**350**
R^2	**0.629**	**0.656**	**0.894**

*Significance levels indicated by ***0.01, **0.05, *0.1*
Regressions are weighted by average production over the study period.

Table A2.2: Piecewise-linear Seasonal Average Panel Model Results: Durian

	(1)	(2)	(3)
Min Temp (< 25) (deg C)	0.058 (0.041)	-0.027 (0.058)	0.131* (0.068)
Min Temp (>25) (deg C)	-0.264*** (0.042)	-0.272*** (0.042)	-0.084 (0.059)
Max Temp (<33) (deg C)	0.037 (0.031)	0.061* (0.035)	0.036 (0.039)
Max Temp (>33) (deg C)	-0.048 (0.055)	-0.048 (0.051)	-0.070 (0.059)
Radiation (mjd^{-1})	0.094*** (0.018)	0.101*** (0.018)	0.070 (0.041)
Rainfall (< 9) (10 cm rain-fed)	-0.019** (0.007)	-0.025*** (0.007)	-0.015** (0.006)
Rainfall (>9) (10 cm rain-fed)	0.057*** (0.013)	0.056** (0.020)	0.031*** (0.010)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**7.078**	**7.078**	**7.078**
No Obs	**333**	**333**	**333**
R^2	**0.527**	**0.605**	**0.645**

*Significance levels indicated by ***0.01, **0.05, *0.1*
Regressions are weighted by average production over the study period.

Table A2.6: Piecewise-linear Seasonal Average Panel Model Results:

Coconut Palm

	(1)	(2)	(3)
Min Temp (< 23) (deg C)	-0.129** (0.062)	-0.019 (0.086)	-0.080 (0.057)
Min Temp (>23) (deg C)	0.019 (0.029)	0.045 (0.028)	-0.068** (0.030)
Max Temp (<35) (deg C)	0.129*** (0.044)	0.073** (0.031)	0.100** (0.040)
Max Temp (>35) (deg C)	0.390** (0.182)	0.187 (0.190)	0.312* (0.162)
Radiation (<19) (mjd^{-1})	-0.123*** (0.021)	-0.114*** (0.020)	-0.081*** (0.027)
Radiation (>19) (mjd^{-1})	-0.020 (0.073)	-0.023 (0.023)	-0.031 (0.072)
Rainfall (< 4) (10 cm rain-fed)	0.035* (0.019)	0.043** (0.017)	0.027 (0.017)
Rainfall (>4) (10 cm rain-fed)	-0.003 (0.012)	-0.024*** (0.008)	0.035* (0.019)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**6.972**	**6.972**	**6.972**
No Obs	**754**	**754**	**754**
R^2	**0.242**	**0.449**	**0.447**

*Significance levels indicated by ***0.01, **0.05, *0.1*
Regressions are weighted by average production over the study period.

Table A2.3: Piecewise-linear Seasonal Average Panel Model Results:

Oil palm

	(1)	(2)	(3)
Min Temp (< 24) (deg C)	-0.040 (0.049)	-0.050 (0.068)	-0.025 (0.031)
Min Temp (>24) (deg C)	0.036 (0.027)	0.067** (0.033)	-0.025 (0.041)
Max Temp (<31) (deg C)	-0.003 (0.027)	-0.014 (0.035)	-0.038* (0.021)
Max Temp (>31) (deg C)	0.010 (0.011)	0.030** (0.011)	0.041* (0.024)
Radiation (mjd^{-1})	-0.018 (0.011)	-0.034** (0.015)	-0.001 (0.016)
Rainfall (< 11) (10 cm rain-fed)	0.007 (0.010)	0.005 (0.008)	0.004 (0.011)
Rainfall (>11) (10 cm rain-fed)	-0.001 (0.000)	-0.001 (0.001)	-0.000 (0.001)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**7.678**	**7.678**	**7.678**
No Obs	**462**	**462**	**462**
R^2	**0.649**	**0.696**	**0.813**

*Significance levels indicated by ***0.01, **0.05, *0.1*
Regressions are weighted by average production over the study period.

Table A2.5: Piecewise-linear Seasonal Average Panel Model Results: Rubber

	(1)	(2)	(3)
Min Temp (< 24) (deg C)	-0.025	-0.042*	-0.019
	(0.022)	(0.022)	(0.021)
Min Temp (>24) (deg C)	0.057	0.071*	-0.008
	(0.035)	(0.038)	(0.021)
Max Temp (<33) (deg C)	0.075***	0.073***	0.039**
	(0.016)	(0.015)	(0.017)
Max Temp (>33) (deg C)	-0.033	-0.030	-0.075***
	(0.028)	(0.033)	(0.022)
Radiation (<16) (mjd^{-1})	0.232**	0.217**	0.113**
	(0.097)	(0.096)	(0.045)
Radiation (>16) (mjd^{-1})	-0.098***	-0.100***	-0.032*
	(0.014)	(0.017)	(0.018)
Rainfall (< 6) (10 cm rain-fed)	0.007	0.007	0.002
	(0.005)	(0.005)	(0.005)
Rainfall (>6) (10 cm rain-fed)	-0.021***	-0.022***	0.006
	(0.006)	(0.007)	(0.004)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**5.421**	**5.421**	**5.421**
No Obs	**921**	**921**	**921**
R^2	**0.798**	**0.829**	**0.896**

*Significance levels indicated by ***0.01, **0.05, *0.1*
Regressions are weighted by average production over the study period.