Challenges and Opportunities for Climate Adaptation in Thailand Agriculture:

Maize, Soybean, Cassava, and Sugarcane

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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Agricultural Production Systems

Annually Planted Crops

Maize

Maize is an important crop in Thailand for both animal feed and consumption. With the exception of the south, maize is planted across every region in Thailand. Typically, maize is planted as a first crop annually at the beginning of the rainy season. However, it can also be grown as a second crop after rice on paddy fields (Ekasingh et al 2007). Planting is done primarily April through June and harvesting August through November (Figure 1). While there have been some extreme weather events that greatly diminished maize years for a particular period[1], in general yields have grown steadily so that, national average yields in 2010 were approximately 80% higher than in 1985 (Figure 2).

Soybeans

Soybeans are grown across all regions in Thailand other than the south. The north is the largest producer where many farmers grow soybeans as a second crop in the dry season after growing rice in the wet season. Nationally, soy growing can be grouped into two planting and harvesting periods, early and late. Harvesting for the early season begins in late July and continues through November, at which time growers in many reasons begin planting for the later season. Growing in the central, eastern, and western regions takes place primarily in the early season, planting in June and July and harvesting primarily in September and October.

[1] For example, an extended drought from 1988 – 1992 in the northeast led to greatly diminished yields in that region and lower annual yields nationally for several years (Ekasingh et al 2007).

While soybean production does require rain in early growth stages, the water requirements for production are much lower than for rice (Gonsalvez). However, soybean production may require irrigation if it is grown in areas without sufficient early growing season rainfall.

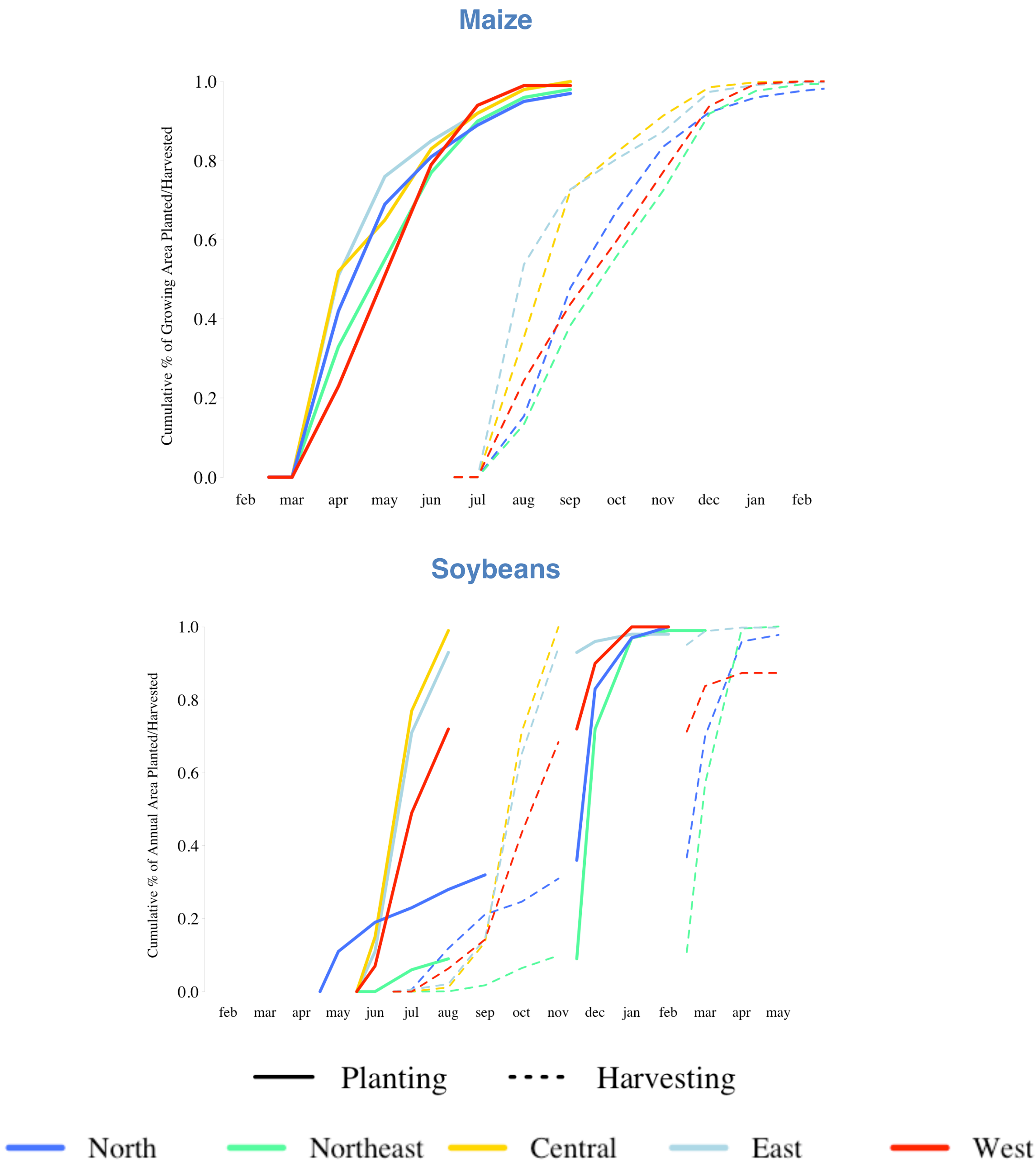
Cassava

Cassava yields have been slowly rising over the past two decades, and the crop has recently become more important as an input to biofuel production. Cassava can be used or sold for consumption as well as sold as an input to animal feed or ethanol. About half of Thai cassava production is used domestically and half is exported. Thailand is typically Asia's largest exporter of cassava (Gonzalves). One of the benefits of producing cassava is that it can be grown on marginal land with poor soil quality and low levels of rainfall. Moreover, because it is a perennial crop, it can be harvested only as necessary.

Sugarcane

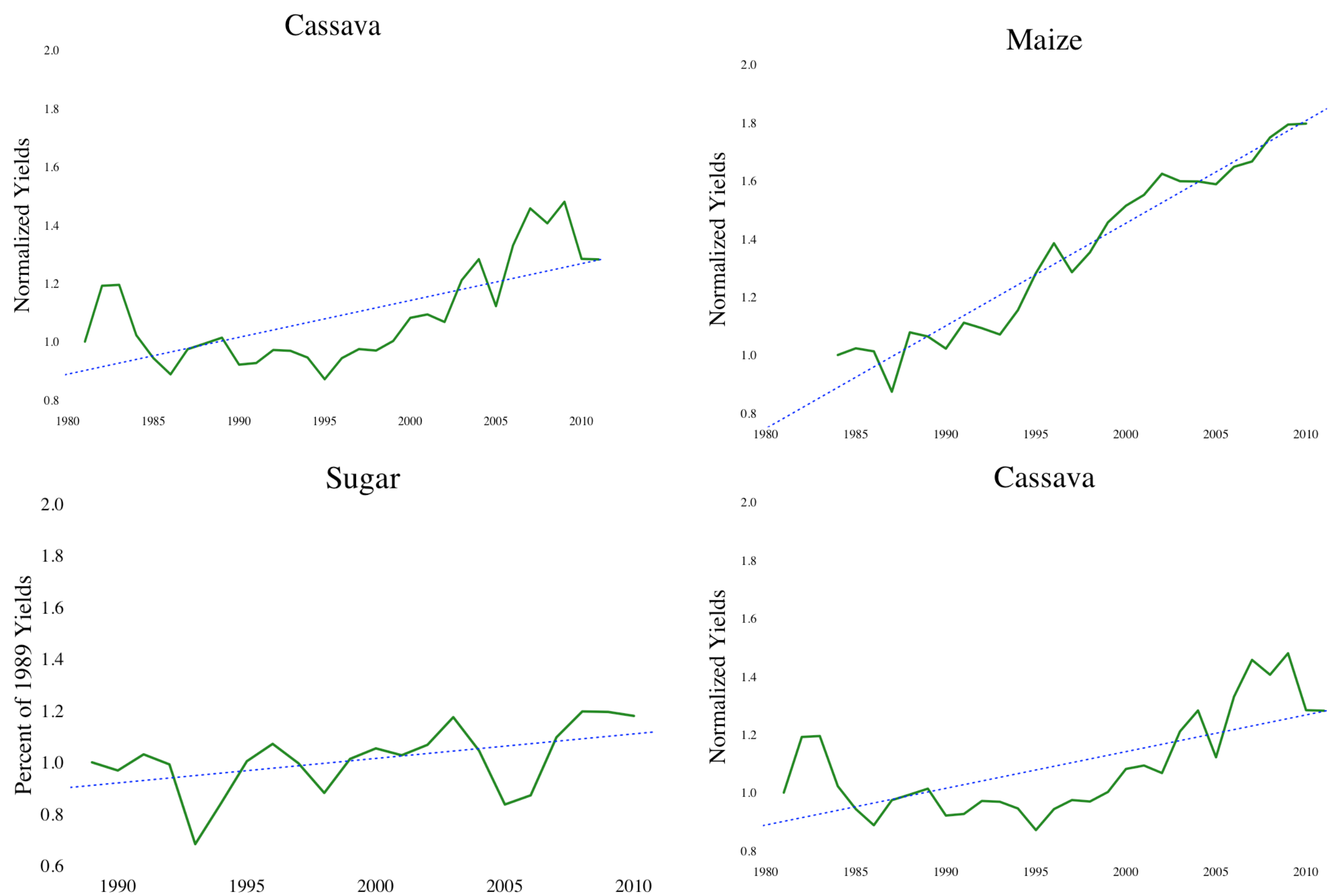
Over the past two decades, sugar yields have slowly but steadily increased. However, year-to-year variation remains high. Sugarcane is increasingly being used as an input to biofuels rather than for consumption. Recent estimates suggest that 15-20% of sugar produced in Thailand is consumed domestically, while the remaining portion is exported. However, sugar used for export has slowly begun to be utilized for domestic biofuel production (Gonzalvez,). In general, sugarcane is often grown in hotter, drier areas. In fact, from our data, we estimate that approximately 90% of sugar production is grown in rain-fed areas without access to irrigation.

Figure 1: Distribution of Maize Growing Season



Notes: *Figure shows average distribution of maize and soy planting and harvesting by month. Data are averaged over the years (2006 – 2010).*

Figure 2: Long Run Yield Trends



Estimation Approach

In order to evaluate the effect of weather fluctuations on maize, soy, sugar, anc yields, we apply statistical models using plausibly random variations in year-to-yea Typically, statistical studies use average growing season (or sub-season) con represent the weather inputs in the production function. The simplest approach esti yields as a function of mean temperature, mean precipitation, and their squares. several studies have emphasized the differential effects of non-linearities yiel relationships (e.g., Schlenker and Roberts, 2010). Consequently, much of our analys on estimating panel regression fixed-effect models where weather covariates are m piece-wise linear in their effects on yield.

We begin with a baseline approach of estimating the effects of weather on rice yiel panel regression with a single growing season metric for each weather covariate growing season min T, max T, radiation, and precipitation). Using average conditions, we estimate both linear and piecewise-linear models, which are late predict yields under various climate scenarios. For some crops, (maize, cassava, use GIS data[2] in order to interpolate weather over planted areas and divide rainfa variables: rainfall over rain-fed cropland, and rainfall over irrigated cropland. For o (soy) we interpolate weather over the entire provinces with production data available single rainfall variable in our analysis.

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

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, however, 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 and 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. The benefit of this approach is that it 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 are also included for the piecewise-linear models.

III. Results

Maize

Maize yields are found to be highly sensitive to rising minimum and maximum temperatures. In the linear model, rising minimum temperatures are found to have the larger effect, with a one-degree increase in average minimum temperature across the growing season reducing yields by nearly 6%. Radiation is also found to be negatively associated with maize yields. In the linear model, maximum temperatures are weakly negatively correlated with maize yields, however, when we separate the range of maximum temperatures in order to estimate the piecewise linear model, we find that maize yields are sharply reduced by temperatures above 33 degrees. The negative effect of temperatures is found to nearly double in most cases when temperature surpass this threshold. Nighttime minimum temperatures are also found to be significant in the non-linear model, however, the magnitude of the coefficients are significantly smaller (~2%).

At initial low levels or rainfall, additional precipitation is found to increase yields by 7-10%. However, at intermediate rainfall levels, additional rainfall is found to neither hurt nor help maize yields. The estimated cutoff point where rainfall stops contributing to sharply increasing yields is low, relative to other crops (20cm), suggesting that maize yields may be more robust to water shortages than other crops in our study.

Soy

Our results in the linear model suggest that soy yields are most sensitive to changes in average daily maximum temperatures, where a one-degree increase in temperatures is associated with a 2% decline in yields. The relationship between yields and minimum temperature, as well as yields and radiation, are not found to be significant.

When we allow for weather effects to differ nonlinearly, we find maximum temperatures above 34 to be extremely harmful, reducing soy yields by up to 20% from a one-degree rise in temperature. The effect size is significantly smaller (although still negative) when initial temperatures are below 34. A similar pattern of sharp drops in soy yields from temperatures above a given threshold was also found in soy production in the U.S. (Schemer 2010)

Cassava

Of all the crops discussed here, cassava appears to be the crop most robust to temperature rises (in terms of percentage yield changes). Both our linear and non-linear models suggest that rising minimum temperatures, as well as maximum temperatures above 23.5 degrees C, will actually *increase* yields. Rainfall in cassava growing areas is found to be beneficial (2% increase) for the first 160cm, but then slightly negative thereafter.

Sugarcane

In the linear model we find do not find a strong relationship between minimum temperature and sugar yields. However, we find that higher maximum temperatures are generally associated with lower yields. The relationship between radiation and sugarcane yields is estimated to be positive in two of three specifications and negative the in the third, while rainfall effects are not significant.

In the piecewise-linear model for sugarcane, the thresholds that fit the data best are at 23 degrees for average minimum temperature, 34 degrees for average maximum temperature, 19 mjd^{-1} for radiation, and 40cm of rainfall. Below the minimum temperature threshold, we find that rising temperature are associated with 5-7% higher yields. However, above 23 degrees, a one-degree increase in average minimum temperature is associated with 6% lower yields.

Rising maximum temperatures, on the other hand, are found to be associated with lower sugar yields across the range of observed temperatures. However, above the thresholds the yield reductions are much larger. In two of three specifications we find that a one-degree increase in maximum temperature below 34 degrees reduces yields by 1-7%. However, above 34 degrees (20% of observations), we find that the effect of a one-degree increase in maximum temperature is nearly double, ranging from a 7-16% reduction in yields.

We do not find a significant relationship between our measure of rainfall and sugar yields below the threshold, however, above the threshold we find that an additional 10cm of rainfall is associated with 3% higher yields. These findings are consistent with a scenario where less than 40cm of rainfall is insufficient to improve sugar yields, however, above 40cm additional rainfall results in higher yields.

In summary, we find that rising maximum temperatures are likely to hurt sugar yields, however, above 34 degrees there is a sharp drop-off in yields. We find that rising minimum temperatures increase sugar yields, up to 23 degrees, and above the threshold reduce yields. We find the same increasing and then decreasing relationship with radiation. Finally, we estimate a positive relationship between sugar yields and rainfall above 40cm, but an insignificant relationship below 40cm.

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.

Yield Forecast Results

Maize

Under the linear model, maize yields are found to decrease steadily each decade with approximately 5-10% losses predicted by 2050. All temperature and radiation covariates are found to be negatively associated with higher maize yields in the linear model and rainfall is not found to be significant. In the non-linear model, we find similar results, where all temperature and radiation variables are found to be negatively associated with higher maize yields. In these specifications, additional rainfall is found to be highly beneficial (+9% in yields) when rainfall levels are initially low. However, at higher levels of seasonal rainfall, additional rainfall is not found to be significantly beneficial. Moreover, rainfall above the upper threshold of 170cm is found to be negatively associated with maize yields. Collectively, this suggests that maize is one of the more robust crops with respect to water shortages.

Soybean

Under both models, median losses of 3-5% are forecast by 2050. The linear specifications predict that losses are incurred immediately. However, in the non-linear model, yields are forecast to initially decrease with rising temperatures, but to sharply decrease after temperatures cross the respective thresholds. The two-part response is predicted because temperatures under the thresholds are found to be positively associated with higher yields, however, once temperatures cross the thresholds, yields begin to decline sharply, with a one-degree increase in maximum temperature over 34 degrees reducing yields by 5%.

Cassava

Under the linear model we forecast *higher* future yields (up to 5% by 2050) relative to baseline forecasts under no climate change. This is because our linear model finds that rising minimum and maximum temperatures are both positively associated with higher yields. Under the non-linear model, we find similar results, with a wider variety for predictions. Both maximum and minimum temperatures are found to be positively associated with yields, although higher radiation levels are found to be negatively associated with yields. In addition, lower levels of rainfall are found to reduce potential cassava yields. However, in most cases the positive temperature effects around found to outweigh the negative effects from reductions in rainfall. That being said, in cases of extreme water shortages, cassava yields are vulnerable to major losses. Compared to rice and tree crops though, cassava is relatively robust to water shortages.

Sugar

Under the linear models, we find that sugar yield losses under climate change are minimal. Relative to baseline trends, the linear models predict that median losses will be less than 1%, with about one-third of sugar areas gaining from changing climate. However, under the piece-wise median linear models yields losses exceed 1%, with some models predicting 2% losses by 2050. The reason for the different finding under the non-linear model is that we find sharp yield declines with maximum temperatures over 34.5 degrees, and minimum temperatures over 23 degrees. Above the maximum temperature threshold, we find that losses associated with a one-degree increase in temperature double. Above the minimum temperature threshold, we find that yield changes associated with rising minimum temperature switch from being positive to negative. Consequently, taking into account the differential yield effects over different ranges of temperatures, we predict a 1-2% decline in sugar yields by 2050, relative to baseline yields forecast under current conditions.

Figure 3: Forecasted Change in Maize Yields Under A1B Scenario

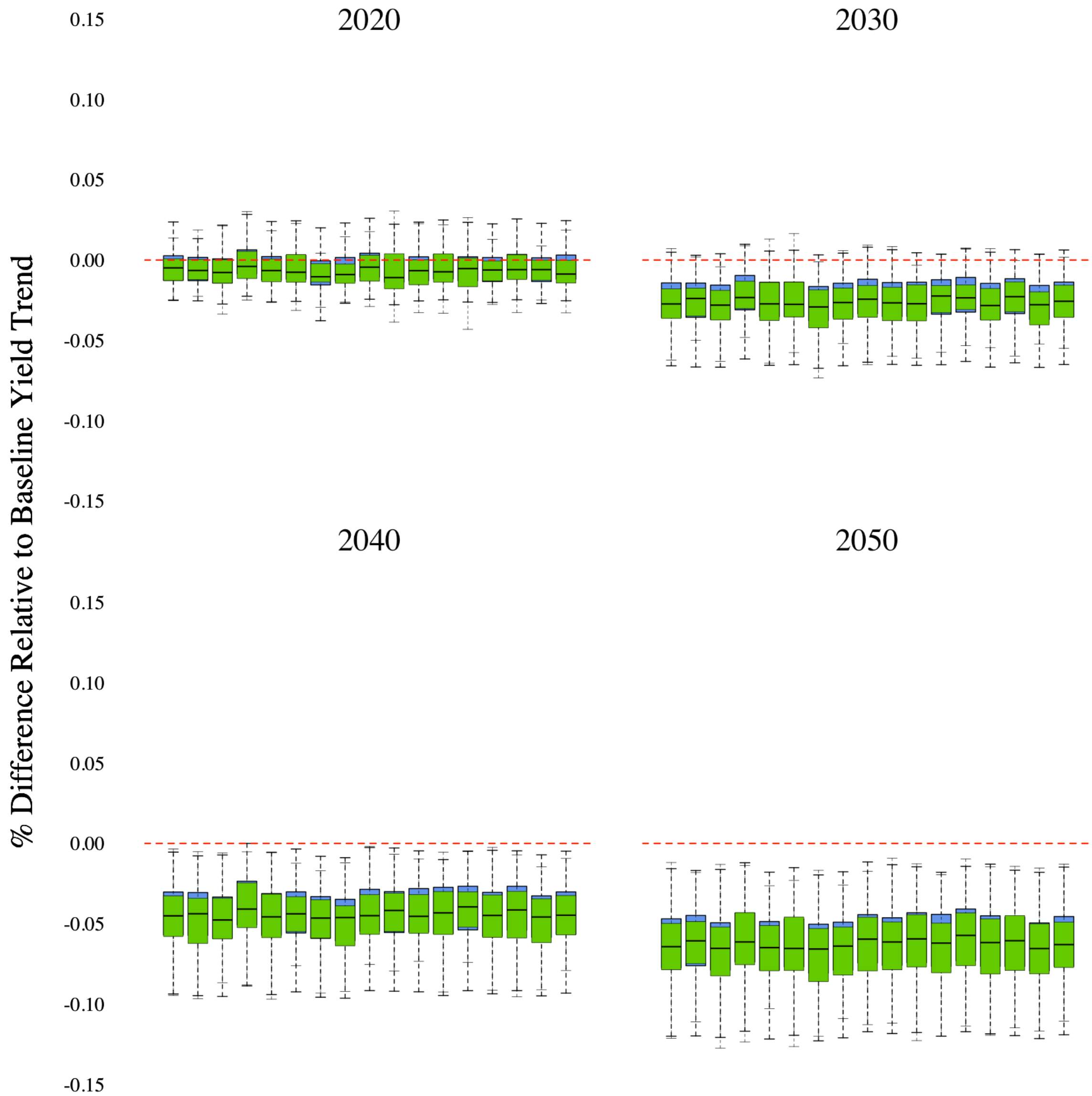


Figure 4: Forecasted Change in Maize Yields Under A2 Scenario

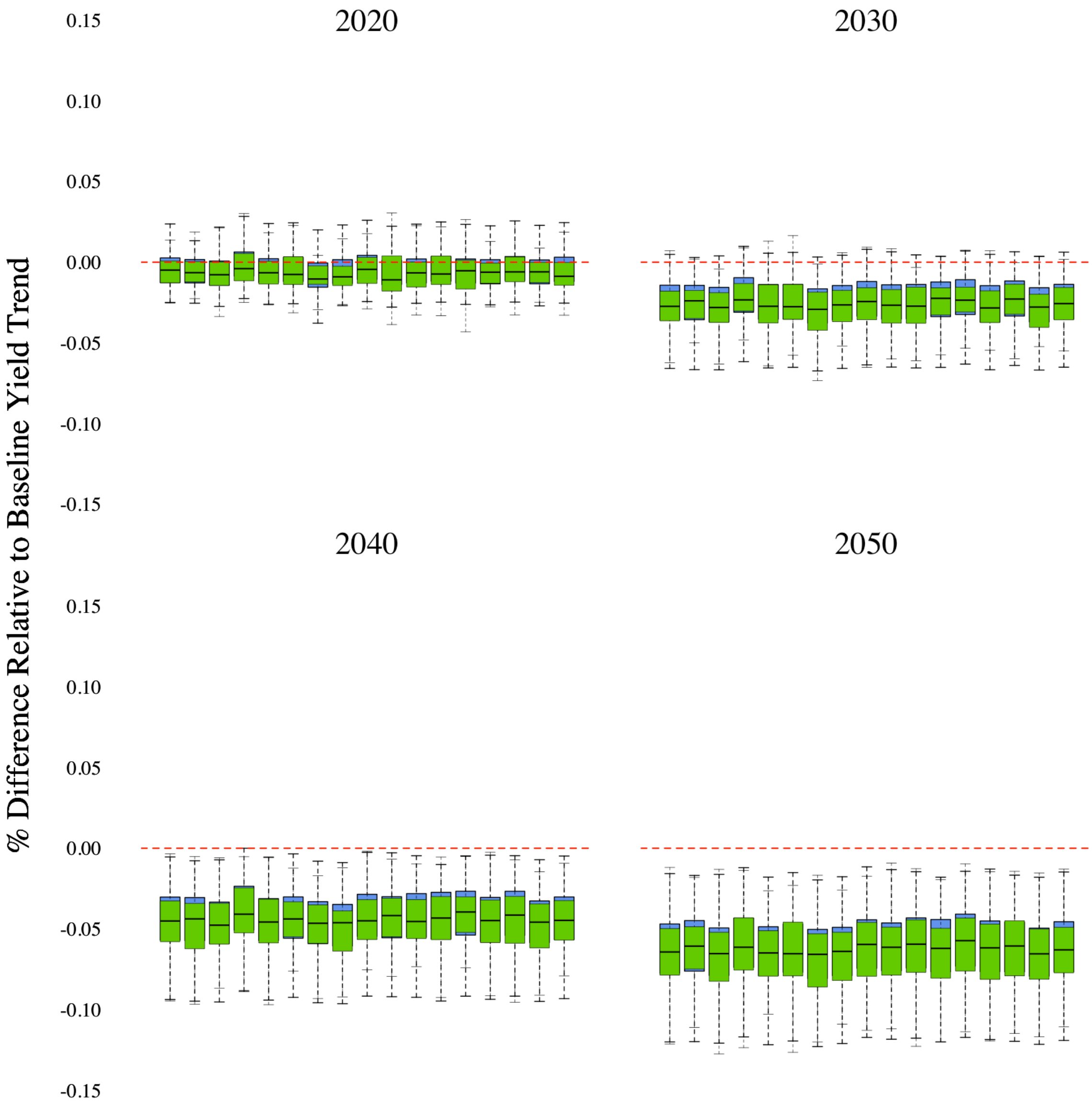


Figure 5: Forecasted Change in Maize Yields Under B1 Scenario

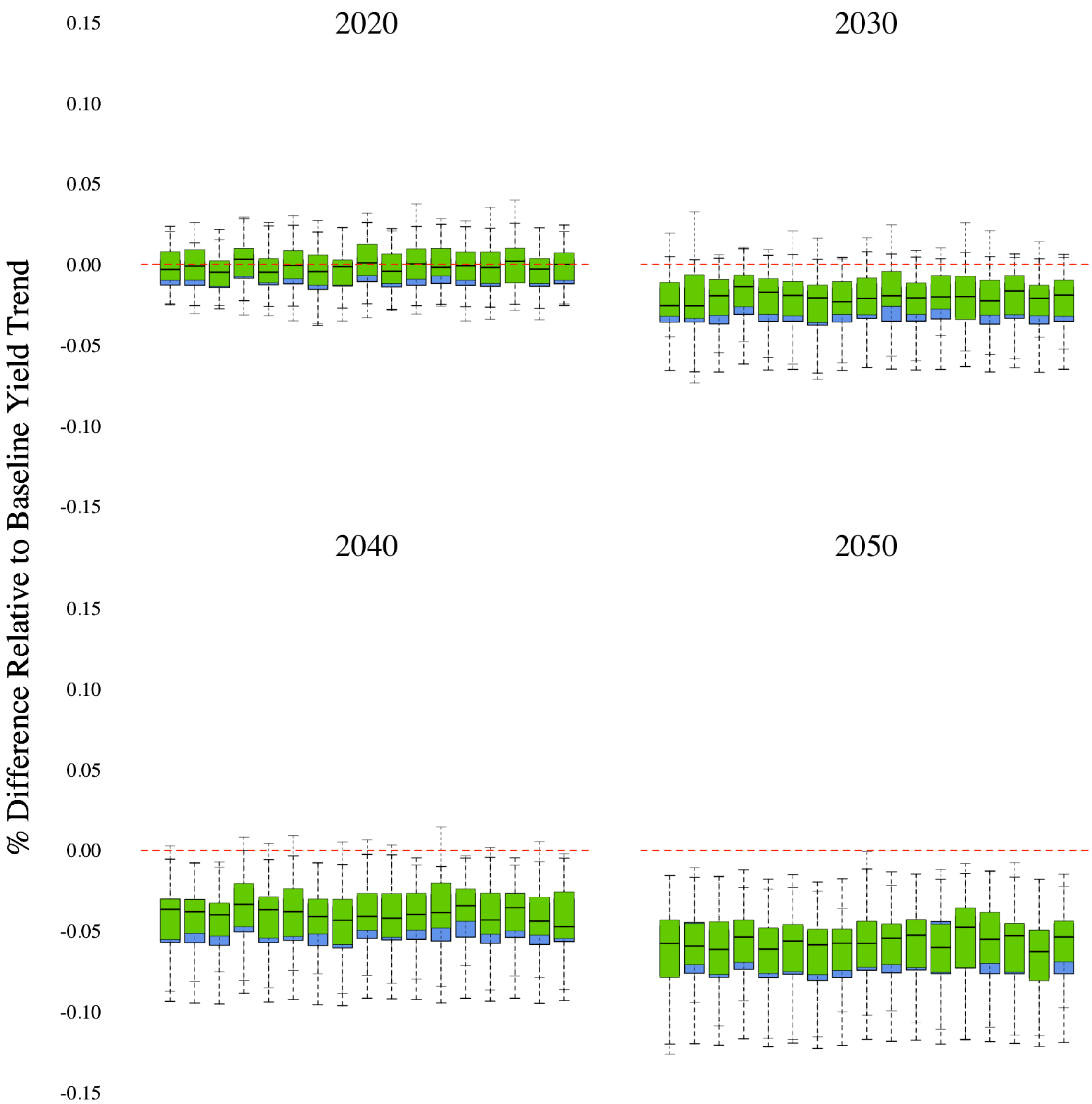


Figure 6: Forecasted Change in Soy Yields Under A1B Scenario

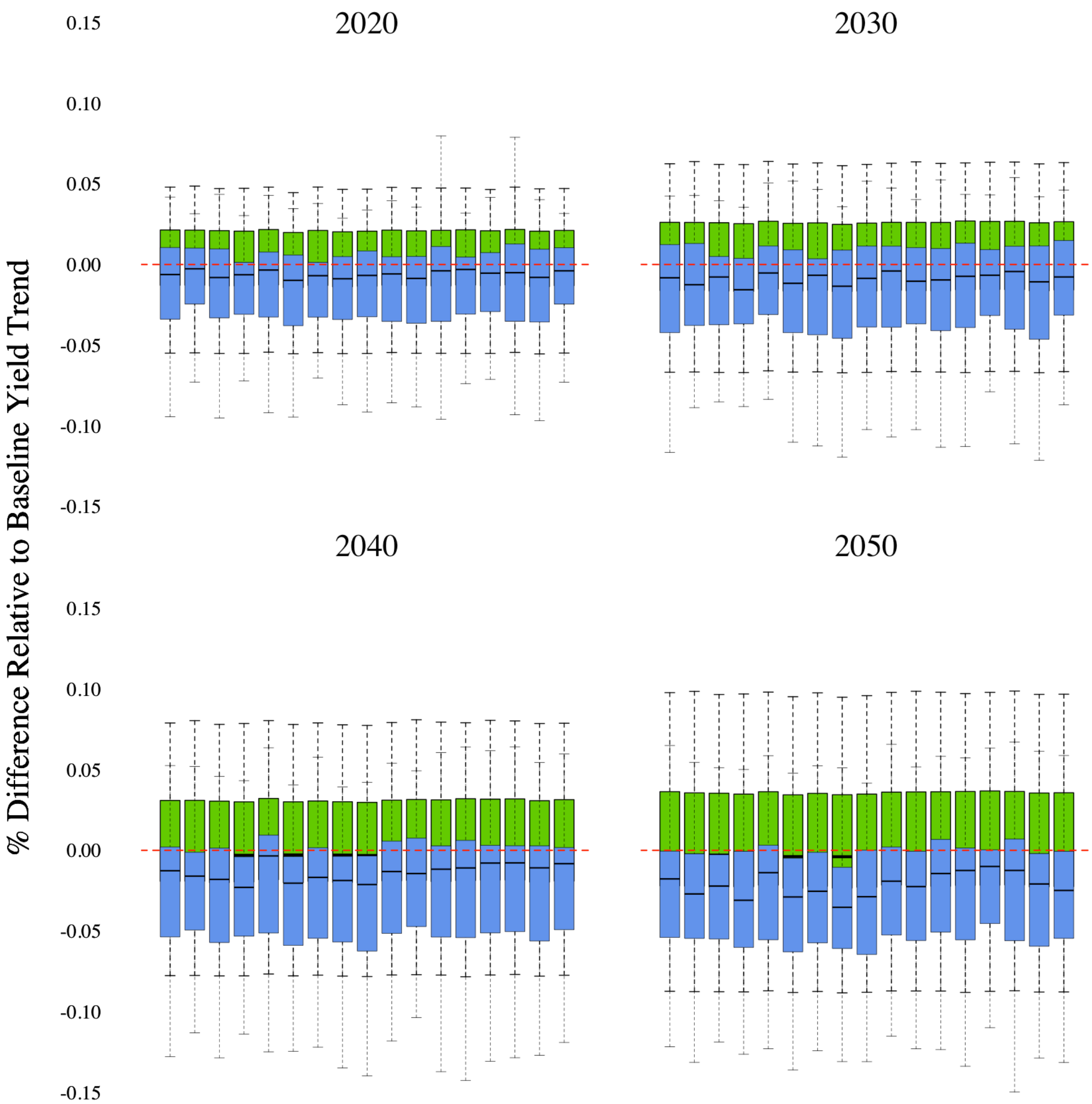


Figure 7: Forecasted Change in Soy Yields Under A2 Scenario

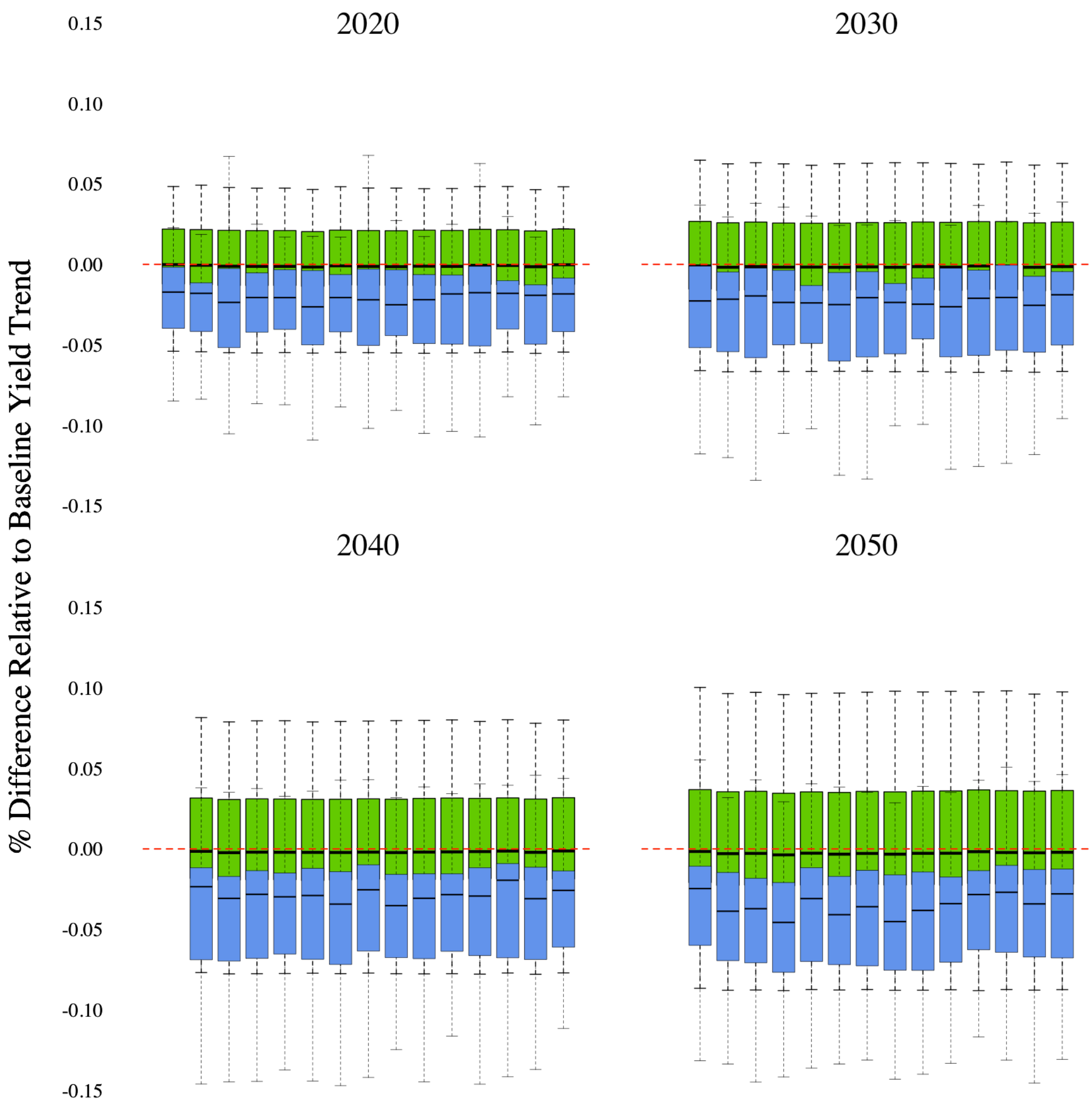


Figure 8: Forecasted Change in Cassava Yields Under A1B Climate Scenario

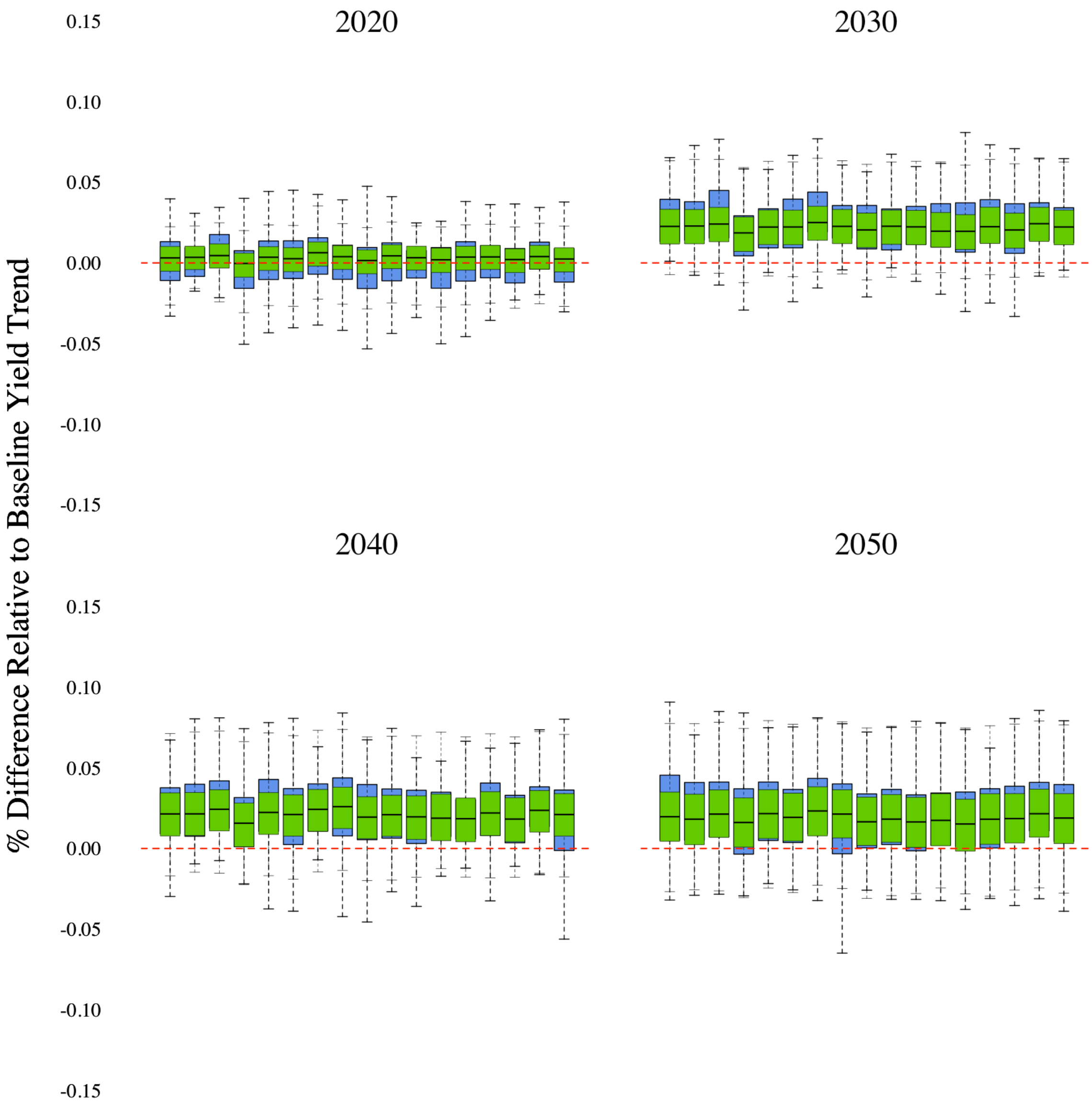


Figure 9: Forecasted Change in Cassava Yields Under B1 Climate Scenario

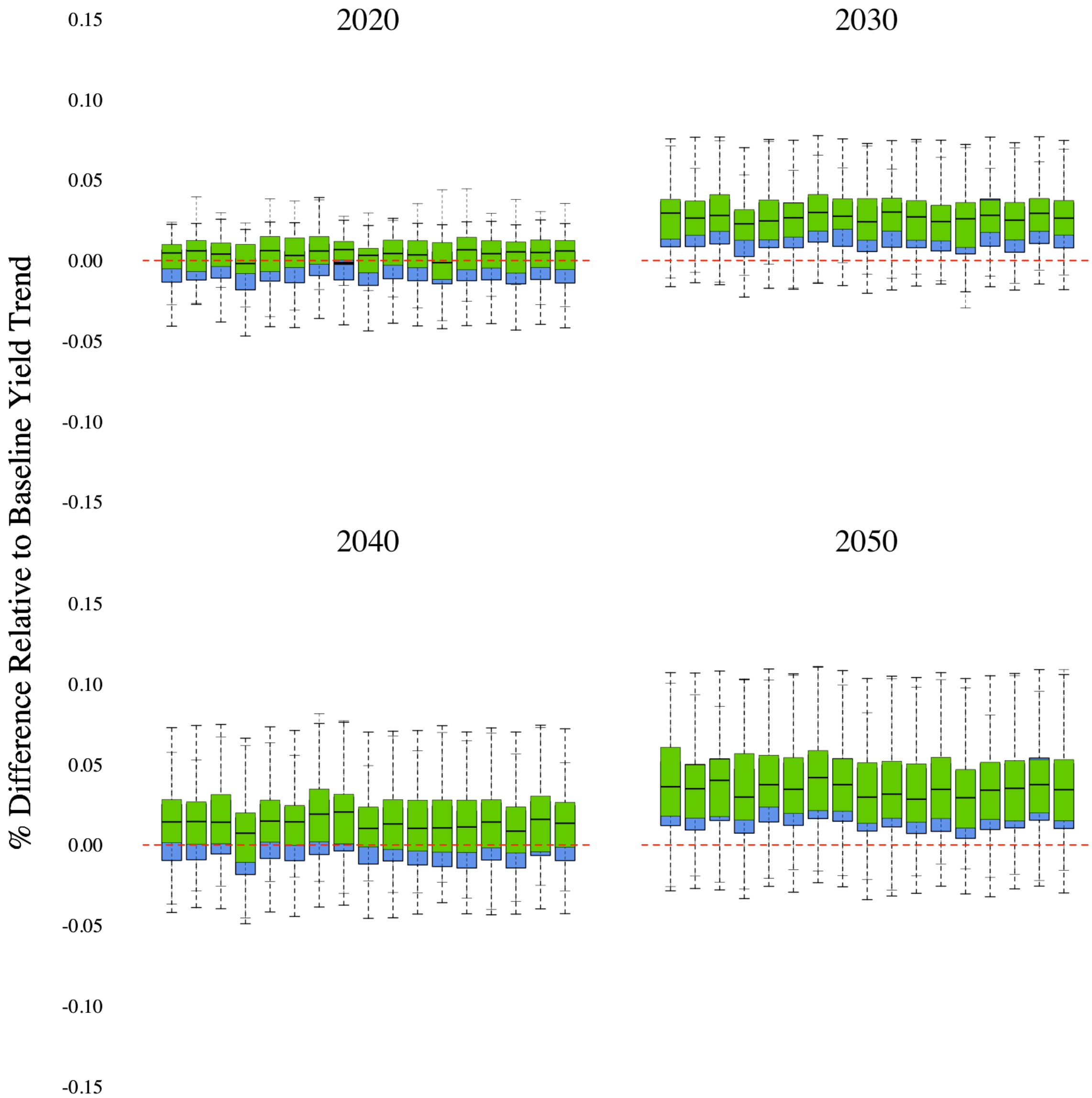


Figure 10: Forecasted Change in Sugar Yields Under A1B Climate Scenario

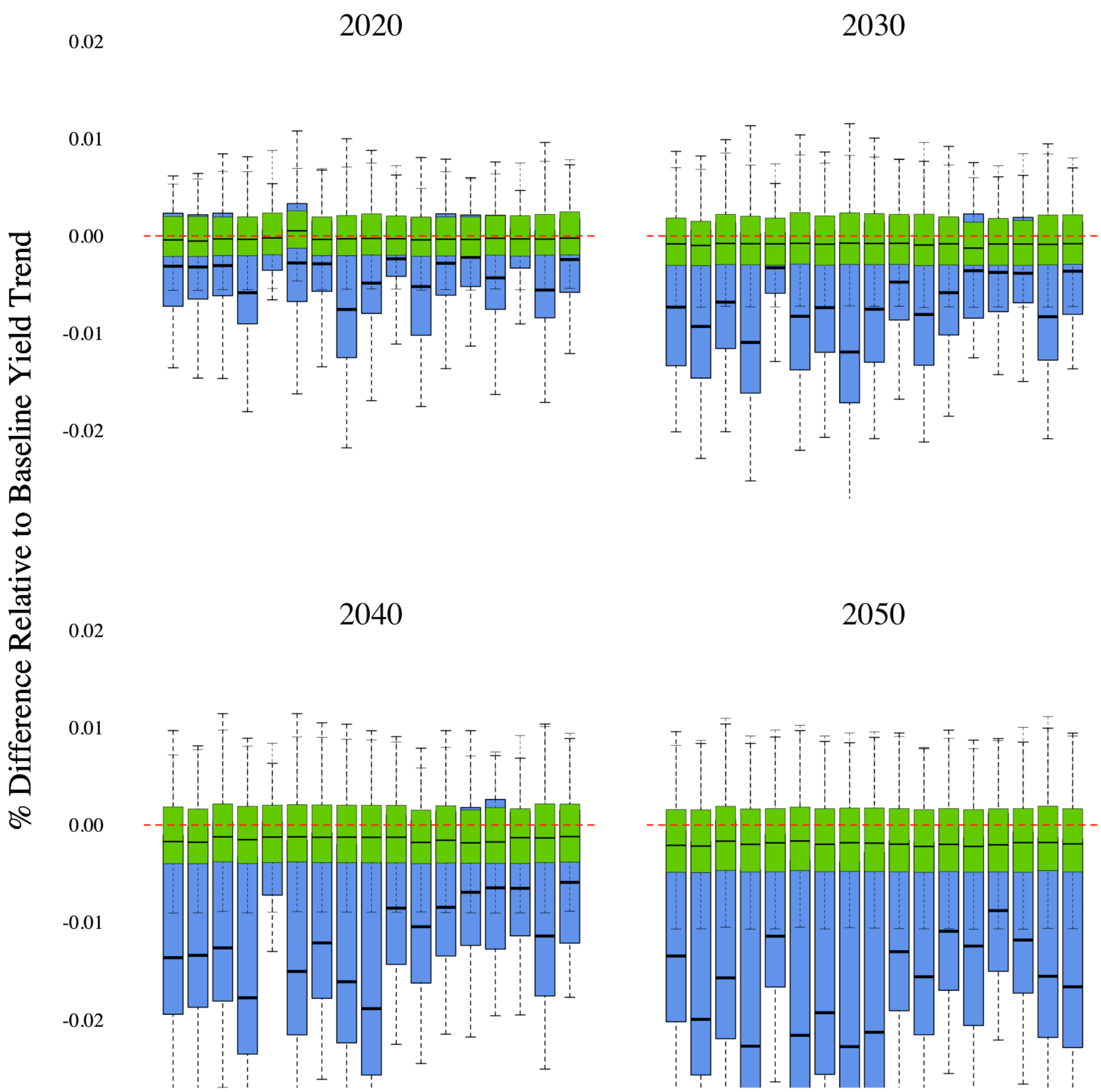


Figure 11: Forecasted Change in Sugar Yields Under B1 Climate Scenario

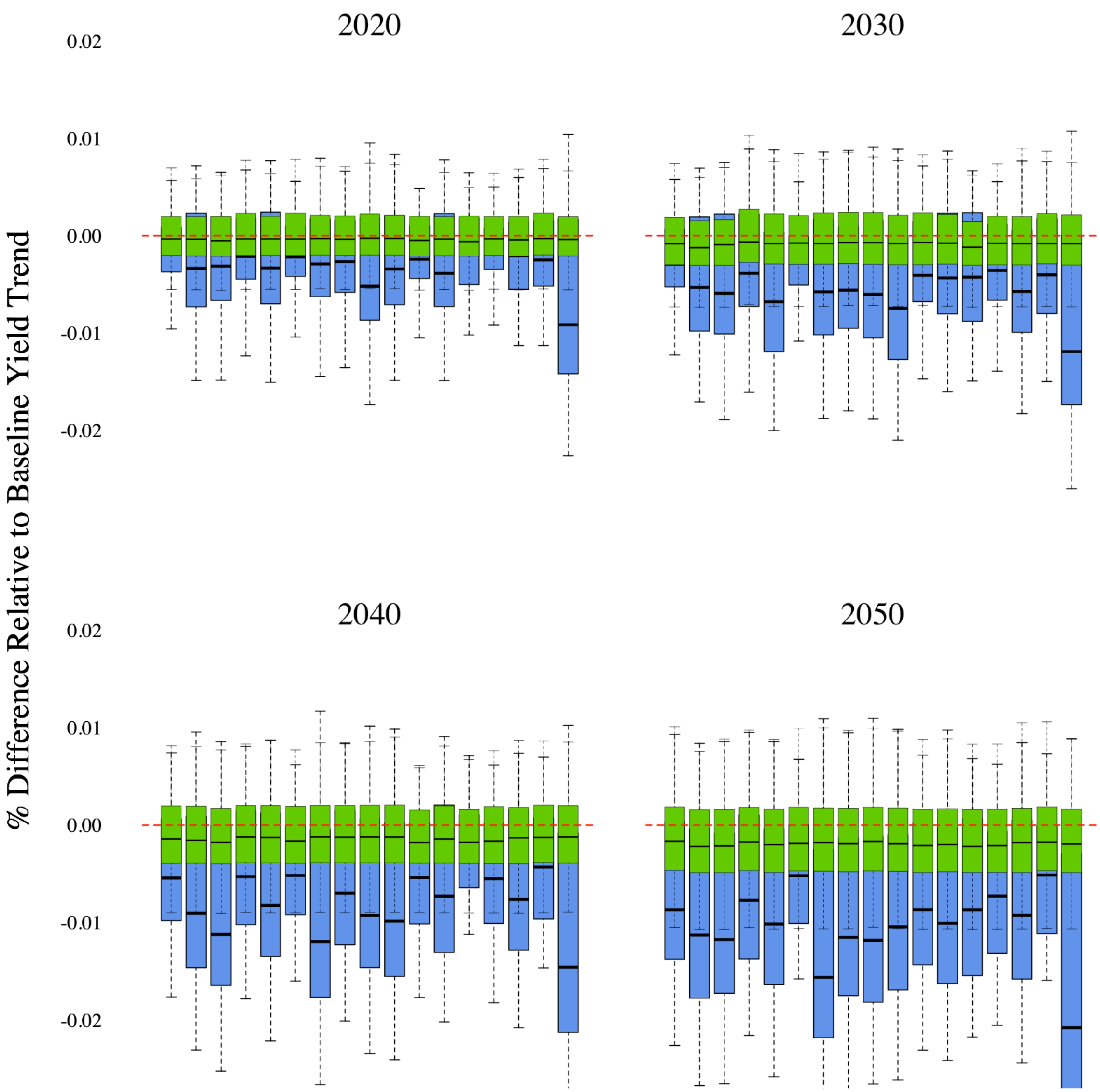


Figure 12: Forecasted Change in Sugar Yields Under A2 Climate Scenario

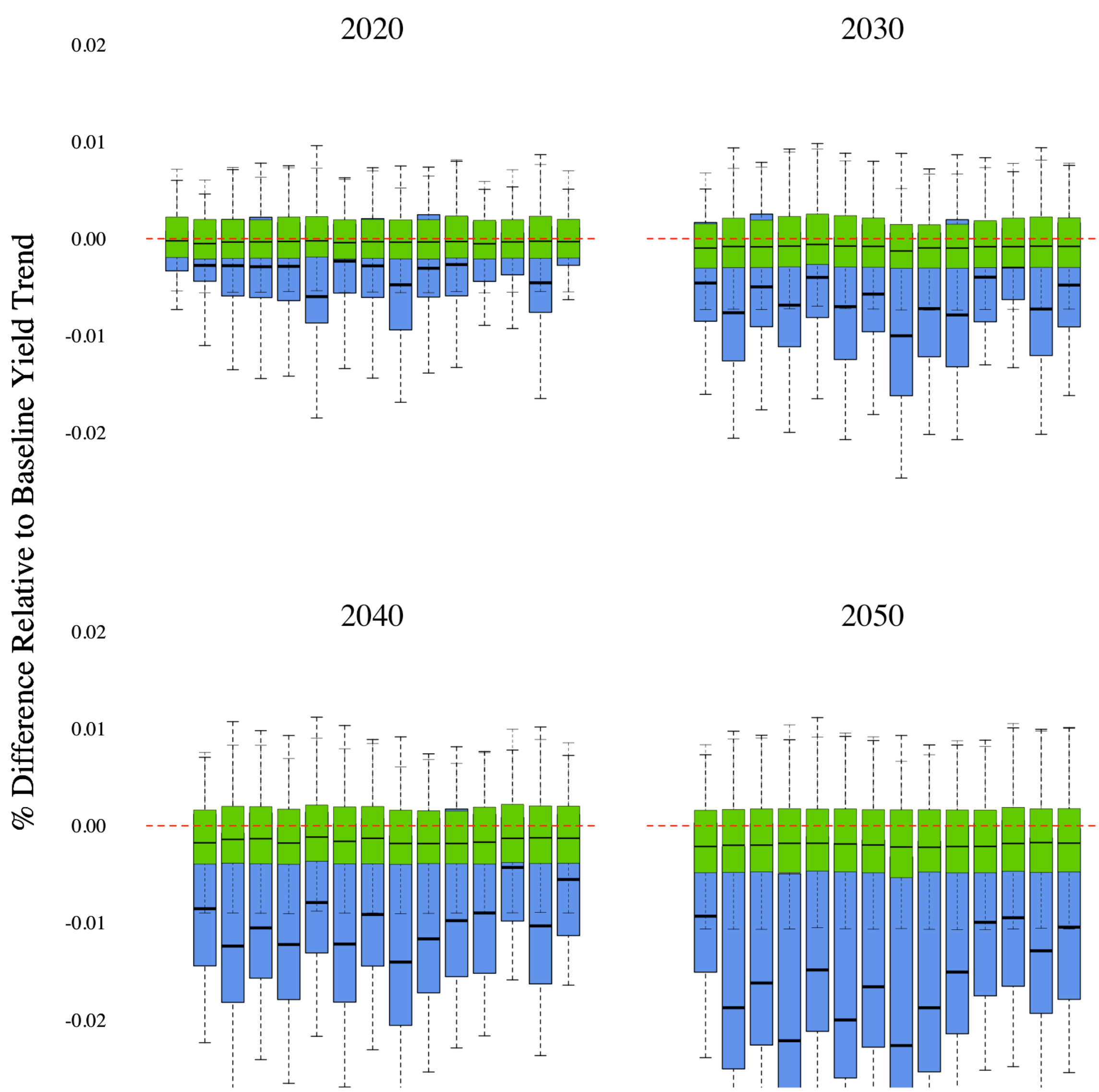
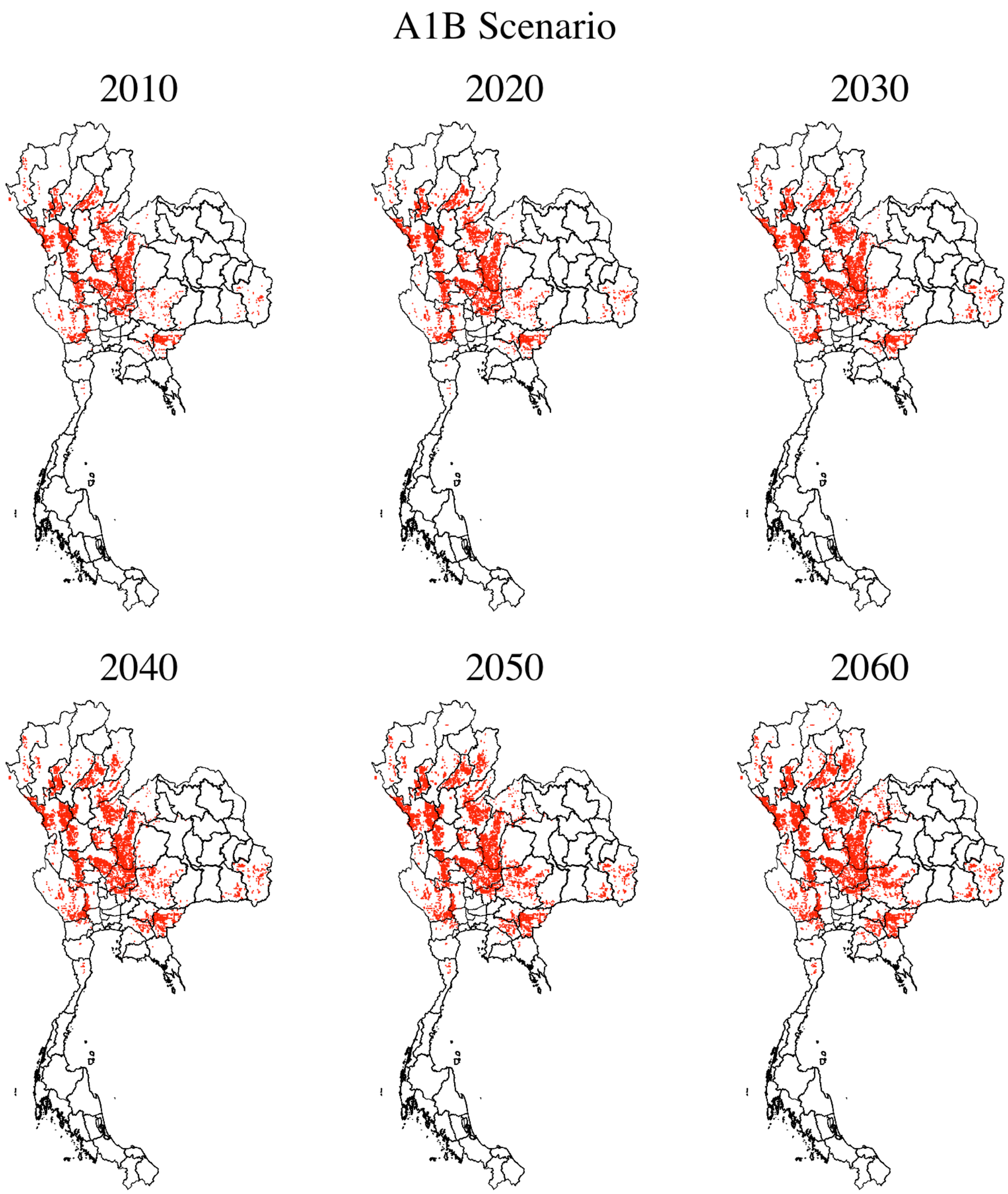
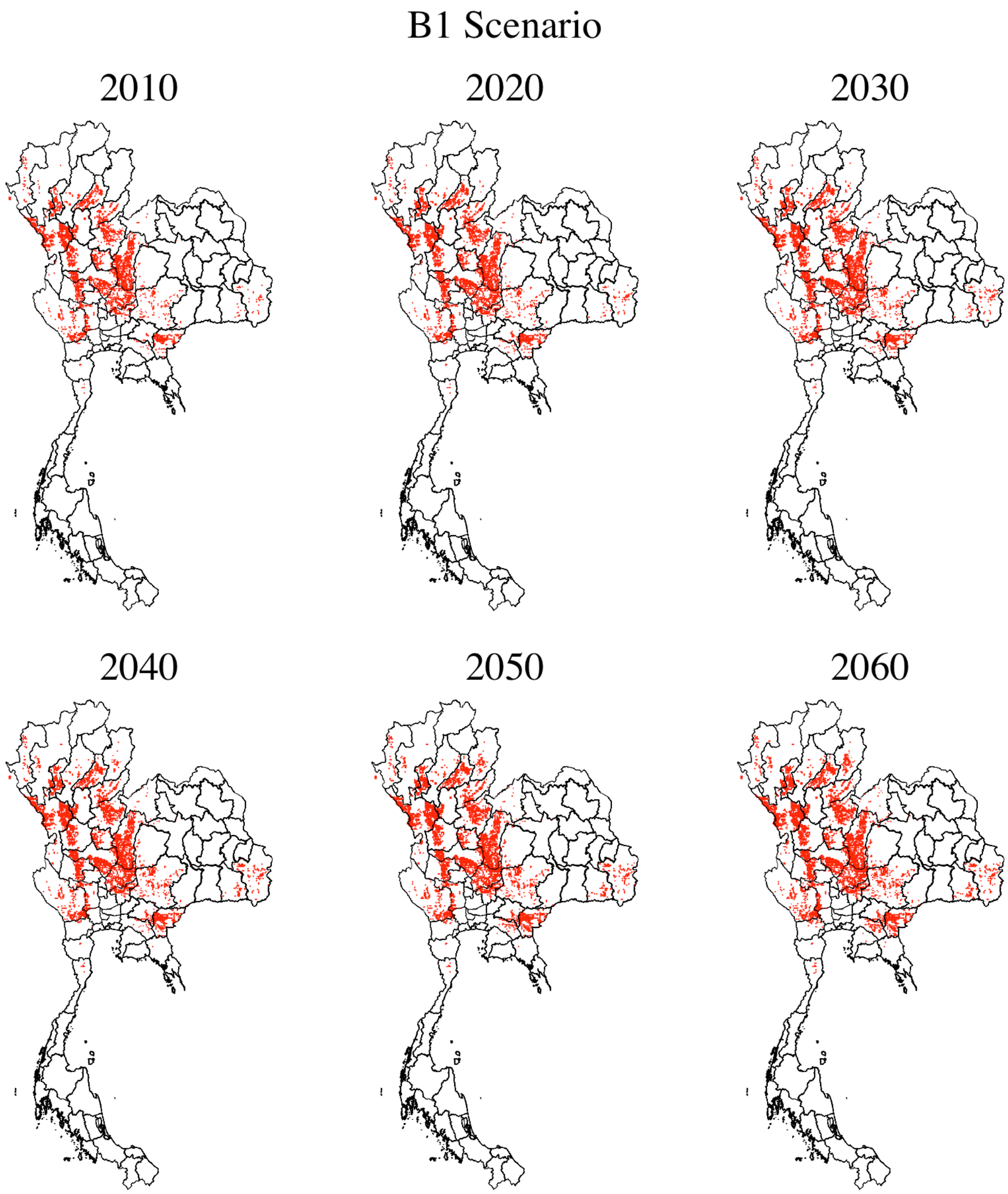


Figure 13: Maize Growing Area Forecast to be Above Maximum Temperature Threshold



Notes: *Figure shows the maize growing areas that are predicted to have average daily maximum temperatures above the estimated 33-degree threshold during the current maize growing season. Above the threshold, our models predict sharp declines in yields.*

Figure 14: Maize Growing Area Forecast to be Above Maximum Temperature Threshold



Notes: *Figure shows the maize growing areas that are predicted to have average daily maximum temperatures above the estimated 33-degree threshold during the current maize growing season. Above the threshold, our models predict sharp declines in yields.*

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Annex 1: Tables

Table A2.7: Linear Seasonal Average Panel Model Results: Maize

	(1)	(2)	(3)
Min Temp (deg C)	-0.061***	-0.061***	-0.017
	(0.017)	(0.014)	(0.027)
Max Temp (deg C)	-0.013	-0.015	-0.021
	(0.010)	(0.010)	(0.025)
Radiation (mjd^{-1})	-0.032***	-0.031***	0.013
	(0.010)	(0.010)	(0.015)
Rainfall (10 cm rain-fed)	-0.002	-0.001	-0.014
	(0.003)	(0.003)	(0.009)
$Rainfall^2$ (10 cm rain-fed)	-0.000	-0.000	0.000**
	(0.000)	(0.000)	(0.000)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**6.229**	**6.229**	**6.229**
No Obs	**1043**	**1043**	**1043**
R^2	**0.763**	**0.801**	**0.821**

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

Table A2.7: Linear Seasonal Average Panel Model Results:

Soybean

	(1)	(2)	(3)
Min Temp (deg C)	-0.005 (0.009)	-0.009 (0.010)	-0.002 (0.019)
Max Temp (deg C)	-0.020** (0.008)	-0.019** (0.008)	-0.015 (0.019)
Radiation (mjd^{-1})	0.013 (0.012)	0.015 (0.012)	0.010 (0.018)
Rainfall (10 cm rain-fed)	0.007* (0.004)	0.007* (0.004)	-0.009 (0.008)
Rainfall^2 (10 cm rain-fed)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**5.418**	**5.418**	**5.418**
No Obs	**989**	**989**	**989**
R^2	**0.531**	**0.584**	**0.574**

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

Table A2.7: Linear Seasonal Average Panel Model Results:

Cassava

	(1)	(2)	(3)
Min Temp (deg C)	0.046*** (0.009)	0.051*** (0.008)	0.001 (0.010)
Max Temp (deg C)	0.022*** (0.007)	0.024*** (0.007)	-0.005 (0.017)
Radiation (mjd^{-1})	-0.052*** (0.007)	-0.053*** (0.007)	0.006 (0.011)
Rainfall (10 cm rain-fed)	0.020*** (0.002)	0.020*** (0.002)	0.009** (0.004)
$Rainfall^2$ (10 cm rain-fed)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000** (0.000)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**7.871**	**7.871**	**7.871**
No Obs	**1179**	**1179**	**1179**
R^2	**0.585**	**0.602**	**0.871**

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

Table A2.7: Linear Seasonal Average Panel Model Results:

Sugar

	(1)	(2)	(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 rain-fed)	-0.023 (0.018)	-0.023 (0.017)	0.011 (0.015)
Rainfall^2 (10 cm rain-fed)	0.004* (0.002)	0.004* (0.002)	-0.000 (0.002)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**9.096**	**9.096**	**9.096**
No Obs	**989**	**989**	**989**
R^2	**0.276**	**0.315**	**0.766**

*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)	
Maize	22	22	23	32	32	33	17	17	19	2	2	1	**2%**
Soy	24	24	22	32	32	34	16	16	16	17	17	4	**3%**
Cassava	22	22	22	30	30	35	19	19	19	16	16	17	**1%**
Sugar	20	23	22	34	35	35	19	19	19	6	4	4	**3%**

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 A2.8: Piecewise-linear Seasonal Average Panel Model Res

Maize

	(1)	(2)	(3)
Min Temp (< 22) (deg C)	-0.010 (0.020)	-0.028 (0.018)	0.029 (0.023)
Min Temp (>22) (deg C)	-0.015*** (0.024)	-0.013*** (0.023)	-0.079*** (0.025)
Max Temp (<33) (deg C)	-0.031*** (0.011)	-0.028*** (0.010)	-0.068** (0.032)
Max Temp (>33) (deg C)	-0.069*** (0.017)	-0.055 (0.016)	-0.125*** (0.021)
Radiation (<17) (mjd^{-1})	0.035 (0.030)	0.043* (0.022)	0.045** (0.019)
Radiation (>17) (mjd^{-1})	-0.036*** (0.011)	-0.035*** (0.011)	0.008 (0.016)
Rainfall (< 2) (10 cm rain-fed)	0.108*** (0.029)	0.091*** (0.030)	0.073*** (0.026)
Rainfall (2<r<17) (10 cm rain-fed)	0.000 (0.001)	-0.001 (0.001)	-0.000 (0.001)
Rainfall (>17) (10 cm rain-fed)	-0.004 (0.003)	-0.006** (0.003)	-0.008** (0.004)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**6.239**	**6.239**	**6.239**
No Obs	**1043**	**1043**	**1043**
R^2	**0.775**	**0.809**	**0.827**

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

Table A2.7: Piecewise-linear Seasonal Average Panel Model Results: Soybean

	(1)	(2)	(3)
Min Temp (< 24) (deg C)	0.003 (0.012)	-0.001 (0.013)	0.003 (0.019)
Min Temp (>24) (deg C)	-0.016* (0.009)	-0.014 (0.009)	-0.012 (0.020)
Max Temp (<34) (deg C)	0.020 (0.030)	0.067*** (0.018)	0.043 (0.040)
Max Temp (>34) (deg C)	-0.184*** (0.033)	-0.197*** (0.032)	-0.061* (0.035)
Radiation (>16) (mjd^{-1})	-0.046** (0.020)	-0.038* (0.019)	-0.035 (0.025)
Radiation (<16) (mjd^{-1})	0.023* (0.013)	0.024* (0.014)	0.022 (0.019)
Rainfall (< 17) (10 cm rain-fed)	0.004 (0.003)	0.004 (0.003)	-0.008 (0.005)
Rainfall (>17) (10 cm rain-fed)	-0.001 (0.004)	0.000 (0.004)	-0.003 (0.006)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**5.418**	**5.418**	**5.418**
No Obs	**989**	**989**	**989**
R^2	**0.543**	**0.596**	**0.579**

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

Table A2.9: Piecewise-linear Seasonal Average Panel Model Results:

Cassava

	(1)	(2)	(3)
Min Temp (< 22) (deg C)	0.025*** (0.008)	0.034*** (0.007)	0.022** (0.010)
Min Temp (>22) (deg C)	0.069*** (0.019)	0.078*** (0.017)	0.010 (0.013)
Max Temp (<32.5) (deg C)	-0.012 (0.021)	-0.032 (0.030)	-0.027 (0.038)
Max Temp (>32.5) (deg C)	0.018** (0.007)	0.020** (0.008)	-0.006 (0.016)
Radiation (<19) (mjd^{-1})	-0.056*** (0.006)	-0.056*** (0.006)	-0.004 (0.011)
Radiation (>19) (mjd^{-1})	0.005 (0.020)	0.006 (0.021)	0.058*** (0.014)
Rainfall (< 16) (10 cm rain-fed)	0.012*** (0.001)	0.012*** (0.001)	0.011*** (0.003)
Rainfall (>16) (10 cm rain-fed)	-0.008*** (0.001)	-0.008*** (0.001)	-0.001 (0.002)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**7.871**	**7.871**	**7.871**
No Obs	**1179**	**1179**	**1179**
R^2	**0.591**	**0.607**	**0.875**

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

Table A2.4: Piecewise-linear Seasonal Average Panel Model Results: Sugar

	(1)	(2)	(3)
Min Temp (< 23) (deg C)	0.056** (0.024)	0.071** (0.028)	0.021 (0.015)
Min Temp (>23) (deg C)	-0.062** (0.026)	-0.061** (0.029)	-0.001 (0.015)
Max Temp (<34.5) (deg C)	-0.065*** (0.015)	-0.078*** (0.019)	0.011 (0.010)
Max Temp (>34.5) (deg C)	-0.155*** (0.031)	-0.144*** (0.030)	-0.070*** (0.018)
Radiation (<19) (mjd^{-1})	0.032** (0.012)	0.036*** (0.011)	0.029* (0.017)
Radiation (>19) (mjd^{-1})	-0.006 (0.031)	-0.005 (0.031)	-0.067** (0.032)
Rainfall (< 4) (10 cm rain-fed)	-0.006 (0.008)	-0.006 (0.008)	0.005 (0.006)
Rainfall (>4) (10 cm rain-fed)	0.030*** (0.008)	0.027** (0.011)	0.014 (0.009)
Fixed Effects	**Province**	**Province**	**Province, Year**
Time Trend	**National**	**Provincial**	**--**
Mean Log Yield	**9.096**	**9.096**	**9.096**
No Obs	**989**	**989**	**989**
R^2	**0.304**	**0.343**	**0.772**

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