Annex 2f

Crop Model Study of Rice Yields Under Climate Change Impacts

GCF Funding Proposal

Thai Rice:

Strengthening Climate-Smart Rice Farming

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Version 1

Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH

A Theoretical Assessment of the Future of Rice Yields in Thailand using ORYZA and Projected Climate Data

1. Introduction

Climate change represents a significant disruption, and potentially an outright threat, to the global agricultural sector. Rice production is likely to be one of the most severely affected crops in the context of climate change. Thailand is one of the world's top producers and exporters of rice.

Rice is cultivated on approximately 11 million hectares, representing roughly 40% of the total cropped area of Thailand. Rain-fed and irrigated ecosystems are the dominant rice production systems. Specifically, rain-fed lowland conditions prevail across a large proportion of the rice area planted with photoperiod-sensitive rice varieties, such as aromatic rice and glutinous rice.

The objective of this study is to investigate the possible effects of climate change on rice yield potentials in Thailand by simulating rice growth using future climate data.

2. Methodology

The study uses the ORYZA model, an ecophysiological process-based paddy crop growth model capable of simulating rice yields as a response to weather variables, soil conditions, genotype information and agronomic management information (such as establishment date and method, water management and N fertilizer management) (Bouman, Tuong, Wopereis, Ten-Berge, & Laar, 2001) (Setiyono, et al., 2019). The model has been evaluated under potential, water-limited and nitrogen-limited conditions in Asian countries, including the Philippines, Indonesia and India.

The study augments similar modelling exercises – which arrive at broadly similar conclusions – undertaken in the academic literature, using, for example, the CERES-rice model (Babel, Agarwal, Swain, & Herath, 2011), the SIMRIW model (Horie, 2019) and the ISI-MP model (Prodhan, et al., 2022).

As with all such modelling studies, the results of the current study should be considered indicative rather than definitive. The agricultural yields presented are necessarily theoretical, as they relate to the future, under changed climatic conditions and under ideal cropping conditions (soil conditions, fertilizer application, water management, etc.) (Pasquel, et al., 2022). The proportionate (percentage) *changes* in yields are generally considered to be more revealing, and more robust, than the absolute yield predictions (Lischeid, Webber, Sommer, Nendel, & Ewert, 2022).

To generate yield results, simulations were performed using model inputs (variety files, soil information and crop management) derived from previous projects in the IRRI database.

Three rice varieties were used in the yield simulations: IR72, MTR140 and MTR070PS. The three varieties were calibrated in a simplified manner given the absence of systematic experimental data for the specified geography. Under the calibration method, the phenological characteristics (leaf area index, plant height, biomass information, etc.) of the selected varieties are similar to common Thai cultivars. IR72, with a maturity duration of around 110-120 days, corresponds to the rice varieties mostly planted in the Central Plains region (e.g. OM1490, SPR1, PTT1 and

RD31). MTR070PS is a photoperiod-sensitive variety and is similar to varieties such as KDML105 that are planted in the North and North-East regions, as well as in other rain-fed lowland conditions. MTR140 is a transitional variety, located between IR72 and the long-duration varieties that are commonly planted in Thailand.

For this study, the simulated rice yields (potential and water-limited scenarios) were generated from modelled weather data (provided by Climate Analytics) commissioned for the GCF Thai Rice project, combined with further model inputs to quantify changes in rice yields in the near-term climate scenario (2025-2049).

To establish a baseline, crop simulations were run for the period 2001-2020 using data from Global Circulation Models (GCMs), namely the GFDL-ESM2M, HadGEm2-ES, IPSL-CM5A-LR and MIROC5 GCMs. Weather variables used were solar radiation (SRAD), minimum temperature (TMIN), maximum temperature (TMAX), vapour pressure (VP), wind speed (WIND) and precipitation (PREC). For future climate, a near-term period covering 2025-2049 was chosen. Data from the four GCMs were extracted for the years 2025-2049. GCM data was provided by *Climate Analytics;* this data was then extracted and reformatted by IRRI. Vapour pressure is not available from GCMs, so it was derived from average temperature instead.

Potential yield simulations were performed for dry and wet seasons with two time periods, the current (2001-2020) and near-term (2025-2049) scenarios. Dry season peaks in the months of December, January and April, depending on the region, while the wet season peaks in the months of May, August, and October, also depending on the region. Average yields by period were then compared to measure the effect of the changes in climate.

Using the same variety files and weather information, water-limited (rain-fed) simulations were also processed for the wet season, primarily to develop a detailed understanding of simulated yields using actual farming practices in the North and North-East regions.

3. Results

3.1 Climate Data

Current and Near-Term Future

Among the variables in the climate data, temperature and precipitation tend to exert the greatest influence on simulation outcomes. This is reflected in the water-limited modelling scenario. In the yield potential scenario, water requirements are explicitly set to be met 100% of the time (precisely because the focus is on yield *potential*) – and, therefore, by design the role of precipitation is negligible.

Based on the four models (as provided by Climate Analytics) used in this exercise, the difference between current and near-term temperature is about 1.8 and 3.3 % change for TMax and TMin respectively, but goes up to ~3.8% change in TMax in March and up to ~6.4% for TMin in December.

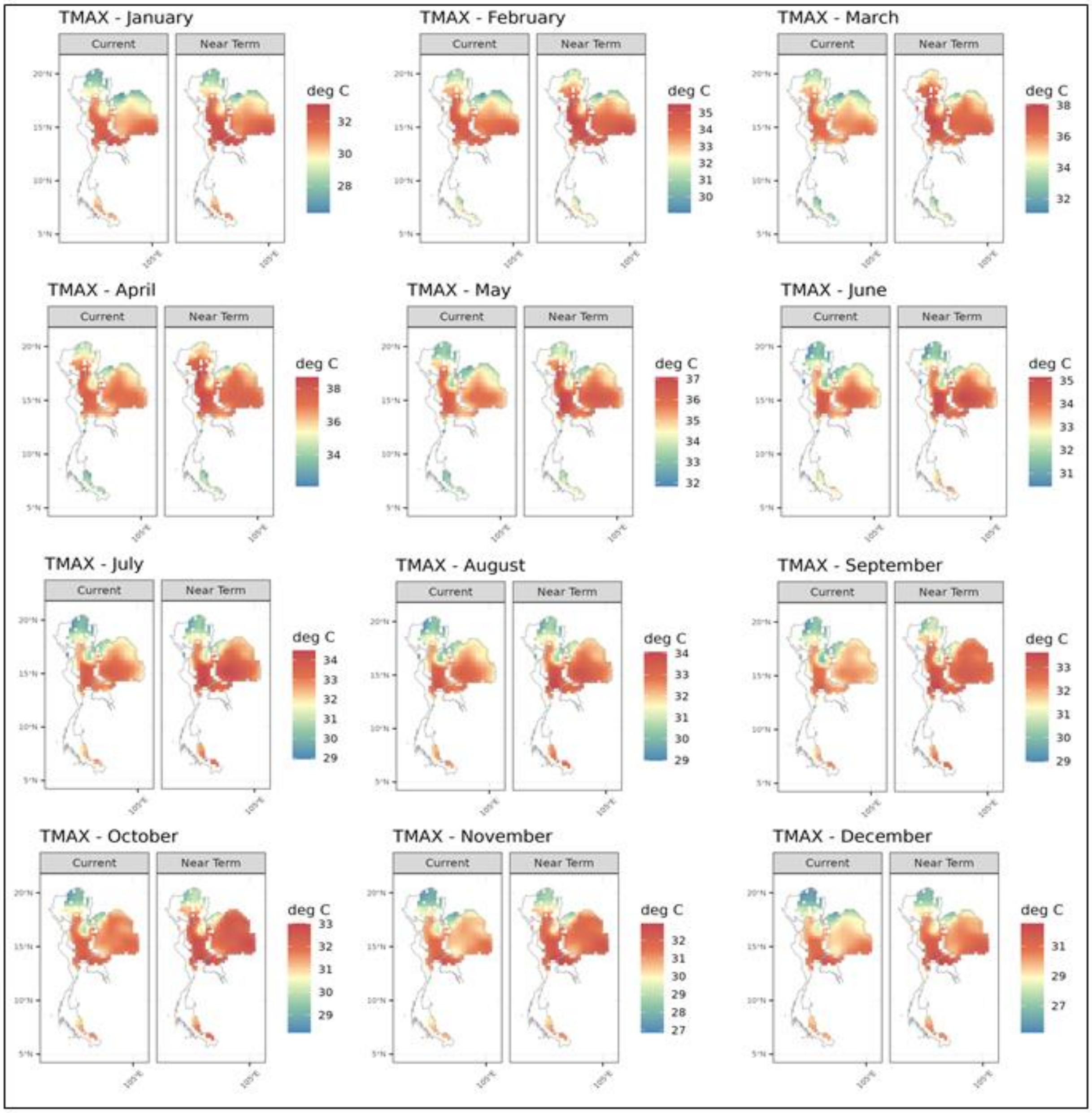


Figure 1a. Monthly maximum temperature, current (2001-2020) and near-term future (2025-2049), Thailand

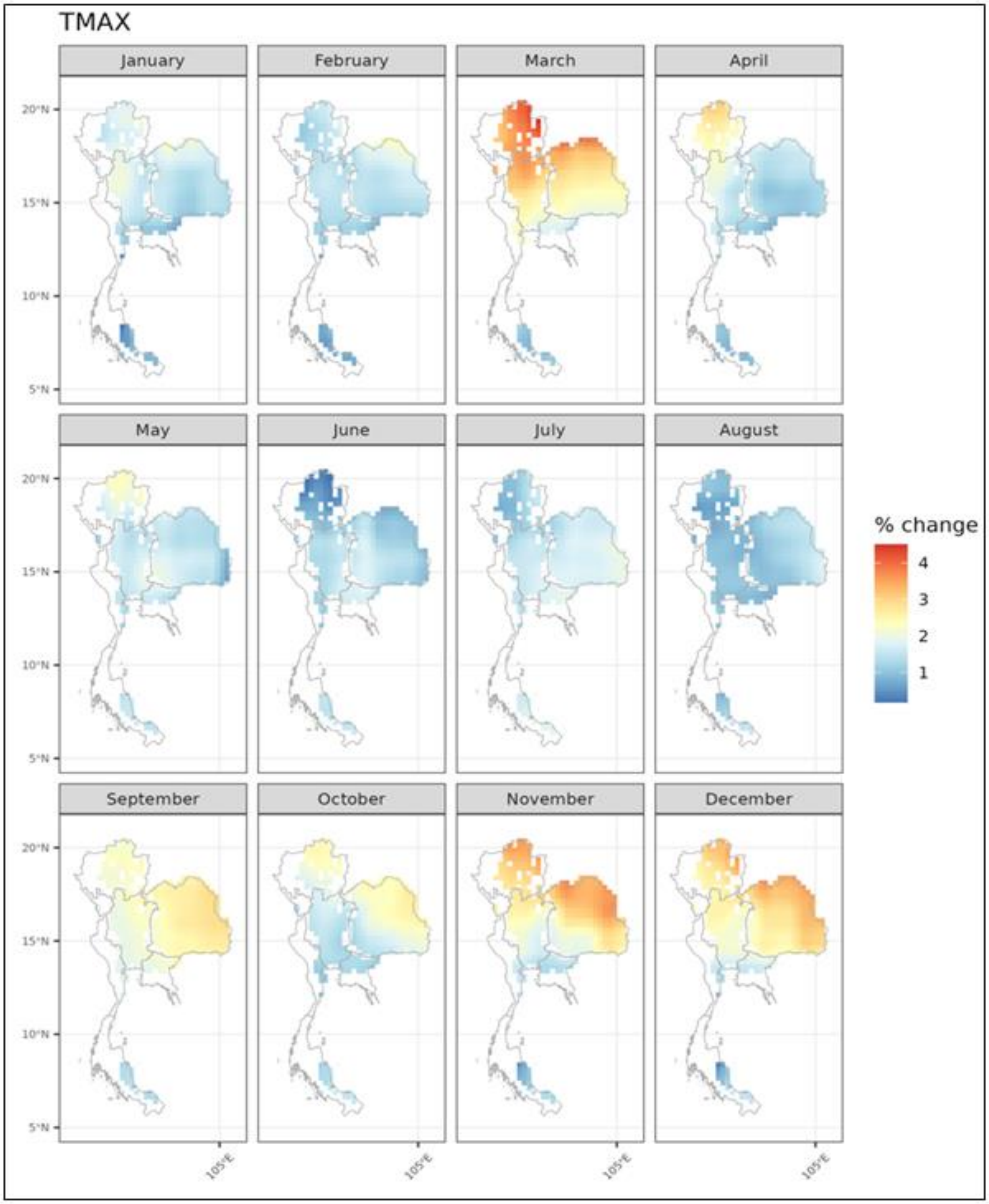


Figure 1b. Percentage change in monthly maximum temperature from current (2001-2020) to near-term future (2025-2049), Thailand

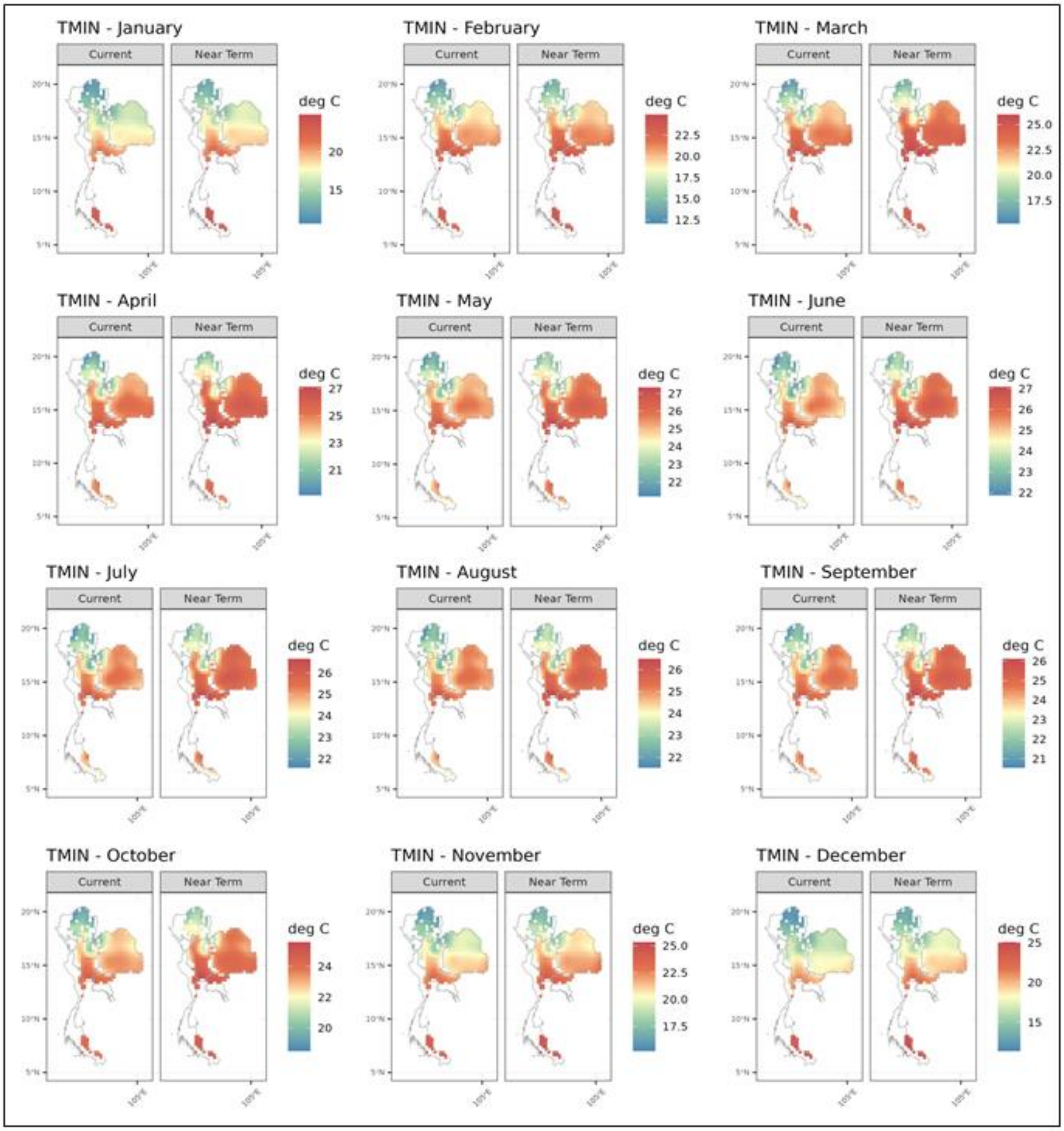


Figure 2a. Monthly minimum temperature, current (2001-2020) and near-term future (2025-2049), Thailand

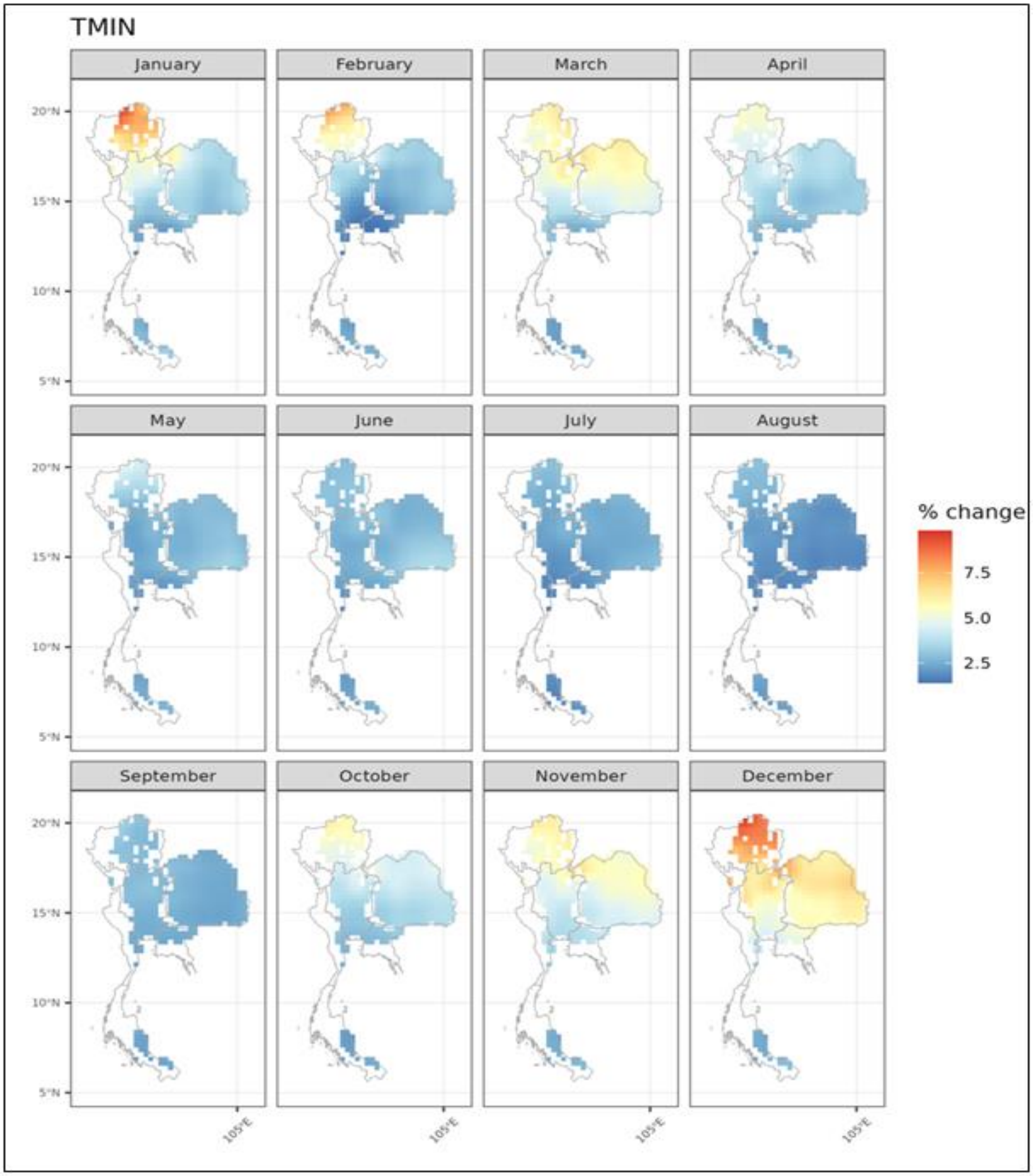
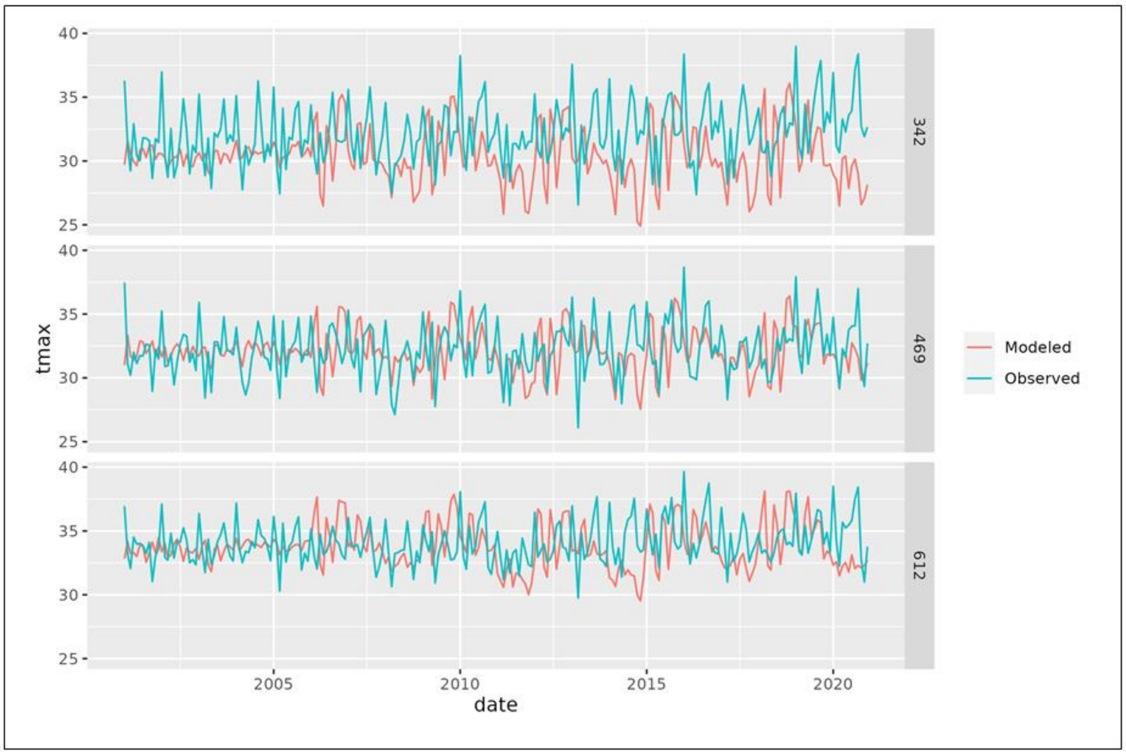


Figure 2b. Percentage change in monthly minimum temperature from current (2001-2020) to near-term future (2025-2049), Thailand

Comparison Between Modelled and Observed Data

To assess the modelled data against actual observed conditions, 3 pixels from the gridded data were selected. For each of these pixels, the modelled data was compared with meteorological station data from the Thailand Meteorological Department (TMD).

The pixels were chosen such that they cover 2 weather stations. The 3 pixels chosen are pixel numbers 342, 469 and 612, which are located in the Central, Northern and North-Eastern regions, respectively. Monthly averages were computed both from the modelled data and the station data from 2001 to 2020.



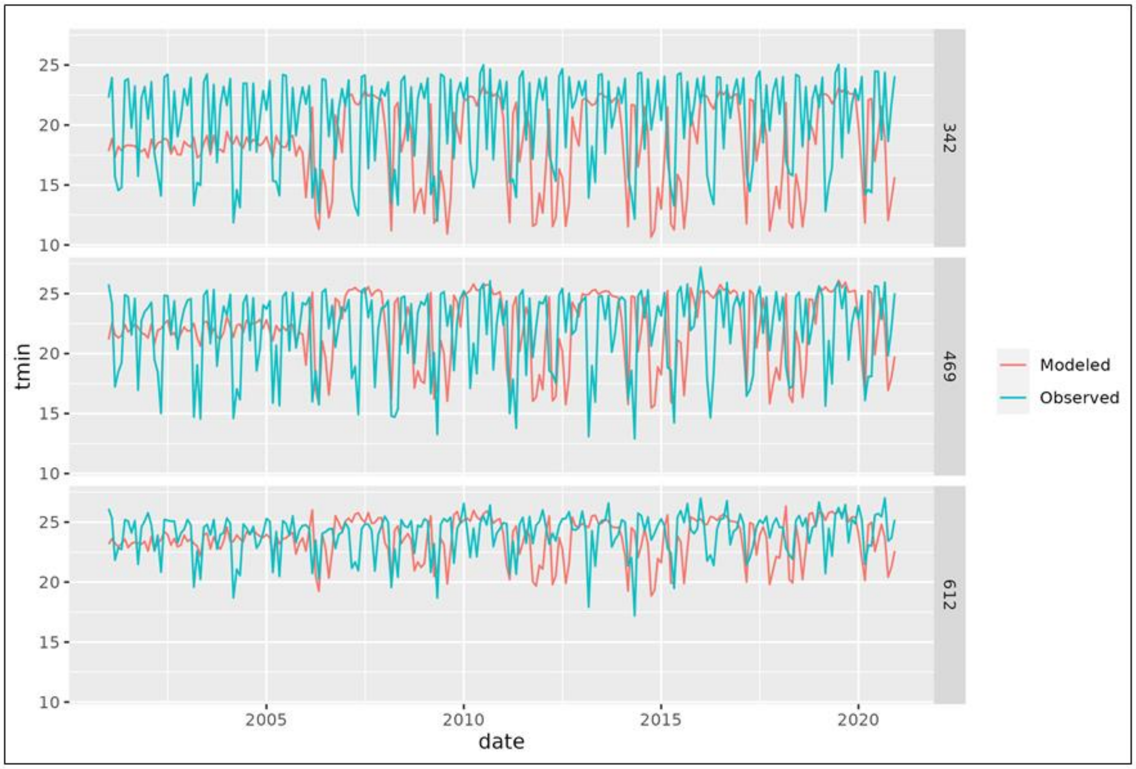
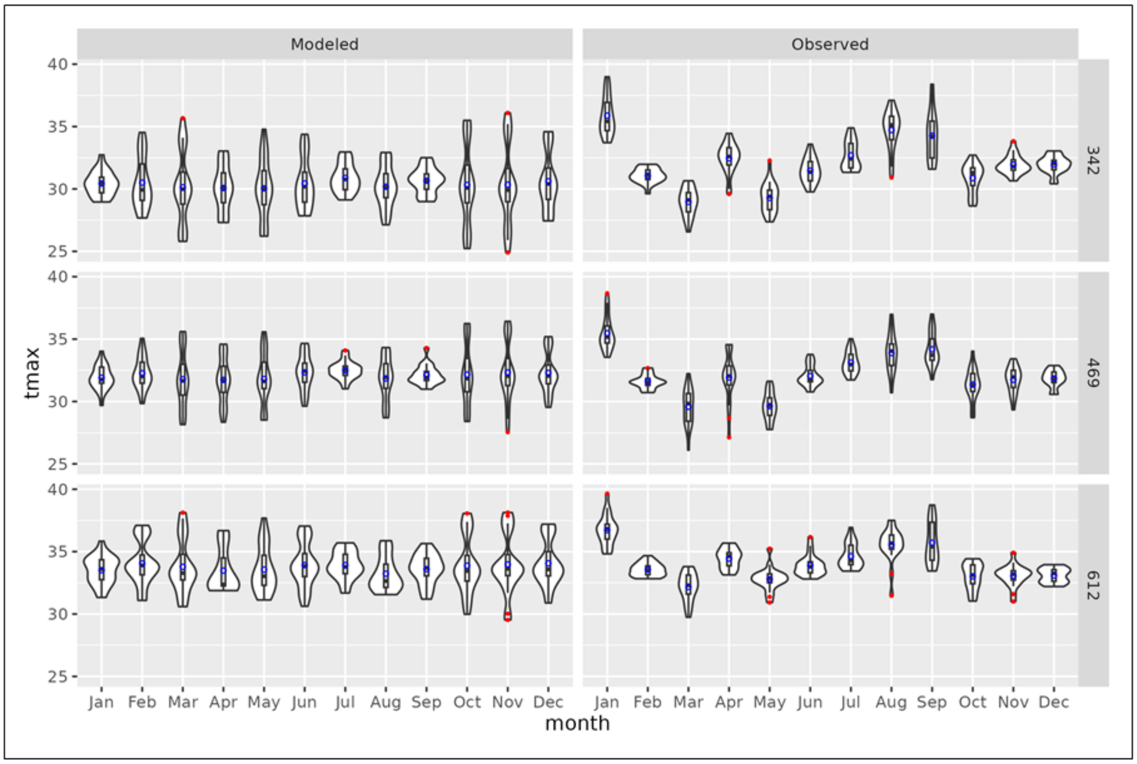


Figure 3. Comparison between observed and modelled minimum (below) and maximum (above) temperatures, 2001-2020

The violin plots show the difference between the modelled and station data in terms of density and variability of the two temperature variables. The modelled data-points seem to have a wider spread than the observed counterparts. Upper quartiles also appear to be more probable than lower quartile temperatures in the modelled data, but this is not the case for the station data. The means (blue circles) seem stable across the 12 months for the modelled data, but in the observed data, fluctuations can be observed both in the TMIN and the TMAX.



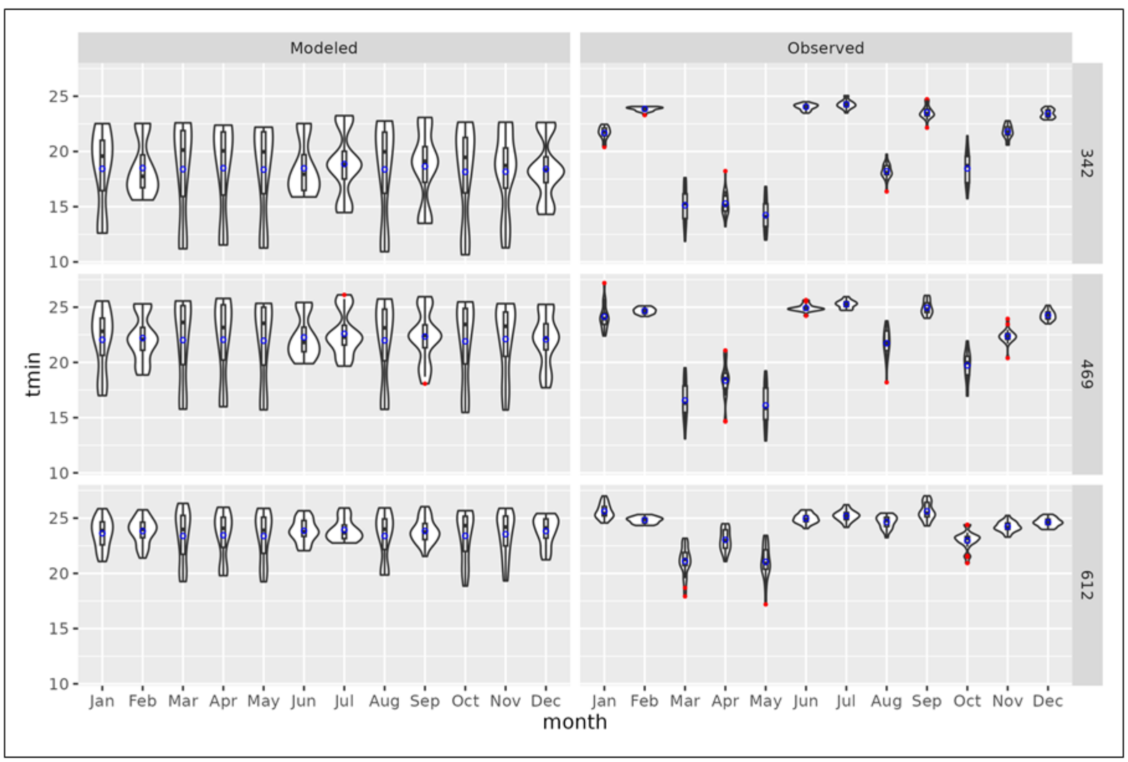


Figure 4. Comparison of monthly density and variability between modelled and observed minimum (lower diagram) and maximum (upper diagram) temperatures, 2001-2020

3.2 Yield Simulation Results

At the national level, the average potential yield during the current period (2001-2020) for the three simulated varieties ranges from 5.80 t/ha to 7.22 t/ha (dry season) and 6.04 t/ha to 7.38 t/ha (wet season). Average potential yield is consistently lower in the near-term (2025-2049) scenario, with 0.6 t/ha (dry season) and 0.4 t/ha (wet season) declines in yield. This is an expected result, as an increase in temperature is theoretically anticipated to adversely affect rice yield.

Figure 5 shows the yield potential during the dry season for IR72 and MTR140. IR72 exhibits the higher percentage reduction in yield (from current to near-term): approximately 10% across regions. However, note that the Central Plains region seems to be more vulnerable to the effect of climate change, particularly the increase in temperature: potential yield is projected to be at least 20% lower in some locations. For MTR140, average yield is expected to decrease by 8% from the current to the near-term periods, from 6.1 t/ha to 5.79 t/ha. Most of the affected areas are concentrated in the North-East.

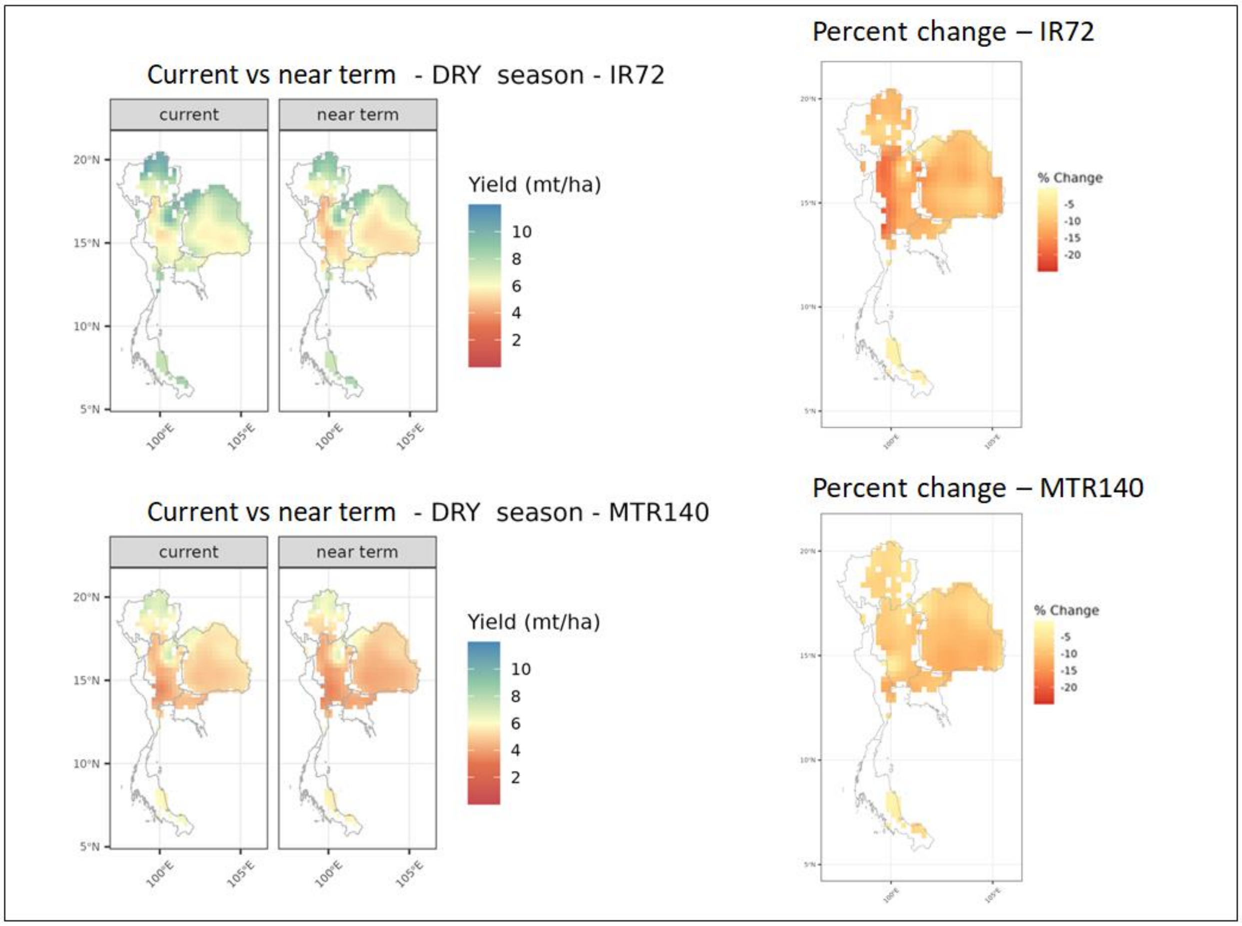


Figure 5. Dry season (with planting peaks in December, January, and April) potential yield and percentage change, by rice varieties and period, Thailand

As shown in Figure 6, the yield potential during the wet season for IR72 is currently around 7.3 t/ha and it declines to ~6.8 t/ha in the near-term period. With MTR140, yield falls to 5.8 t/ha, a 0.3 t/ha reduction from the current yield. MTR070PS, a long-duration rice variety that is similar to the KDLM105 variety and that is planted only during the wet season, records an average yield potential of 6.80 t/ha (baseline) and 6.5 t/ha (near-term), equivalent to a 4.4% decline in yield (Figure 7).

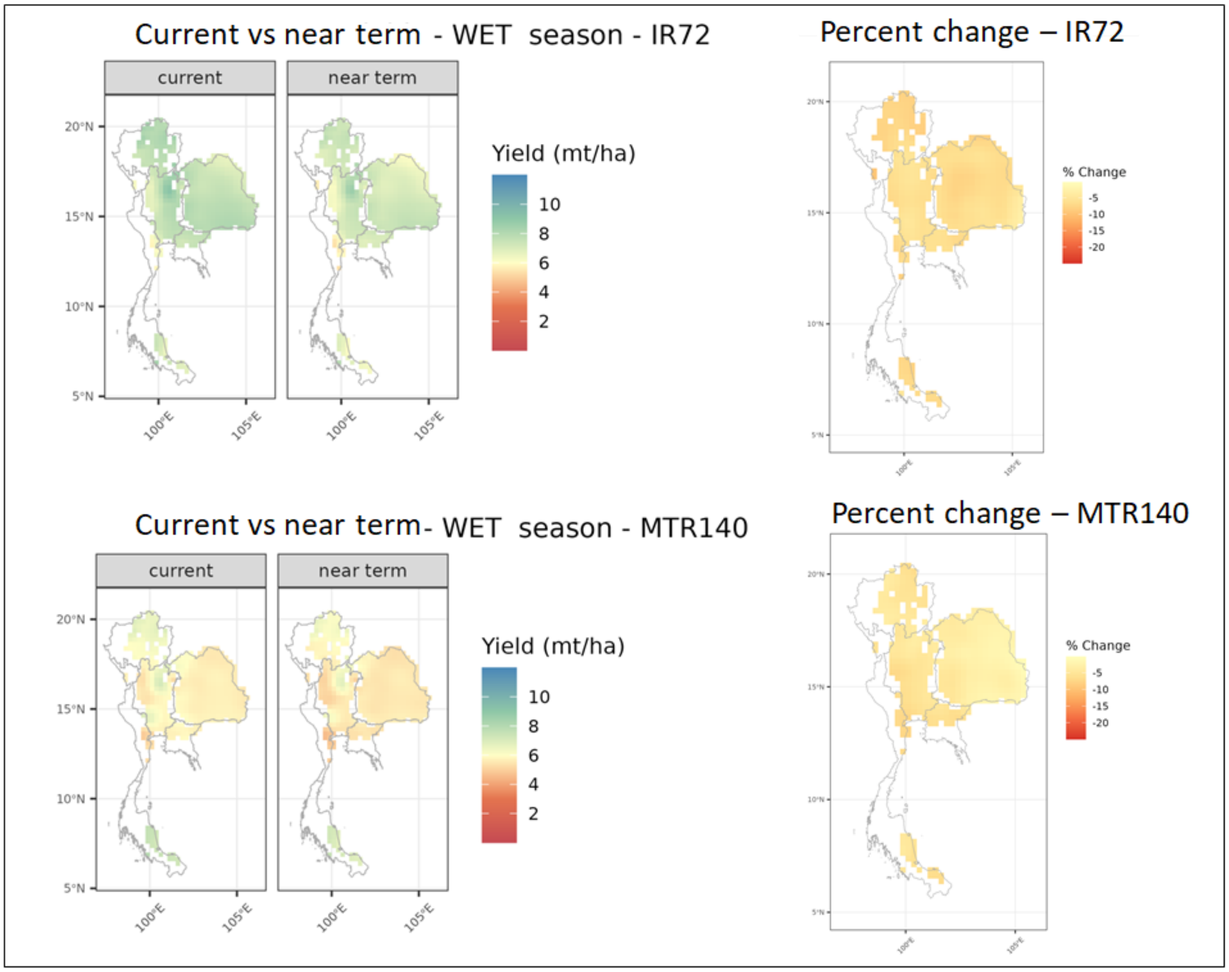


Figure 6. Wet season (with planting peaks in May, August and October) potential yield and percentage change for IR72 and MTR140 rice varieties, Thailand

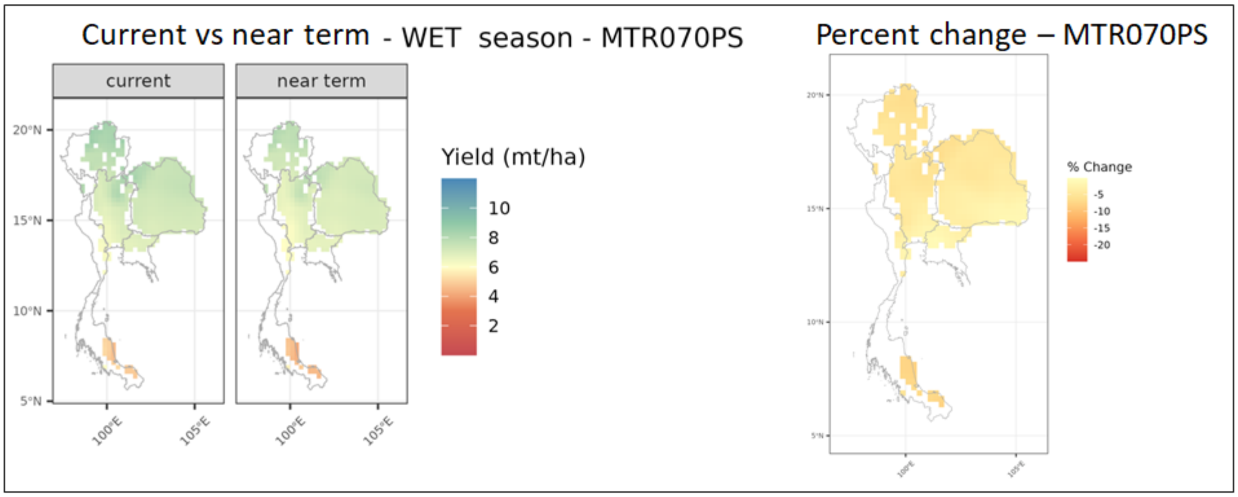


Figure 7. Wet season (with planting peaks in May, August and October) potential yield for current (2001-2020) and near-term (2025-2049) periods and percentage change for MTR070PS rice variety, Thailand

Figures 8a and 8b show the simulated yield using the water-limited (rain-fed) scenario in the North and North-East regions. The MTR140 and MTR070PS simulated yields during the current period are approximately the same, at 4.0 t/ha in both the North and North-East regions and with a slight reduction in the near-term period.

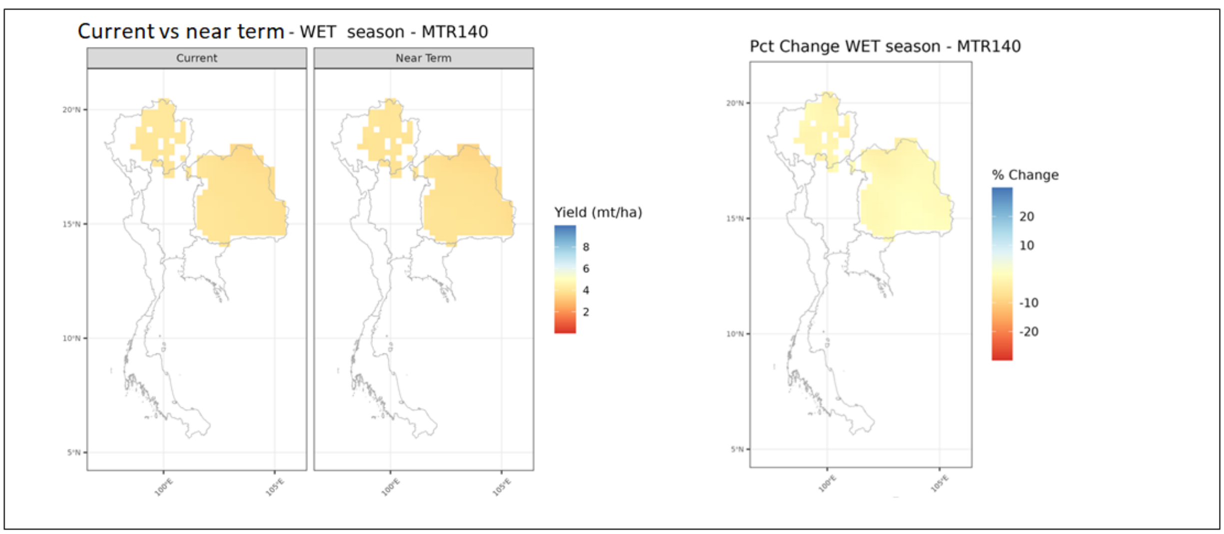


Figure 8a. Wet season simulated yield (water-limited) for current (2001-2020) and near-term (2025-2049) periods and percentage change for MTR140 rice variety, Thailand

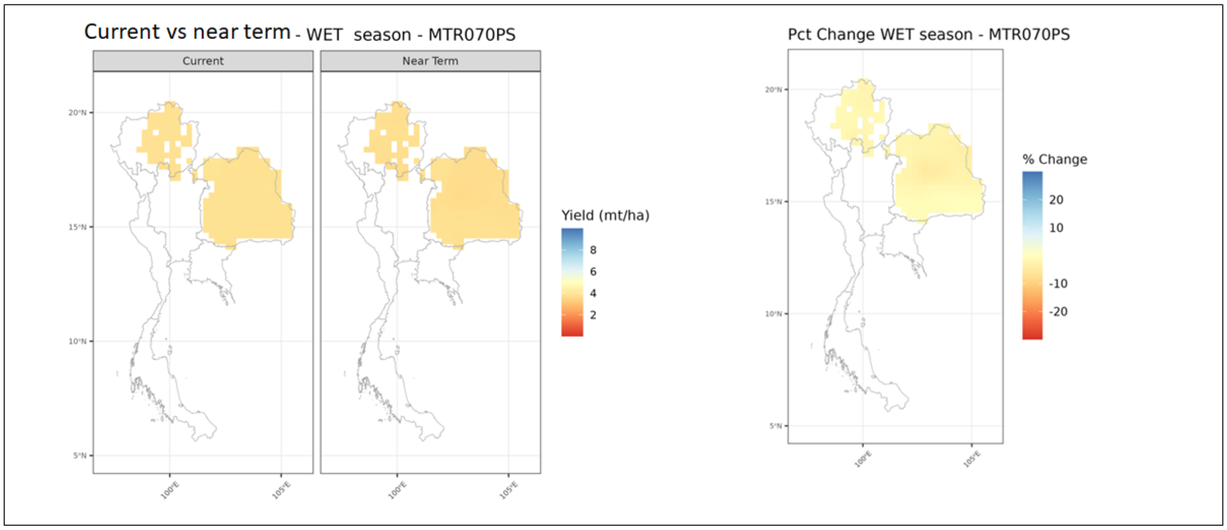


Figure 8b. Wet season simulated yield (water-limited) and percentage change for MTR070PS rice variety, Thailand

Table 1 shows the current and near-term average potential and water-limited yields and percentage changes by region and rice variety. Across the Central, North-East and North regions during the wet season, percentage changes in potential yields are estimated as -6.0% to -7.3%, -3.1% to -5.4% and -0.8% to -5.7% for IR72, MTR140 and MTR070PS, respectively. The percentage change during the dry season is higher for both IR72 and MTR140, ranging from -8.6% to -12.8%. The higher percentage change in the dry season can be attributed to the much higher temperatures during this period.

The simulated yields of MTR140 and MTR070PS rice varieties under the water-limited scenario range from 3.8 t/ha to 4.0 t/ha during the current period and decline to 3.7 t/ha to 3.9 t/ha during the near-term period.

Table 1. Average simulated potential and water-limited yield (in t/ha) in Central, North-East and North regions of Thailand

Season	Region	Variety	Current (2001-2020)	Near-Term (2025-2049)	Percent Change (%)
	Potential				
Wet	Central	IR72	7.68	7.22	-6.0
	Central	MTR140	5.96	5.64	-5.4
	Central	MTR070PS	7.08	6.77	-4.4
	North-East	IR72	7.59	7.10	-6.5
	North-East	MTR140	5.73	5.55	-3.1
	North-East	MTR070PS	7.35	7.29	-0.8
	North	IR72	7.86	7.29	-7.3
	North	MTR140	6.33	6.03	-4.7

	North	MTR070PS	7.94	7.49	-5.7
Dry	Central	IR72	6.72	5.86	-12.8
	Central	MTR140	4.91	4.49	-8.6
	North-East	IR72	6.95	6.26	-9.9
	North-East	MTR140	5.28	4.78	-9.5
	North	IR72	8.17	7.31	-10.5
	North	MTR140	6.26	5.84	-6.7
	Water-Limited				
Wet	North-East	MTR140	3.86	3.81	-1.3
	North-East	MTR070PS	3.82	3.74	-2.3
	North	MTR140	4.03	3.94	-2.3
	North	MTR070PS	3.81	3.73	-2.1

The graphs below (Figure 9a and 9b) show the average potential yield and percentage change at the regional level by rice variety and season. Figure 9c shows the water-limited average yield and percentage change in the North and North-East regions during the wet season.

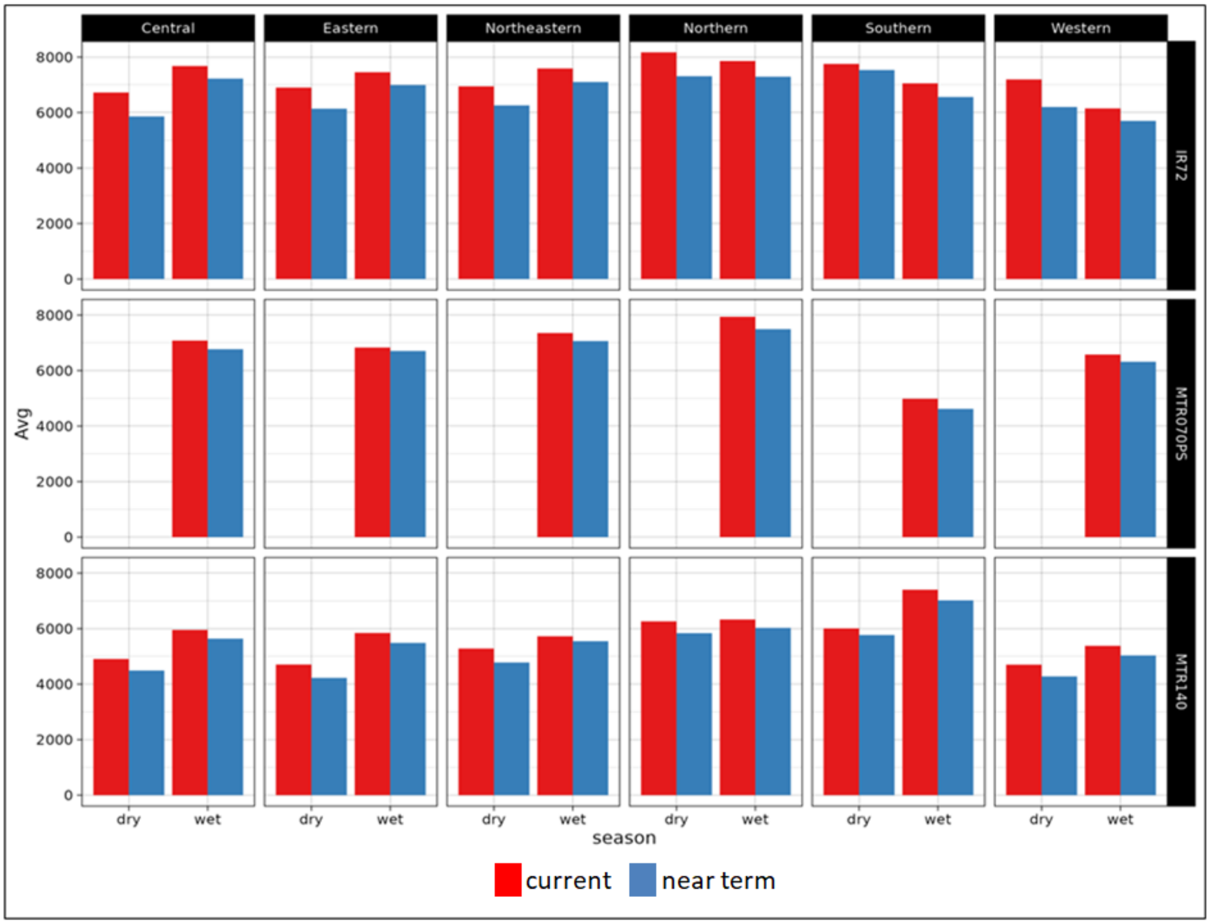


Figure 9a. Rice potential yield at regional level, by rice variety and period (current is 2001-2020; near-term is 2025-2049), Thailand

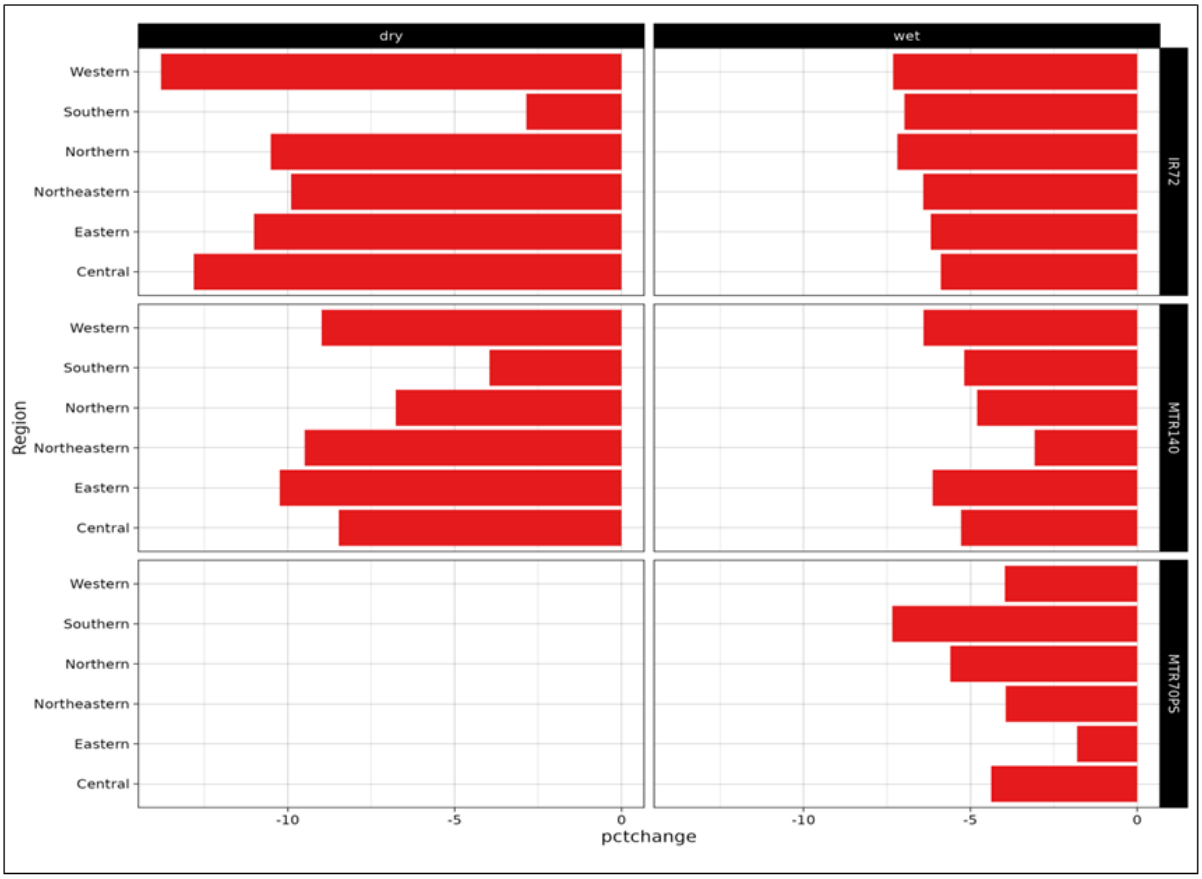


Figure 9b. Regional percent change in potential yield, by rice variety and season, Thailand

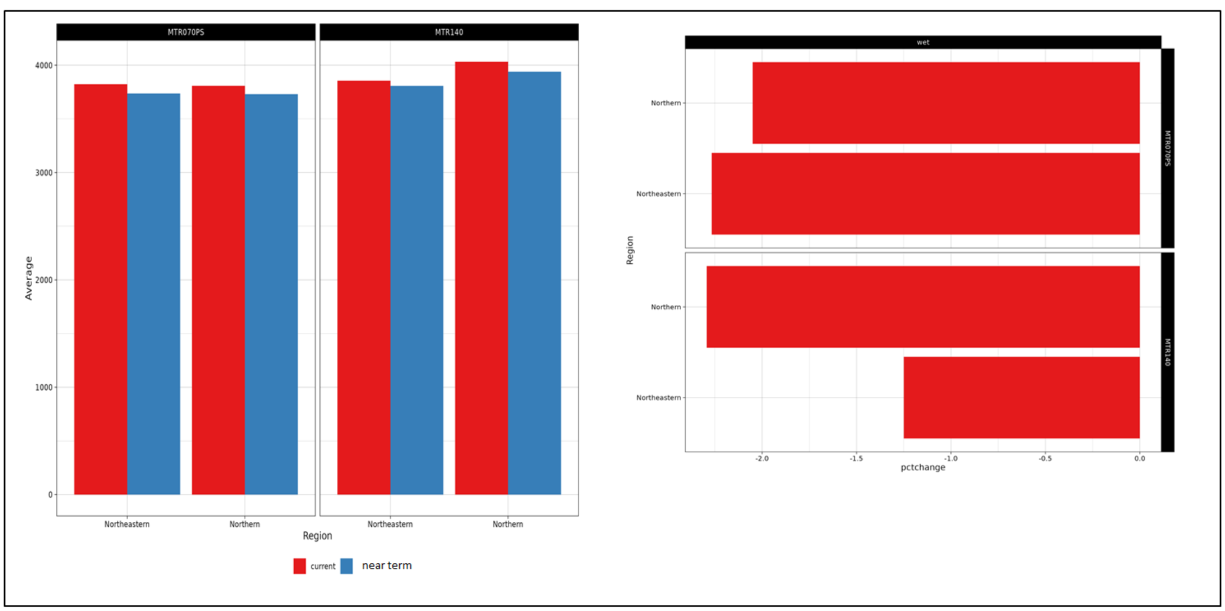


Figure 9c. Water-limited rice yield and percent change by rice variety and season, North and North-East, Thailand

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