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Article

Projection of Rice and Maize Productions in Northern Thailand under Climate Change Scenario RCP8.5

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Abstract: Climate change has an effect human living in a variety of ways, such as health and food security. This study presents a prediction of crop yields and production risks during the years 2020–2029 in northern Thailand using the coupling of a 1 km resolution regional climate model, which is downscaled using a conservative remapping method, and the Decision Support System for the Transfer of Agrotechnology (DSSAT) modeling system. The accuracy of the climate and agricultural model was appropriate compared with the observations, with an Index of Agreement (IOA) in the range of 0.65–0.89. The results reveal the negative effects of climate change on rice and maize production in northern Thailand. We show that, in northern Thailand, rainfed rice and maize production may be reduced by 5% for rice and 4% for maize. Moreover, rice and maize production risk analysis showed that maize production is at a high risk of low production, while rice production is at a low risk. Additional irrigation, crop diversification, the selection of appropriate planting dates and methods of conservation are promising adaptation strategies in northern Thailand that may improve crop production.

Keywords: future rice production; future maize production; climate change; agriculture; Thailand

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1. Introduction

Global climate change, which refers to increases in the average global temperature, has become a megatrend which will lead to major global changes in the future. According to the United Nations IPCC's sixth report in 2021 on climate change, global warming is undoubtedly having a severe impact on the Earth. Since agriculture is climate-dependent and therefore susceptible to climate change, it is very urgent to prepare for climate change adaptation in this area. Climate change disrupts the agricultural ecosystem and causes a change in temperature, precipitation and sunlight, while also further influencing the arable, livestock and hydrological sectors [1]. The evaluation of the consequences of recent climate change complements long-term forecasts and identifies which crops and sites are most vulnerable. Agricultural productivity in several Southeast Asian regions has decreased due to the increase in heat and water stresses, and climate variability has threatened food security in the region. For example, a study by Peng et al. [2] found that in the period from 1991 to 2003, rice output decreased by 10% for every level of increase in the minimum temperature. Climate change has also affected the global scale of major crops, as shown by Zhao et al. [3]. Dabi and Khanna, [4] reported that extreme abiotic factors such as high and low temperatures, droughts, salinity, osmotic stress, heavy rainfall, floods and frost damage pose serious threats to rice production, as well as being detrimental to farmers' incomes. Approximately 41.5% (21.28 million hectares) of the total area of Thailand is comprised of farms, some 17.5% of which are currently under irrigation. Among the large number of economically significant crops, rice is the most important crop that is widely grown in all regions, covering approximately half the cultivated area of the country. Other major field crops include cassava, corn, sugarcane, oil crops, perennial trees such as para rubber and fruit trees in the rest of the area. Farmland use is as follows: 51% of farmland is used for paddy, 24% for field crops, 17% for fruit trees and other tree crops, and 8% of land is used for other purposes. The main planted areas of the selected crops are rice, maize, cassava and rubber.

To understand and provide a context for national or regional impact studies on food safety, agriculture and climate change, a crop model is crucial to understanding the cumulative effects of climate change on agricultural sectors across the region. The methods used in local and regional studies are often identical or similar; therefore, there are economies of scale in the management of crops, species and ecosystems in regional areas. The Decision Support System for Agrotechnology Transfer (DSSAT) [5] is a software application program that includes crop simulation models for more than 42 crops and instruments to enhance the effective use of these models. The crop simulation models simulate soil–plant–atmosphere dynamic growth, development and yield. DSSAT and its crop simulation models have been used for a broad array of applications at different spatial and temporal scales. This includes farming and precision management, regional climate variability impact assessment and climate change impact assessments, gene-based modeling and selection, water use, emissions of greenhouse gases and long-term sustainability through the use of organic soil carbon and nitrogen balance. It has been widely used for the analysis of crop yields, decision making and planning, and strategic, tactical and climate change research. For example, Hasan and Rahman [6] estimated the effect of climate change on rice yield in Bangladesh using DSSAT version 4.0. They found that temperature change was responsible for rice reduction. Alejo [7] used the DSSAT Crop Environmental Resource Synthesis (CERES)–Rice model to assess the effect of climate change on aerobic rice with four Representative Concentration Pathway (RCP) scenarios. The results indicated that the seasonal variation of precipitation and temperature leads to a decrease in aerobic rice. It has been used by more than 14,000 researchers, educators, consultants, expanders, growers and policymakers. Araya et al. [8] analyzed the effect of climate change on future maize in Kansas, USA, using DSSAT CERES–Maize. The model results showed that maize yield will decline by 18–33% under RCP4.5 and 37–46% under RCP8.5 over the mid-21st century.

In Southeast Asia, there have been several crop modeling studies which have aimed to predict agricultural products under the impact of climate change. Townsend et al. [9] presented an innovative approach to estimate the multi-stage functions of farm production by integrating the scientific crop model with a simultaneous economic production approximation in China. Azdawiyah et al. [10] studied the effect of different planting dates on the yield production of rice under changing climate conditions in Malaysia. Anser et al. [11] quantified the economic impacts of climate change using five global circulation models (GCMs) on the agricultural production system and quantified the impacts of the suggested adaptation strategies at the farm level in Pakistan. To cope with climate change, a plan for the worst-case scenario is an excellent way to identify possible risks. In the context of the effects of climate change on agriculture, there have been no studies which have aimed to identify the effect of the worst-case climate change scenario on agricultural production in Southeast Asia. In this study, we predict future rice and maize production under the worst-case scenario of climate change with RCP8.5 using a crop model which is embedded in the Decision Support System for Agrotechnology Transfer (DSSAT). Moreover, adaptation strategies are also suggested.

2. Materials and Methods

Environmental inputs such as precipitation, temperature and solar radiation have been estimated on the basis of statistical downscaling for the scaling of the low-resolution regional climate model output (10 km) to a higher resolution (1 km). The regional climate output was based on the simulation of the Nested Regional Climate Model (NRCM) with a 10 km grid spacing [12]. To examine the reliability of 1 km meteorological parameters such as temperature and precipitation, they were compared with observations such as ground-based measurements from the Thai Meteorological Department and satellite data from Highly Resolved Observational Data Integration Towards Water Resource Evaluation (APHRODITE). The output from DSSAT was validated with an on-farm dataset from the Department of Agriculture in Thailand.

2.1. Study Area Description

The north of Thailand is mainly mountainous and is the origin of Thailand's rivers, including the Chao Phraya River, which forms at the convergence of four rivers: the Ping, Wang, Yom and Nan. Summer storms often occur due to the natural features of high mountains, steep river valleys and highlands. The mountains of the north are incised by steep river valleys and highlands on the central plain. These natural characteristics have traditionally enabled several different types of agriculture, including rice farming in the valleys and upland moving cultivation. The topography is predominantly high in the mountains. The area includes the headwaters of the major rivers of the country, including the Ping, Wang, Yom and Nan, with one-fifth of the country's agricultural land and the most farmers. Rice is an important food commodity in the northern upper provinces. Specifically, the quality of jasmine rice (Khao Dawk Mali (KDML) 105) is internationally recognized for its high quality, with a total yearly rice yield area of approximately 405,801 hectares and 1,487,506 tons. There is a large amount of paddy soil in this region. The annual crop of rice is harvested from November to December. Maize is usually seeded after the rice season.

2.2. Regional Climate Data

The environmental inputs such as precipitation, temperature and solar radiation for the DSSAT model are from the statistical downscaling of the output from the simulation of the Nested Regional Climate Model (NRCM) [13,14] in Amnuaylojaroen and Chanvijit [12]. The NRCM output was used for both present-day (1990–1999) and future climatology (2020–2029) over Thailand with a resolution of 10 km grid spacing under the Representative Concentration Pathway (RCP) 8.5 scenario. RCP8.5 was intended to be a very high baseline emission scenario representing the 90th percentile of the no-policy baseline scenarios available at the time.

The NRCM is a regional climate model that is based on the Weather Research and Forecasting (WRF) model [15] and has been adapted by the Community Climate System Model version 4 (CCSM4) [16]. It is similar to the WRF model, in which the initial and boundary conditions are determined using a limited field. During simulation, a regional oceanic model is included for the consideration of land–sea interaction by the Price–Weller–Pinkle (PWP) model [17]. The PWP model is an oceanic bulk layer mixing model which consolidates the mixing layer convection adjustment and shear stability. It was developed in the Hybrid Coordinate Ocean Model (HYCOM) [18] for vertical mixing. The approach was set up in the work by Amnuaylojaroen et al. [19]. The Runge–Kutta integration method includes a number of meteorological factors including wind, temperature, water vapor and cloud hydrometeorology [15]. The feedback and evolution of atmospheric aerosols with short and long-wave radiation were also calculated in the model through the Rapid Radiative Transmission Model (RRTMG). At the same time, the model includes feedback from aerosols on meteorological processes, such as cloud and precipitation effects calculated under the Thompson scheme [20]. The Grell-3 system was responsible for the convection of the subgrid scale in a simulation. Land and atmospheric interactions are measured through the Noah Land Surface Model [21]. Grid nudging [22] is used precisely to provide large-scale meteorology for all vertical levels of the model with nudging coefficients of 0.0003 s^{-1} for all variables including horizontal wind, temperature and water vapor at 6 h.

To assess the impact of climate change on agriculture, we need fine-resolution regional climate data as an input for the crop model. Because of the NRCM's high-quality output, we used a conservative remapping scheme to increase the grid spacing from 10 km to

1 km. The key method of conservative restoration is the transition of data from one grid to another while maintaining the regional and local integrations, and this has many very promising applications in atmospheric science. The maximum and minimum temperature, precipitation and radiation from the 1 km climate data were used as input data to DSSAT in the planting area, as shown in Figure 1.

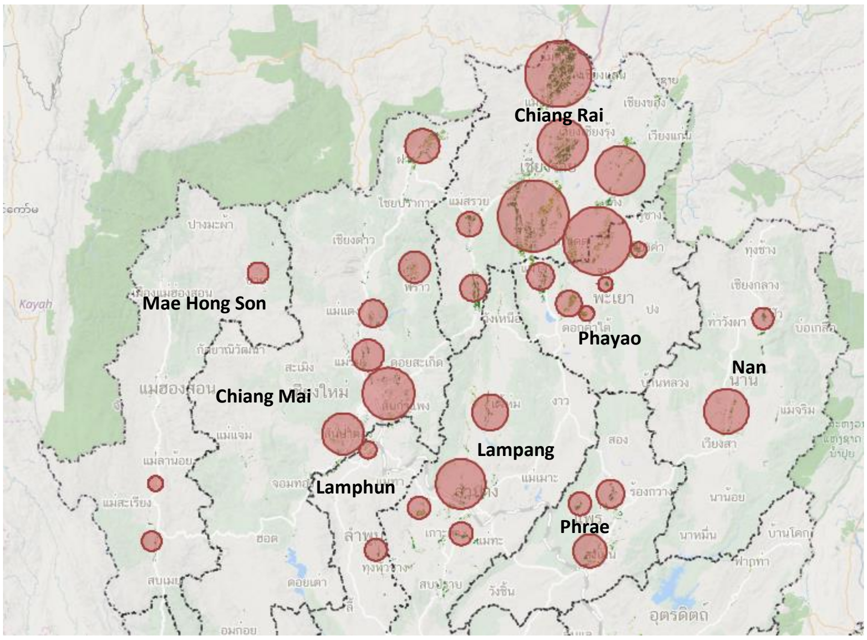


Figure 1. Planting area (red circles) in northern Thailand (gistdat.or.th).

2.3. Crop Model Simulation

Here, we have collected Decision Support System (DSSAT) Version 4.7.5 outputs from June to December 1990–1999 to simulate rice and maize production. The output from DSSAT was validated with on-farm data from the Department of Agriculture in Thailand during 2010–2018. The seed period is defined from June to October, with the harvest period running from November to December. The seasonal growth, development and yield of crops, together with the change in soil, water, carbon and nitrogen balance under the cultivation system, were determined [5]. The production of rice and maize was estimated in northern Thailand based on the Crop Environmental Resource Synthesis–Rice (CERES–Rice) [23] and the Crop Environmental Resource Synthesis–Maize (CERES–Maize) [24] models that are embedded in DSSAT. We have selected eight provinces—Phrae, Chiang Mai, Nan, Lamphun, Lampang, Mae Hong Son, Chiang Rai and Phayao—based on complete information regarding their overall crop production. Every month, the water demand for rice was set as in Table 1 [25]. The cultivars used in the study were KDML105 for rice and short-season varieties for maize. The genotype coefficients for the cultivars KDML105 and short-season maize (SW3601) were as reported by Buddhaboon et al. [26] and Lana et al. [27] and are given in Table 2. Genetic coefficients for KDML105 were used from the initial results by Jongkaewattana and Vejpas [28]. They estimated the values from a monthly planting experiment for 12 consecutive months which started in May 1997 at the Multiple Cropping Center, University of Chiang Mai. Data collection followed the standard procedures of The International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) [29]. Data from the experience were used to estimate the genetic parameters by using the "genotype coefficient calculator" provided by the DSSAT shell [30], while the genetic coefficient for maize used the values from Boonpradub and Jongkaewattana [31]. The CERES–Maize model was validated at the Phitsanulok Field Crops Experiment Station (PSL FCES) during 1997–1999 on various planting dates, while the fertilizer level used followed the report of the Department of Agriculture of Thailand, with N: 6 kg/ha, P_2O_5: 7.5 kg/ha and K_2O:

7.5 kg/ha. The soil analysis layers were set up with a bulk density of 1.035 g/cm3, total organic carbon of 1.46%, total nitrogen of 0.601%, a pH in buffer of 5.63, a pH in water of 6.59, extractable phosphorus of 5.766 mg/kg, exchangeable potassium of 5.766 cmol/kg and 1.46% of stable organic compounds.

Table 1. Water demand for the rice grown in each month.

Month	Water Demand (mm/month)
June	274
July	67.8
August	49.3
September	58.5
October	32.2

Table 2. Genotype coefficient of Khao Dawk Mali 105 (KDML105) and short-season (SW3601) cultivars.

Cultivar	P1	P2	P5	P2R	P2O	G1	G2	G3	G4
KDML105	502.30	-	386.50	1233.00	12.70	45.47	0.027	1	0.95
SW3601	352.0	0.60	845	-	-	-	824	6.87	-

P1: Time period (Growing Degree Days, GDD) of basic vegetative phase; P2: extent to which development is delayed for each hour of increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (12.5 h); P5: thermal time from silking to physiological maturity (above a base temperature of 8 °C); P2R: extent of phasic development (GDD); P2O: critical photoperiod (hours); G1: potential spikelet number; G2: single-grain weight; G3: tillering coefficient; G4: temperature tolerance coefficient.

For the production risk analysis used to support decisions on rice and maize farming, stochastic efficiency rules were applied in this study. The stochastic efficiency rules are an important class of decision criteria and are especially suitable for the analysis of the output of the model simulation. These are the foundation of Bernoullian utility theory and are different from the assumptions about the risk-taking attitude of the decision-maker [32–34]. These rules were designed to address the problem of investment theory portfolio selection but are now firmly established risk analysis tools for all types of applications. This involves a pairwise comparison of random variables, which should relate strictly to financial gains and losses. The analysis resulted in an efficient set of treatments. The efficient set contained a subset of superior treatments. To make this decision, we applied three decision criteria, namely the expected value (EV) [35], stochastic dominance analysis (SD) [36] and mean-Gini dominance analysis (MGD) [37–39]. The three criteria are commonly used in agricultural economic analysis. Three variations are briefly described below [39].

2.3.1. Mean–Variance (EV) Analysis

The main equation of Mean–Variance (EV) Analysis is described in Equations (1) and (2). For two risky prospects, A and B, with means E(.) and variances V(.), respectively, then A dominates B if

$$E(A) = E(B) \text{ and } V(A) < V(B) \text{ or if} \tag{1}$$

$$V(A) = V(B) \text{ and } E(A) > E(B) \tag{2}$$

A is then said to be EV-efficient. If prospects are plotted in EV space (where V is the ordinate and E is the abscissa), then utility increases in a northwesterly direction. EV analysis assumes that the decision-maker has a quadratic gain and loss utility function and/or that risky prospects are normally distributed (or at least distributed symmetrically). These are often untenable assumptions and the EV criterion has fairly weak discriminatory power (i.e., the efficient sets tend to be large).

2.3.2. Stochastic Dominance Analysis

For two risky prospects, A and B, A prevails over B by primary stochastic domination (FSD) if the cumulative distribution function (CDF) of A increases over the full probability interval 0 to 1, lying exactly on B's CDF. If, however, the area between the two CDFs below the cross point is larger than that between the two CDFs above the intersection point, then A dominates B by second-order stochastic domination (SSD); otherwise, no dominance can be established, and the two CDFs are both A and B-efficient. No assumption is made regarding the decision-maker's attitude to risk for FSD; the decision-maker is assumed, for SSD, to be averse to risk to some unknown degree. There must also be no assumptions about the distributional properties of the random variables.

2.3.3. Mean-Gini Dominance Analysis

Mean-Gini Dominance Analysis is described in Equation (3). For two risky prospects, A and B, A dominates B by MGD if

$$\mathrm{E(A)} \geq \mathrm{E(B)} \text{ and } \mathrm{E(A)} - \mathrm{G(A)} \geq \mathrm{E(B)} - \mathrm{G(B)} \tag{3}$$

with strict inequality for one of these expressions, where E(.) is the mean and G(.) is the Gini coefficient of distributions A and B (which is half the value of Gini's mean difference: the absolute expected difference of a pair of randomly selected values of the variable). MGD, as with SSD, assumes that the decision-maker is averse to risk but, unlike SSD, the extremely risk-averse are excluded from the analysis. It is thus a more discriminating decision rule than SSD (since the MGD efficient set is usually smaller) and, computationally, MGD is generally much easier to establish than SSD.

2.4. Validation

Since we downscaled the regional climate data from 10 km to 1 km using a statistical method, the baseline of the 1 km regional climate model output (1990–1999) needs to be examined regarding the reliability. The model output is compared with ground-based measurements from the Thai Department of Meteorology and Highly Resolved Observational Data Integration for the Water Resources Assessment (APHRODITE). APHRODITE is a project involving several datasets; i.e., a Global Telecommunication System (GTS). The pre-compiled information set is a project included in the APHRODITE project. APHRODITE is also a highly resolved observational data integration source for the assessment of water resources. Two datasets are based on GTS, including a Global Summary of the Day (GSOD) and the Global Historical Climatology Network (GHCN) network. In addition, the pre-compiled dataset contains data from the GEWEX (Global Energy and Water Cycle Experiment) Asian Monsoon Experiment (GAME). APHRODITE project data were collected from national meteorological and hydrological services or individuals from Japan, China, Mongolia, Russia, Taiwan and Nepal. The data feature a resolution of $0.5 \times 0.5°$ across Asia from 1973 to 2007 [40]. The crop model validation is also examined by comparing it with the on-farm dataset from the Department of Agriculture in Thailand for 2010–2018. A set of statistical methods was applied to evaluate the performance of this model, including mean bias, the standard deviation of residuals and the index of agreement.

The mean bias is calculated following Equation (4):

$$Mean\ Bias = \overline{M} - \overline{O} \tag{4}$$

where $\overline{M}$ is the mean of the model data and $\overline{O}$ is the mean of the observation data.

The standard deviation of residuals is calculated following Equation (5):

$$SDR = \sqrt{\frac{\sum\left[(X_O - X_M) - \left(\overline{X_O} - \overline{X_M}\right)\right]^2}{n}} \tag{5}$$

where X_O is the observation data, X_M is the model data, $\overline{X_O}$ is the mean of the observation data, $\overline{X_M}$ is the mean of the model data and n is the amount of model and observation data.

The index of agreement (IOA) which is based on Willmott et al. [41], is calculated following Equation (6):

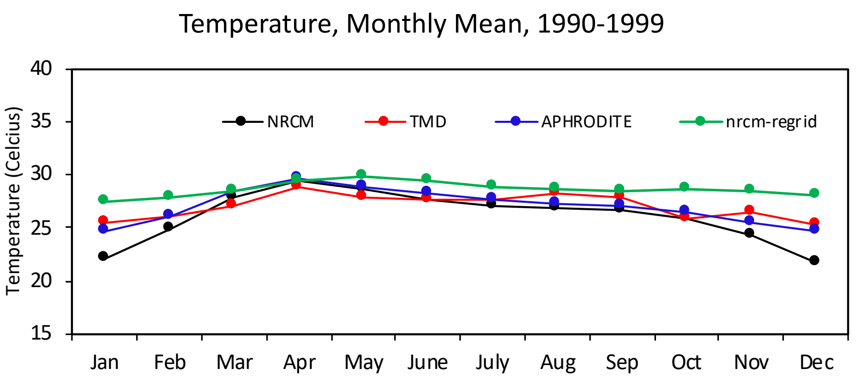
$$IOA = 1.0 - \frac{\sum_{i=1}^{n}(O-M)^2}{\sum_{i=1}^{n}|M-\overline{O}| + |O-\overline{O}|)^2} \tag{6}$$

where O is the observation data, M is the model data, $\overline{O}$ is the mean of the observation data and n is the amount of the model and observation data.

3. Results and Discussion

3.1. Climate Model Data Evaluation

The remapping output with a 1 km grid spacing was compared with the original NRCM output with a 10 km grid spacing and observation data including data from APHRODITE and the Thai Meteorological Department (TMD) averaged over 1990–1999 (Figure 2). In general, the remapping output captured the pattern of monthly and daily temperature and precipitation well. In terms of temperature, the remapping output tended to improve compared with NRCM. Compared with the original NRCM, which was cold-biased data, the remapping output was about 0.2–2 °C warmer than the NRCM output. Compared with the observation, the trend was close to both TMD and APHRODITE data, while the remapping output's precipitation was slightly different from NRCM; the trend was similar to the NRCM but slightly higher than the NRCM by approximately 1 mm/day from October to December. The remapped precipitation remained lower than in both TMD and APHRODITE.



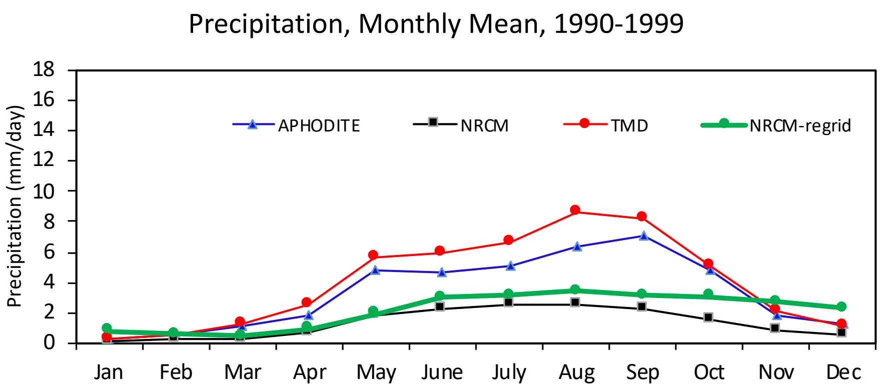


Figure 2. Monthly mean temperature (°C) and precipitation (mm/day) averaged over 1990–1999 based on 44 station locations from the Thai Meteorological Department (TMD), Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE), Modern-Era Retrospective Analysis for Research and Applications (MERRA), Global Precipitation Climatology Project (GPCP) (Plus) and the Nested Regional Climate (NRCM) model.

The statistical analysis of temperature and precipitation between model and ground-based observation data from the Thai Meteorological Department (TMD) was averaged over the period 1990–1999 from 44 TMD stations, while on-farm data for rice and maize were averaged over the period 2010–2018 from the planting area as shown in Table 3. In general, the reliability of the NRCM model output was indicated by statistical analysis; for example, the R^2 showed a range of 0.89–0.98 and the index of agreement (IOA) showed a range of 0.89–0.9. The uncertainty of the model output was revealed by the standard deviation of the residuals of the model, at 1.8–2.1 and 2.00–3.00 for temperature and precipitation. Compared with the NRCM data, the remapping output still had a high ability to capture both temperature and precipitation, which was indicated by the IOA being in the range from 0.65 to 0.78.

Table 3. Statistical analysis of the model and ground-based observations from the TMD. IOA: index of agreement.

Statistical Analysis	Temperature		Precipitation		Crop Production	
	NRCM	Remapping	NRCM	Remapping	Rice	Maize
IOA	0.76	0.78	0.63	0.65	0.89	0.81
Mean-Biased	−0.92	1.62	−2.68	−1.88	−245	−176
SDR	1.87	1.21	2.54	2.38	615	226

3.2. Crop Model Evaluation

Since no on-farm crop production data were available for 2019, simulated DSSAT rice and maize data based on CERES–Rice and CERES–Maize were compared with the on-farm dataset for 2010–2018. In Figure 3, the box plots of the models for rice and maize and on-farm data show the evaluation of rice and maize production. We found on-farm data regarding the thickness of wires from both rice and maize, while simulated rice and maize exhibited a thinner wire. The box plot analysis shows that the modeled crop production is lower than the on-farm data for both rice and maize. The actual rice production was 3200–3800 kg/ha, while the modeled rice production was 3000–3200 kg/ha; while the modeled maize production was 4000–4100 kg/ha, the observed maize production was 3900–4400 kg/ha.

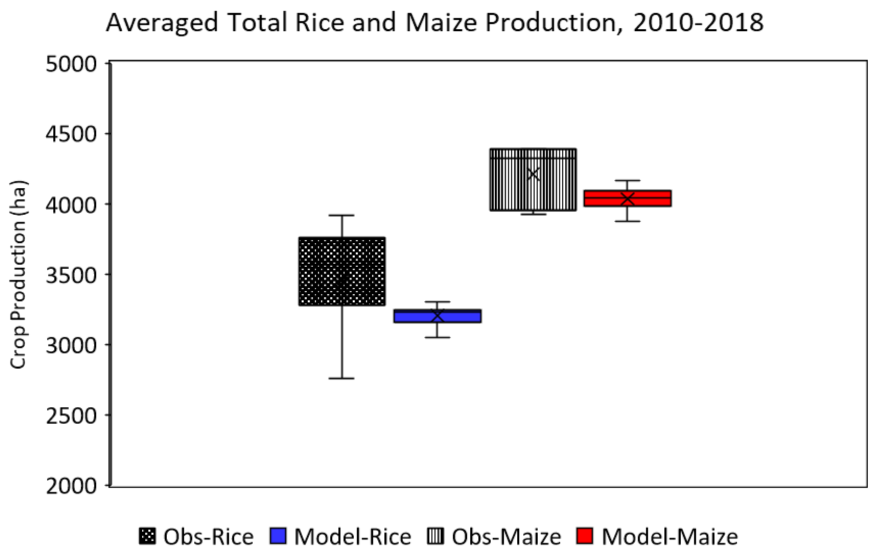


Figure 3. Box plot of simulated rice and maize from the Decision Support System for Agrotechnology Transfer (DSSAT) and on-farm datasets.

By statistical analysis, the modeled production of rice and maize had high IOA values of 0.81 and 0.89. Remapped temperatures tended to be slightly overestimated, with a mean bias of 1.62, while remapped precipitation for modeled rice and maize was underestimated compared with observations, with a mean precipitation bias of −1.88 and −245 for rice yield and −176 for maize yield. While the standard deviation of the remapping output residue ranged from 1.21 to 2.38 for the meteorological factor, crop yields ranged from 615 to 226 for rice and maize.

In summary, the model performance assessment was acceptable for the re-mapping of both climate output and crop production. The remapping output, including the temperature and precipitation, remained at a high IOA value of 0.78 and 0.64, while the temperature and precipitation changed slightly compared with the NRCM by 1.62 and −1.88. As the concept of a conservative remapping method preserves the trend of the original data, the quality of the remapping data was similar to that of the NRCM data. Simulated crop production was also acceptable compared with the IOA with on-farm yields of 0.81 and 0.89 for rice and maize, although the model output showed an underestimation of crop production. This is likely to be due to a number of factors, such as information on irrigation and fertilization. The demand for water in this work followed Intaboot [25], which is a constant value for the entire simulation, but in reality, the planting irrigation schedule was set. Irrigation is severely affected by planting efficiency. It was identified, for example, as being key to improving agricultural productivity [42,43], and Nonvide [44] reported a percentage increase in irrigation rice yield between 55% and 60%. However, as reported in Yousaf et al. [45], fertilization can enhance crop production. They found that crop yields increased by 19–41% (rice) and 61–76% (rape) over 2 years of N–P–K fertilization rotation compared with P–K fertilization across the study area.

3.3. Prediction of Rice and Maize

The future total production of rice and maize during 2020–2029 under the worst climate change scenario (RCP8.5) is shown in Figures 4 and 5. In general, DSSAT predicted a decrease in aggregate yields by 5.15% and 3.9% for rice and maize compared with last year's simulations. We found that Chiang Rai, Chiang Mai and Phrae had the region's lowest yields, with a decrease of about 7%, while Lampang was the only province with an impact from climate change of less than 1% (Figure 6). Climate change shows a negative impact on rice and maize due to temperature and precipitation changes. The predicted precipitation during 2020–2029 tended to decrease by approximately 0.5 mm/day, while temperature tended to increase by about 2–5 °C across northern Thailand [12]. The decreasing amount of precipitation affected water resources for rice and maize production, since around 40% of the total rice area is classified as rainfed, whereas about 3.5 million ha of rice is still classified as deep or flood-prone [46]. Variability in rainfall quantity and distribution is the most important factor limiting rainfed rice and maize production [47,48]. In the meantime, rising temperatures also reduced the production of rice and maize. This agrees with the work of Mohandrass et al. [49] and Peng et al. [2], which suggested that rice productivity under global warming will also decrease as global temperatures increase. Extreme temperatures, both low and high, damage the rice plant. High temperatures are a constraint on rice production in tropical regions.

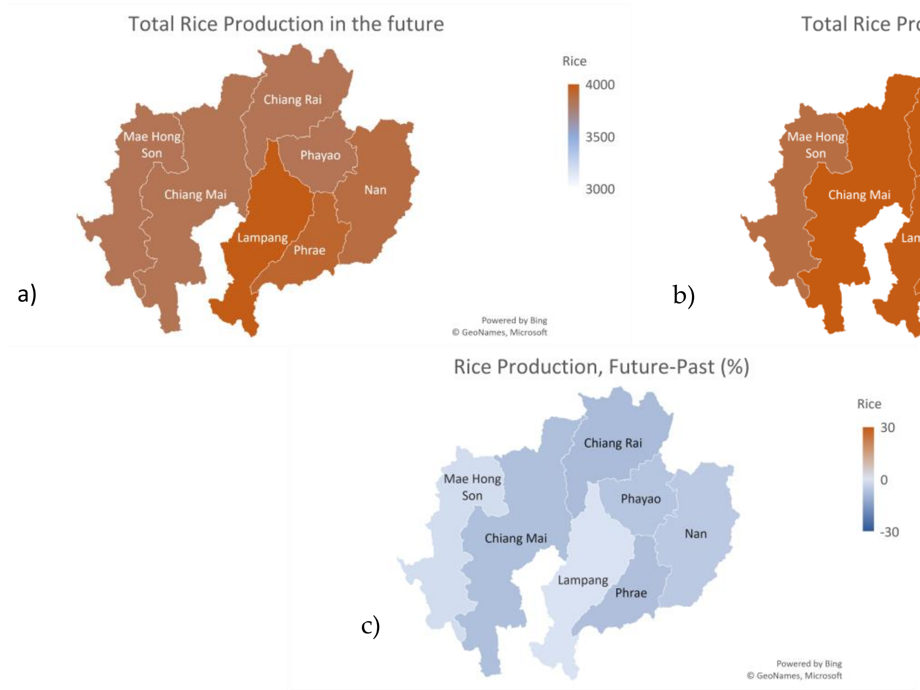


Figure 4. Average rice production in the wet season in (**a**) 2020–2029 and (**b**) 2010–2018, and (**c**) the difference between 2020–2029 and 2010–2018.

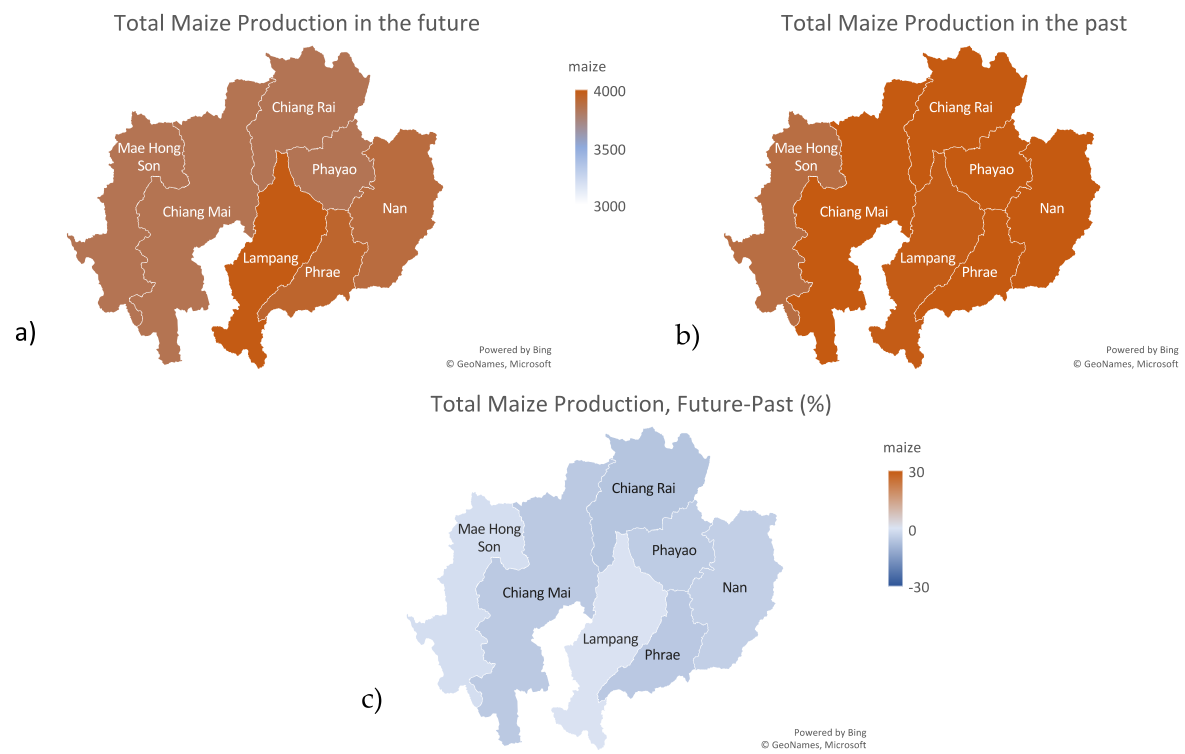


Figure 5. Average maize production during (**a**) 2020–2029 and (**b**) 2010–2018, and (**c**) the difference between 2020–2029 and 2010–2018.

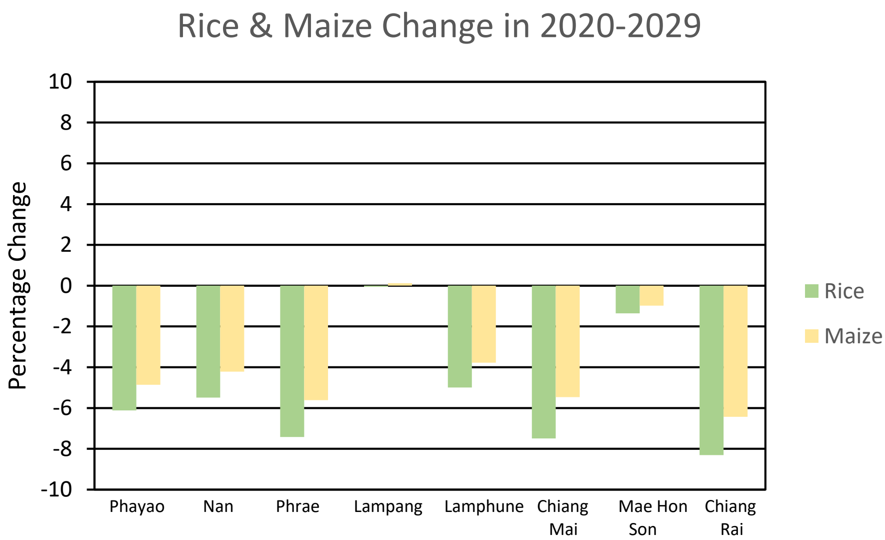


Figure 6. Percentage change of rice and maize in 2020–2029 compared with 2010–2018.

3.4. Crop Production Risk Analysis

The cumulative probability distribution (CPD) plots at 0.5 show that both rice and maize were predicted to have the highest mean yield (Figure 7). Even with the predicted mean yield variance, which was smaller for maize and maximal for rice, this pattern was consistent and suggested that maize could be considered as risky for risk-averse farmers. With approximately 3000 kg ha^{-1} and 4312 kg ha^{-1} estimated for rice and maize yields in northern Thailand, maize showed a cumulative probability of yield below the minimum acceptable threshold of 50%, while rice showed an acceptable probability above the minimum of 30%. This suggests that maize is highly likely to provide a yield below the lowest acceptable yield target. Likewise, stochastic dominance analysis showed that the two rice systems were less dangerous than maize because both were on the side of rice, with the two rice systems having the lowest variations in money returns (Figure 8). The mean-Gini dominance (MDG) test showed rice to be the most efficient system of management (Table 4).

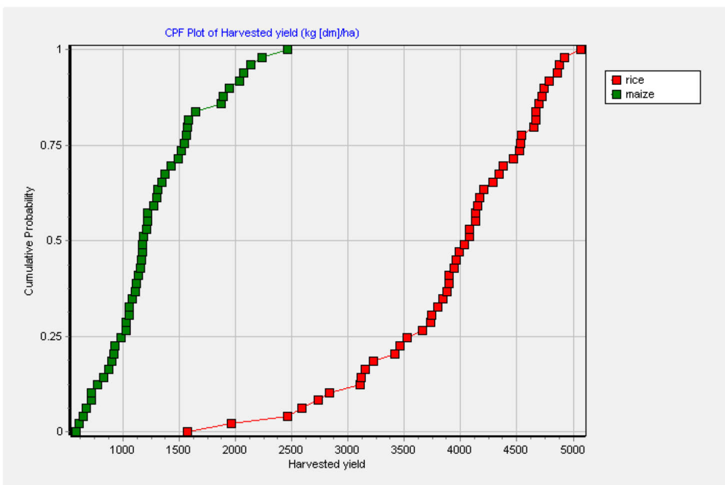


Figure 7. Cumulative probability distribution of rice and maize production in the future.

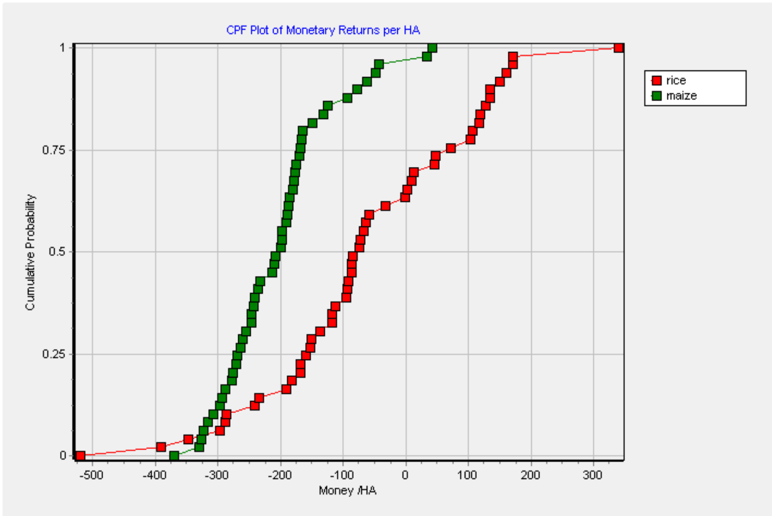


Figure 8. Stochastic dominance analysis ($/ha) of rice and maize production in the future.

Table 4. Dominance analysis of rice and maize in 2020–2029 in northern Thailand.

Treatment	E(x)	E(x)–F(x)	Efficient (Yes/No)
Rice	−63	−157.4	Yes
Maize	−203.7	−253.6	No

To cope with the effects of climate change on agriculture, especially on rice and maize agricultural production, the government of Thailand has launched research into the Global Action Plan on Climate Mitigation and provides information to improve the population's understanding of climate change. Many rice farmers have insufficient expertise to effectively maintain their farms under changing conditions. Historically, farmers have grown domestic rice through seeds and seedlings that are resistant primarily to pre-cultivation pests and diseases. The Thai administration has supported new genetically modified (deep-water) rice (not reusable) species, which typically are in floodwaters of more than 50 cm for more than a month, using DNA technology. The new dry-rice varieties gluten-resistant RD12 and non-gluten-resistant RD33 have been distributed to dry areas. However, as the government does not sufficiently supply all farmers, several private companies also produce this new variety. Therefore, farmers who can buy the strains have shown interest in new rice varieties that produce more than conventional rice. The most common strategies of improvement used for those who cannot supply new seeds are adapting crop patterns and crop planning and improving agricultural management. The government has also built land features to protect rice farms against flood damage. In addition, risk management systems should be included in national household adaptation strategies. This could include crop insurance or flexible livelihoods such as integrated aquaculture and farming systems, which would enable farmers to rely on land adequacy and changes in water availability. In the short term, integrated agriculture will increase the different types of crop yield while the sustainability of agricultural systems will be an advantage over the long term.

We also suggest the technical possibility of adaptation, as the germination and emergence of rice seedlings are more likely to be restricted to low rather than high temperatures, and a rise in temperature due to global climate change is not likely to significantly affect the selection of the appropriate rice planting date in tropical regions. Since the temperature varies from month to month, the right date for cultivation can be selected to reduce the reproductive and grain filling phases of rice to relatively low temperatures in those months. This would minimize the negative impact of the temperature increase on rice yield, as reported by Peng et al. [2]. Therefore, efforts to collect and disseminate data about month-to-month temperature variations in major tropical rice production areas are essential to help crop producers to adapt to climate change. Furthermore, harvesting rainwater can supplement irrigation for rainfed farming.

4. Conclusions

The purpose of this research is to forecast the production of rice and maize in northern Thailand in the years 2020–2029 under the worst-case climate change scenario of RCP8.5. Nested Regional Model Climate (NRCM) climate datasets with 80–90% reliability at a 10 km spatial resolution [12] were reduced to 1 km by using the Conservative First and Second-Order Remapping schemes. This dataset was used as an environmental factor in DSSAT modeling to predict rice and maize production and assess risk levels. The model evaluation of climate and agricultural data kept climate data at the same reliability level as the previous dataset. The data accuracy was calculated at 0.78 for temperature and 0.65 for precipitation according to the Agreement Index (IOA), while the average bias was 1.62 for temperature and -1.88 for precipitation. Simultaneously, the results of the DSSAT model system, including the production of rice and maize, were found to be close to the on-farm data set, with IOA values of 0.89 and 0.81 for rice and maize. The predicted climate in 2020–2029 tended to have a negative effect on rice and maize in northern Thailand, decreasing production. In addition, the risk analysis indicated that maize cultivation is likely to be at a high risk of reduced production. We also suggest promising adaptation strategies to reduce this high risk, such as additional irrigation, crop diversification, the selection of appropriate planting dates and the conservation of natural resources.

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