Assessment of the Potential Climate Change on Rice Yield in Lower Ayeyarwady Delta of Myanmar Using EPIC Model

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ABSTRACT

Climate change has been occurring and its consequences are a threat to rice production and hence food security. In this study, the effect of climate change on rice yield has been assessed by using the Environmental Policy Integrated Climate model under climate change scenarios RCP4.5 (medium emissions) and RCP8.5 (high emissions) and to propose alternative adaptive measures for farmers' livelihoods in the lower Ayeyarwady Delta. The results show that the average yield increase of early rice are 11.84% and 7.56% and the average yield reduction of late rice are 37.37% and 50.89% under both scenarios. The study found that rice yield reduction will be significantly higher under the RCP8.5 than that of RCP4.5 for both rice. Yield reductions are attributed to increases in mean maximum and minimum temperatures and variation in rainfall pattern. The model result suggests that changing the sowing date is a good option for compensating the future rice yield reduction. The other adaptations that offset the rice yield response to climate change include providing farming machines, irrigation facilities, improving infrastructure, improvement in cultivars that resist disease, pest and drought, better weather forecast and extension systems.

1. INTRODUCTION

Rice is one of the most essential cereal crops that feed more than three billion people, which represents half of the world's population (Mosleh et al., 2015). The rising temperatures and CO_2 concentration and uncertainties in rainfall associated with global warming may have serious consequences on crop production and food security (Aggarwal and Mall, 2002). The impacts of climate change can affect agriculture in two ways; by the direct effects of CO_2 on plants and by the effects of changes in climate (i.e., temperature, precipitation). These factors have positive as well as negative effects on crop production (Warrick, 1988; IPCC, 2014).

Myanmar is one of the most vulnerable countries to climate change among the ASEAN Countries. According to the Global Climate Risk Index, Myanmar is the second country in the world most affected by climate change from 1993 to 2014 (Kreft et al., 2014). The Department of Meteorology and Hydrology (DMH, 2016) of Myanmar describes that the average daily temperature and maximum temperature increased by about 0.25°C and 0.4°C per decade while annual total precipitation rose slightly between 1981 and 2010. Under the two greenhouse gas emissions scenarios of the Representative Concentration Pathway (RCP4.5 and RCP8.5) developed for IPCC AR5, which are medium emissions scenario and high emissions scenario, the annual average temperature of Myanmar is predicted to increase by 1.3ºC to 2.7ºC above historical level by the middle of the century. Furthermore, the seasonal rainfall patterns are expected to vary across Myanmar. The sea level is predicted to rise by mid-century within the range of 20 to 41 cm (Horton et al., 2016).

Crop models are considered valuable tools in research, teaching and training, yield area forecasting, land use planning, and decision-making (Hilger et al., 2000). A number of modelling assessments have suggested that the considerable increases in rice productivity have occurred due to the increases in temperature and CO_2 concentration (Pumijumnong and Arunrat, 2013; Yin et al., 2014). However, crop production in the tropics is more sensitive to warming since they operate already close to the optimal temperature, hence the sharp yield reduction (Oteng-Darko et al., 2012; Candradijaya et al., 2014).

Although there are numerous models used to simulate crop yield such as DSSAT (Decision Support System for Agro-technology Transfer), GLAM (General Large Area Model for Annual Crops), APSIM (Agricultural Production System Simulator) CropSyst (Cropping System), WOFOST (WOrld FOod STudies), and SCERES (Crop Environment Resource Synthesis), each of them has its own strengths and limitations. DSSAT does not provide one model to simulate crops and combines a series of crops model for all specific crops (Tan and Shibasaki, 2003; Yin et al., 2014). APSIM, CropSyst, and GLAM are not suitable for rice since rice parameters are not well calibrated (Keating et al., 2003). WOFOST requires detailed input data, but it describes crop physiology (Stella et al., 2014). Compared to other models, the Environmental Policy Integrated Climate (EPIC) crop model is a unified approach to simulate more than 100 crops that can be simulated at the same time (Liu, 2007). It is a widely used and tested model and has a good accuracy to simulate many agro-ecosystem processes including plant growth, development, yield attributes, weather, soil and management practices (Bouzaher et al., 1996; Gummadi et al., 2016).

Very few studies have been conducted on climate change impact assessment in Myanmar. Currently the only study by Shrestha (2014) used the ECHAM5 and HadCM3 and the AquaCrop model to analyse the impacts of climate change on irrigation water requirement (IWR) and rice productivity at Ngamoeyeik Irrigation Project under the A2 and B2 SRES scenarios and found an increasing trend in yield of early rice and declining trend in IWR.

In light of this, this study aims to estimate the possible impacts of climate change on the potential rice yield changes to food security under climate change scenarios RCP4.5 and RCP8.5 and to propose alternative adaptive measures for farmers' livelihood in Myaungmya Township, the lower Ayeyarwady Delta. In doing so, the research result of this study will contribute to adaptation options of rice cultivation to the policy makers and all relevant stakeholders in response to future climate changes.

2. METHODOLOGY

2.1 Study area

Myaungmya Township, one of the highest rice growing areas which occupies the southwestern part of Ayeyarwady Delta, lies between 16°19´-16°44´N and 94°40´-95°05´E (Figure 1). The areal extent of Myaungmya Township is 1,152.23 km^2 (DALMS, 2016). The annual mean maximum temperature was 32.6±1.0°C, the annual mean minimum temperature was 22.3±0.9°C and the average annual rainfall was 2,894±429.6 mm over the period of 1986-2015. About 95% of rainfall received during the monsoon period; May to October. Most of the area is flat alluvial plain with an elevation of about 8 m above sea level. The dominant soil types in the township are gleysols and fluvisols (Win, 2010). The total population of the study area was 291,390 (DOP, 2015). The double cropping, early rice and late rice, are practised for their major livelihood activity. Early rice occupies the majority of the sown area, and the largest area of late rice is under irrigation among the township (DALMS, 2016).

2.2 Model description and input data

The EPIC model was developed to estimate soil productivity in the 1980s in the U.S. The EPIC simulates approximately eighty crops with one crop growth model using unique parameters for each crop (Williams, 1989). It is a field-scale crop response model that uses a daily time step to simulate potential yields by taking into account four key factors; crop characteristics, weather, soil fertility and soil properties. It has eight major modules; weather generation, crop growth, soil water dynamics, erosion, nutrient and carbon cycling, soil temperature, tillage and crop, and soil management (Marshall et al., 2015; Xiong et al., 2014). Plant growth is influenced by temperature, water and nutrient stresses (Tan and Shibasaki, 2003). In EPIC simulation, crop yield (*YD*) is calculated by harvest index (*HI*), biomass-energy ratio (*WA*), solar radiation (*RA*), leaf area index (*LAI*) and growth period length (cited from Yin et al., 2014). The equation (1) is expressed as;

$$YD = HI \times \sum_{i=1}^{n} \frac{WA \times RA_i \times [1 - exp(-0.65 \times LAI_i)]}{5000} \quad (1)$$

The necessary data and information for EPIC model to estimate crop yield are climate data, soil data, and field management data.

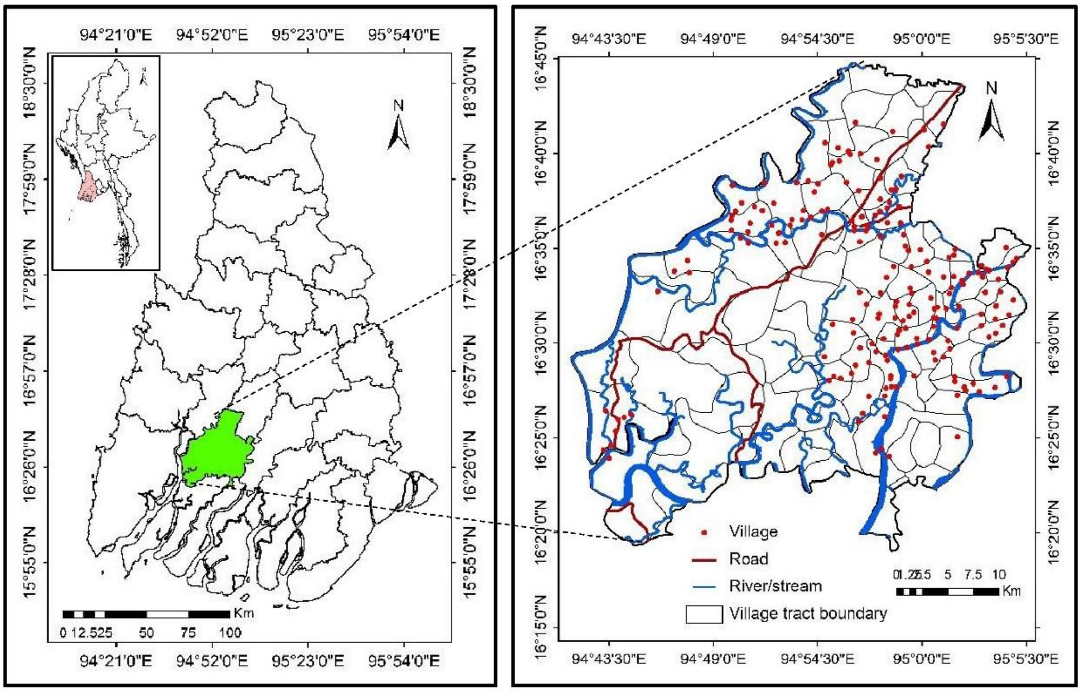


Figure 1. Location of study area; Myaungmya Township (Source: Myanmar Information Management Unit)

2.2.1 Observed climate data

The weather data needed in EPIC are the maximum and minimum temperature (ºC), solar radiation (W/m^2), wind speed (m/s), wind direction (º), precipitation (mm), and relative humidity (%). Although available weather data for 30 years (1986-2015) of minimum and maximum temperature, rainfall, relative humidity, wind direction and wind speed were collected from the nearest meteorological station of Myaungmya Township (Pathein) under DMH, solar radiation data were not available from official sources. Therefore, it was extracted from available literature (Yee et al., 2008; Janjai et al., 2013). Then, based on the available data, an interpolation method (Kriging method) was applied to create a gridded weather data of Myaungmya Township.

2.2.2 Climate change scenarios

To compare the range of climate change impact on rice production in the study area, RCP4.5 and RCP8.5 were used to cover both medium and extreme scenarios. The projected increase in global surface temperature is likely to be 1.1 to 2.6ºC under RCP4.5 and 2.6-4.8ºC under RCP8.5 for the years 2081-2100 relative to 1986-2005 (IPCC, 2014). The General Circulation Model (GCM) used was the BCCCSM1 (Beijing Climate Centre Climate System Model version 1) model developed by Beijing Climate Centre with a resolution of 1.9° x 1.9° downloaded from the Climate Change Knowledge Portal of World Bank Group, available at http://sdwebx.worldbank.org/climateportal/index.cfm?page=countryfutureclimate &ThisRegion=Asia&ThisCcode=MMR. The GCM was divided into four future time slices; near future (2020-2039), mid future (2040-2059), far future (2060-2079) and very far future (2080-2099) (hereafter NF, MF, FF and VFF). In the future model applications, the 18 EPIC runs were performed for the study.

As the spatial resolution of GCM is too coarse to analyse, two steps of downscaling were performed to match the spatial resolution of the study area. First, these monthly data were spatially downscaled into 3km x 3km grids by using the kriging method. Then linear scaling was used to correct monthly 3 km-data based on the differences between observed and raw GCM data (Babur et al., 2016). Monthly differences in the climate data were acquired using an observed period (1986-2005) of raw GCM and observed data. Following equations 2 and 3 were applied to correct GCM future temperature and precipitation data.

$$T_{fut,d} = T_{GCM,d,fut} + (\bar{T}_{(obs,mon)} - \bar{T}_{(GCM,cont,mon)}) \quad (2)$$

$$P_{fut,d} = P_{GCM,d,fut} \times \left(\frac{\bar{P}_{(obs,mon)}}{\bar{P}_{(GCM,cont,mon)}}\right) \quad (3)$$

$T_{fut,d}$ and $P_{fut,d}$ are the corrected temperature and precipitation for the future periods. $T_{GCM,d,fut}$ and $P_{GCM,d,fut}$ are the daily temperature and precipitation of the GCM data for future periods. $\bar{T}_{(obs,mon)}$ and $\bar{P}_{(obs,mon)}$ represent the long-term mean monthly temperature and precipitation. $\bar{T}_{(GCM,cont,mon)}$ and $\bar{P}_{(GCM,cont,mon)}$ refer to the long-term monthly mean temperature and precipitation for the control period of the GCM.

To access the potential impact of climate change on rice yield, the projected climate parameters under RCP4.5 and RCP8.5 were used as the input data for the model. However, no changes in management practices and soil properties were assumed and used same as baseline.

2.2.3 Soil data

Soil sampling was done during January and February 2016. To take soil samples, the study area was divided into 3 km x 3 km grids, resulting in a total of 210 grids. Each grid that had rice grown in 50% or more of the area was chosen for sample sites and, finally, soil samples were collected from 59 sites. A criterion for taking the soil sample is based on the centroid of each grid cell. To avoid bias, soils were collected at the centroid of each site. The Global Positioning System (GPS) was used to record the geographical coordinates of all sampling locations. Two soil samples with two replications were obtained from each site based on soil colour, 118 soil samples were finally obtained from the study area. The soil parameters (not shown) needed for model input were analysed using hydrometer method for soil texture, core method for bulk density, pH meter for soil pH, Walkley and Black method for soil organic carbon, distillation method for total nitrogen, ammonium acetate method for cation exchange capacity, Olsen method for available phosphorus, and flame photometer for exchangeable potassium.

2.2.4 Field management data

In order to simulate complex crop rotations, the EPIC uses detailed descriptions of management data (Wang et al., 2005). The field management data such as tillage operation, crop, and fertilizer parameters and planting/harvesting dates are required to standardize based upon EPIC parameter data files. In this study, relevant crop parameters and rotation operations and fertilizer application were gathered from the farmer households' questionnaire survey (Table 1).

Table 1. Summary of crop management for the year between 2012-2013 and 2015-2016

Rotation operation	Early rice		Late rice	
	Date	Month	Date	Month
Tillage	20-25	May (05)	25-30	December (12)
Planting	5-10	June (06)	1-5	January (01)
Fertilizer	15-20	July (07)	5-10	January (01)
Fertilizer	5-10	September (09)	1-5	February (02)
Fertilizer	-	-	15-20	March (03)
Harvest	20-25	October (10)	15-20	April (04)
Kill	20-25	October (10)	15-20	April (04)

Source: Authors, field survey in 2016

2.3 Model calibration and validation

The approach used for the calibration was to adjust some initial values of the model parameters to repeatedly fit simulation values as close as possible to the observed values (Worou et al., 2004). To access the sensitivity of parameters, ±10% of mean or model default value were performed for adjusting unique parameters; *PHU* (potential heat units from planting to maturity), *PD* (planting density, plant population at the planting), *HI* (harvest index, the ratio of grain to total crop biomass with unstressed conditions), and *WA* (biomass energy to ratio, potential growth rate per unit of intercepted photosynthetically active radiation) (Wang et al., 2005).

To validate the reliability of model, the data of early rice and late rice between 2012 and 2016 were gathered from DALMS of Myaungmya Township. To quantify the difference between simulated and observed data, several criteria were used (Valizadeh and Shafie, 2013). In this study, the normalized root-mean-squared error (*RMSE*) was used to measure the coincidence between observed yield from the study area and simulated yield from the crop model (Equation 4).

$$RMSE(\%) = \left[\frac{1}{n}\sum_{i=1}^{n}(Y_{si} - Y_{ob})^2\right]^{\frac{1}{2}} \times \frac{100}{\bar{Y}_{ob}} \qquad (4)$$

Y_{si} is the simulated crop yield of the model, Y_{ob} and $\bar{Y}_{ob}$ represent the observed yield and long-term mean of observed crop yield of the area, and *n* is the number of observations. The simulation is considered the best with the error less than 10%, good if 10%-20%, acceptable if 20%-30%, fair and poor if the values are more than 30% (Jamieson et al., 1991).

2.4 Data analysis

All statistical analysis was performed using the SPSS 18 and EXCEL 2007. The differences in rice yield over time were determined by paired *t*-test.

3. RESULTS AND DISCUSSION

3.1 Model calibration and validation

Rice was grown as double cropping; early rice and late rice in the study area. Although the varieties of rice were cultivated, the common rice grown were Ma Naw Thu Kha, Sin Thu Kha, Thee Htat Yin, Yadana Toe, Paw San, Hnan Ka, Aye Yar Min and Palethwe (Table 2). The sowing date of early rice was between 25 May and 10 June while the late rice was planted from 25 December to 5 January. Early rice was harvested in October to November and late rice was harvested in May. The majority of the farmers use both organic fertilizer (crop residue, cattle manure) and inorganic fertilizers. The farmers in this study used two types of fertilizers namely 46-0-0 and 0-46-0. The amount of fertilizer used ranged from 28 kg/ha to 300 kg/ha, but the common amount was 57 kg/ha and 190 kg/ha for early rice and late rice respectively. The nitrogen (46%) and phosphorus (46%) fertilizers were applied in about 10 days and 90 days after plantation of early rice. Three applications of the nitrogen and phosphorus fertilizers were used for late rice; around 21 days, 45 days and 60 days after planting, but the phosphorus fertilizer was not used in the last application.

Table 2. Commonly grown varieties of rice in Myaungmya Township in 2016

Varieties	Life time	Height (cm)	Yields (ton/ha)
Thee Htat Yin	105-120	76-91	4.12-5.16
Sin Thu Kha	120-135	80-100	4.64-5.15
Ma Naw Thu Kha	130-135	91-107	4.10-5.16
Hnan Ka	160-170	152-168	2.58-3.61
Paw San	160-170	160-183	2.06-3.09

Source: Ministry of Agriculture, Livestock and Irrigation (MOALI) and Field Survey, 2016

To calculate the potential evapotranspiration in model, the Penman-Monteith method was used. The values of CO_2 concentration were used according to their corresponding forces. Wang et al., (2005) suggests that simulated rice yield is sensitive to several input parameters such as *PHU*, *HI*, *WA* and *PD*. In this study, these parameters were calibrated step by step along with the other default parameters (Table 3). As suggested by Xiong et al., (2014), the *PHU* was first adjusted for this study. It was adjusted by the interval of ±10% from the mean or default value to reach the closest between the measured average (2012-2016) and the simulated yield and was chosen for the adjusted value. The other parameters, *HI* and *WA* were done as same approach as *PHU*. The study found that *HI* was the most sensitive parameter for the study area because the yield change at *HI* was the highest among each unit of change in four parameters.

Once the EPIC crop growth model is performed the closest simulated yield with measured yield, the next approach is its validation. In this step, the measured yield was compared with the simulated yield of the same crop, the same sites and the same period (Adejuwon, 2005). According to the data collected from MOALI, the high yield varieties, which were mostly grown in the study area locally known as Thee Htat Yin (IR 1234), for both rice were used for validation.

Table 3. Input parameters used for model calibration

Parameter	Symbol	Range	Early rice	Late rice
Rotation operation				
Potential heat unit	PHU	1200 - 2400	1200	1650
Planting density	PD		200	250
Crop				
Biomass energy ratio	WA	30 - 45	30	31.25
Harvest index	HI	0.45 - 0.6	0.35	0.45
Optimum temperature for plant growth	TOPC	25	30	33
Minimum temperature for plant growth	TBSC	10	10	15
Parameter				
Water stress HI	PARM (3)	0.3-0.7	0.3	0.3
SCS CN index coefficient	PARM (42)	0.5-2	0.5	0.5

The comparison of the simulated and measured yield of early rice showed that the average yields were 4.34 and 3.99 ton/ha whereas late rice yields were 5.18 and 5.01 ton/ha respectively (Table 4). The *RMSE* values of early rice and late rice were 9.83% and 9.72% respectively. In fact, the result of *RMSE* is less than 10% between simulated and measured rice yields which gives the high confidence to apply the EPIC model for the possible future climate change impacts on rice yields in the study area.

Table 4. The comparison of measured and simulated yields and statistical indices

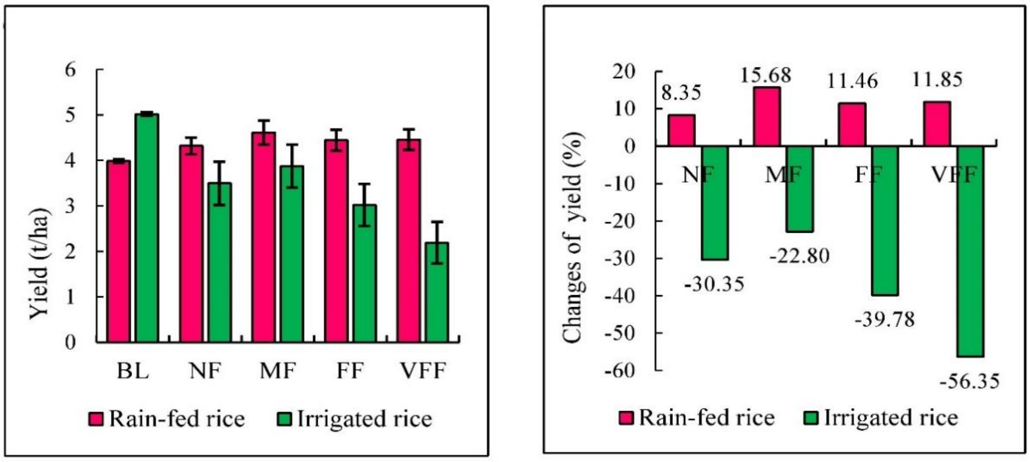
Rotation	Yield (ton/ha)		*RMSE* (%)
	Measured	Simulated	
Early rice	3.99	4.34	9.83%
Late rice	5.01	5.18	9.72%

3.2 Estimated impacts of potential climate change on rice yield

Based on the projected climate change under scenarios RCP4.5 and RCP8.5, the study found that the simulated rice yield of early rice and late rice would vary higher in the future than during the baseline period across the study area.

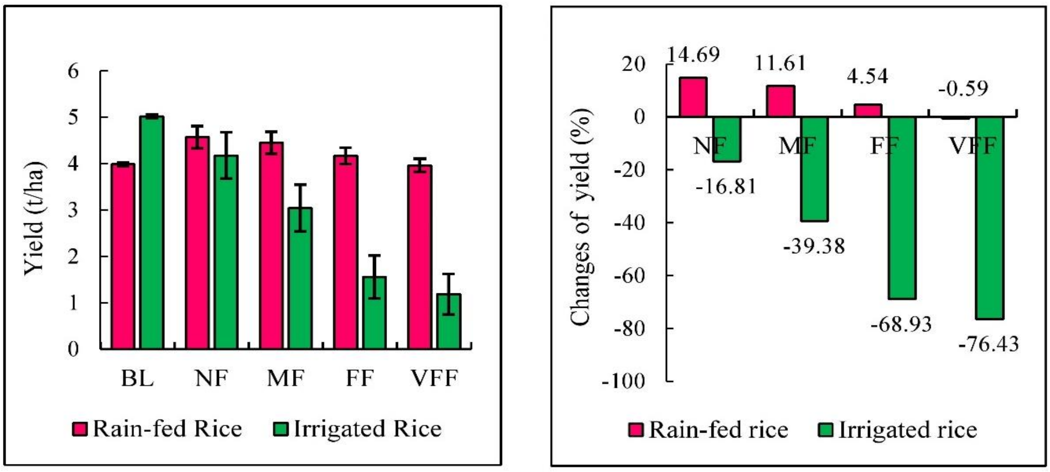
Compared to baseline period, the model showed that the simulated yield of early rice for all sample sites would increase by 8.35%, 15.68%, 11.46% and 11.85% in the future under RCP4.5. In contrast, the decrease in yield of late rice was found to be 30.35%, 22.80%, 39.78% and 56.35% for all future periods under RCP4.5 (Figure 2). The increase of potential early rice can be attributed to the combined effects of climate variables, especially increases in temperature and rainfall. It clearly showed that the rate of increase was smaller in NF than other periods due to the predicted rainfall decrease by 4.29% compared to the baseline period. However, in case of late rice, the significant yield reduction could be explained by the relatively higher temperature and low rainfall in that period.

Under RCP8.5, the model showed that the early rice yield would also increase by 14.69%, 11.61% and 4.54% for NF, MF and FF, however it would slightly decrease by 0.59% for VFF. A similar trend with RCP4.5, the decrease in yield of late rice in the future under RCP8.5 was significant and the reduction estimates range between 16.81% and 76.43% (Figure 3).



(a) (b)

Figure 2. Rice yield under RCP 4.5 and error bars: standard deviation for rice yield (a) and rice yield change under RCP 4.5 (b)



(a) (b)

Figure 3. Rice yield under RCP 8.5 and error bars: standard deviation for rice yield (a) and rice yield change under RCP 8.5 (b)

On average, the yield projection using EPIC model revealed that the early rice over 2020-2099 is expected to increase by 11.84% and 7.56% under RCP4.5 and RCP8.5 respectively. On the other hand, the study showed that the yield of late rice would significantly decrease by 37.32% under RCP4.5 and profoundly drop by 50.89% under RCP8.5 compared to the baseline yield (Table 5). The average yields were significantly different in all future periods from the baseline under both scenarios when tested with paired *t*-test (<0.001).

Heterogeneity of simulated yield response to climate change is often used to identify climate change hotspots for developing adaptation strategies (Xiong et al., 2016). In this study, the sample sites were divided into five groups based on the projected yield changes by the period of 2020-2099 and identified vulnerable and benefit areas for the rice production under climate change.

Table 5. The summary of predicted yield changes for early rice and late rice of possible future climate with relative to the base line period

Scenarios	Period	Changes in rice yield			
		Early rice		Late rice	
		ton/ha	% changes	ton/ha	% changes
Observed	BL	3.99	-	5.02	-
RCP4.5	NF	4.32	8.35	3.50	-30.35
	MF	4.61	15.68	3.88	-22.80
	FF	4.44	11.46	3.02	-39.78
	VFF	4.46	11.85	2.19	-56.35
	Average	4.46	11.84	3.13	-37.32
RCP8.5	NF	4.57	14.69	4.14	-17.30
	MF	4.45	11.61	3.02	-40.02
	FF	4.17	4.54	1.54	-69.37
	VFF	3.96	-0.59	1.16	-76.85
	Average	4.29	7.56	2.46	-50.89

BL = Observed year, NF = Near future, MF = Mid future, FF = Far future, and VFF = Very far future

Some spatial variation of predicted yield reduction could be observed across the township. As shown in Table 6 and Figure 4, the simulation results showed that the majority of farmers in the production area of northern, eastern and south-central parts would benefit from the early rice production since the rice yield would increase with 5-30% for all futures under RCP4.5. On the other hand, under the scenario RCP8.5, the farmers in that area would see a decrease in their yield of early rice. The farmers in the south-central part would be especially susceptible over the period of VFF with a reduction rate of over 60%.

Table 6. Number of study sites identified as susceptible and benefited to climate change by the 2020-2099

Group	Index of yield changes	RCP4.5								RCP8.5							
		Early rice				Late rice				Early rice				Late rice			
		NF	MF	FF	VFF	NF	MF	FF	VFF	NF	MF	FF	VFF	NF	MF	FF	VFF
High susceptible	>-60%	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	48
Medium susceptible	-60% to -30%	0	0	0	0	25	12	45	23	0	0	0	0	3	42	8	3
Low susceptible	-30% to-5%	1	1	1	1	26	36	6	28	1	1	3	10	44	9	0	0
Not sensible	-5% to 5%	10	8	9	9	0	3	0	0	8	9	14	49	3	0	0	0
Benefit	5% to 30%	48	50	49	49	0	0	0	0	50	49	42	0	1	0	0	0
Total grids		59	59	59	59	51	51	51	51	59	59	59	59	51	51	51	51

BL = Observed year, NF = Near future, MF = Mid future, FF = Far future, and VFF = Very far future

Similarly, the simulated results of late rice showed that the farmers in such areas would benefit from the cultivating of late rice with an increase rate of 5-30% except by the VFF period under RCP4.5. However, under the scenario RCP8.5, the majority of farmers in that area would be highly vulnerable to cultivating of late rice in all future periods. The reduction of yield could range by up to over 60%. The rice yield is not only impacted by climate change but also variation in soils (Adhikari, 2015). During the study of Lal et al. (1998) in NW India using SERES rice model, they observed that a 4ºC drop in surface air temperature results in 10% reduction in rice yield, while a 4ºC increase in temperature causes 41% reduction in rice yield.

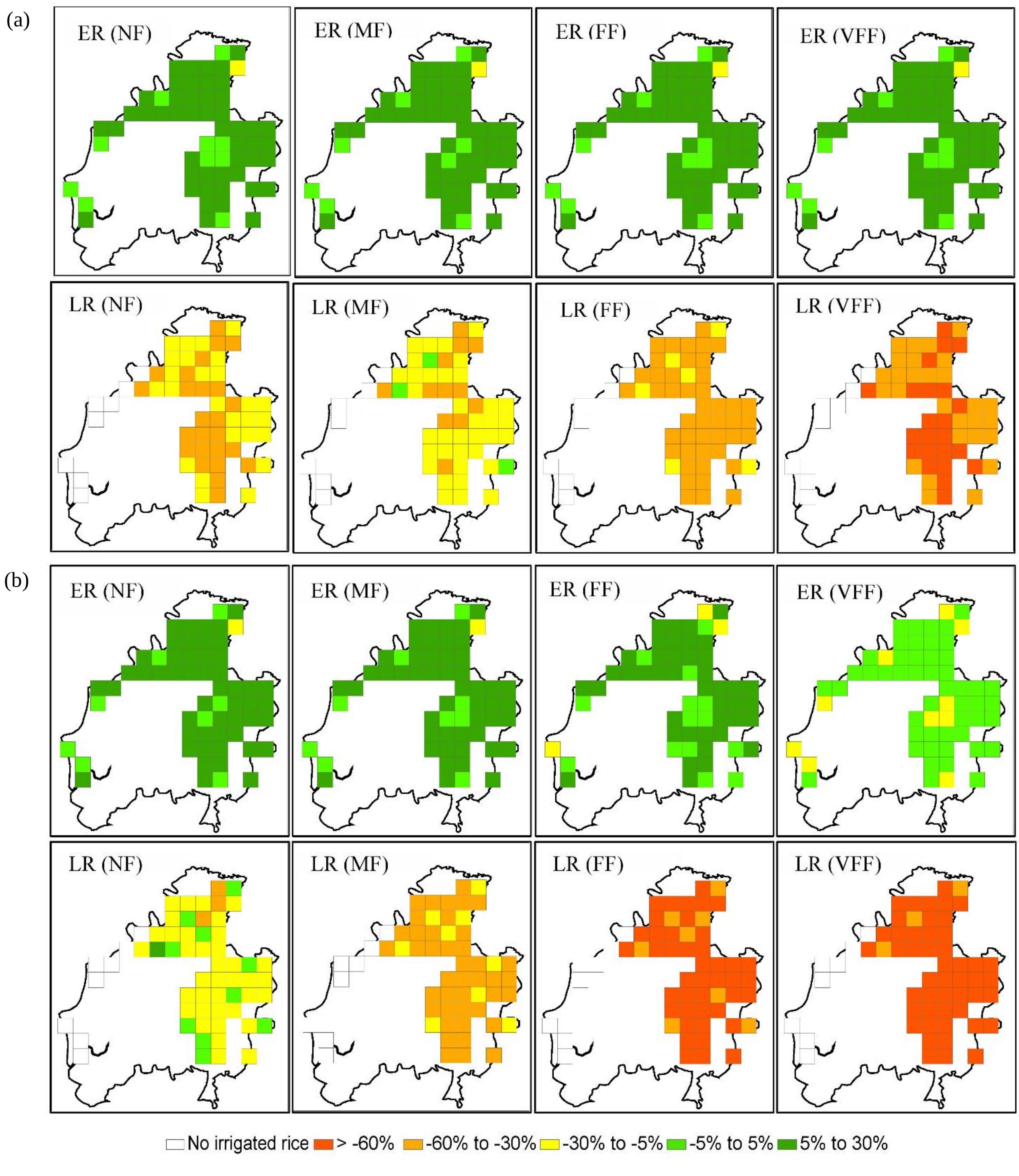


Figure 4. Spatial patterns of yield changes for early rice and late rice for the all future periods under RCP4.5 (a) and RCP8.5 (b)

3.3 Adaptive option of changing planting date on rice yield

In order to respond to potential climate change, rice yield was analysed by changing of planting dates by advancing or delaying (± 10 days or +20 days) from the date that local farmers have practised across the township. In case of early rice, the study found that the yield reduction for planting 10 days later than from the baseline were 3% and 7.64% for the FF and VFF under RCP8.5. For the planting date of 10 days earlier than from the baseline, except from VFF under RCP8.5, the simulated yield would increase for all future periods with the yield changes by 1.54%, 7.86%, 4.49% and

4.88% under RCP4.5 and 18.67%, 12.94%, 4.54% and -3.22% under RCP8.5, suggesting that the early rice should not be grown later than current farmers' practice (Table 7). Candradijaya et al. (2014) describe that the degree of yield reduction is highly sensitive to the planting time and irrigation schedules.

Regarding late rice, the study found that delaying 10 days would cause the reduction of rice yield for almost all the future periods under both scenarios with the ranges from -4.19% to -67.62%. However, when delaying 20 days from the baseline date, the rice yield would increase by 34.49%, 46.05%, 20.09% and 0.98% for all future under RCP4.5 and 52.59% and 22.14% for the NF and MF under RCP8.5. The yield reduction would occur only for the FF and VFF which were 21.98% and 45.80% under RCP8.5, indicating that the late rice should be grown at least 20 days after the current date in order to offset the impacts of climate change on rice yield (Table 8). Our result is in agreement with the studies of Kassie et al. (2015) in Ethiopia and Tachie-Obeng et al. (2010) in Ghana, showing the delaying planting dates provided the increase in crop yield. The recent studies suggest that the high temperatures during the reproductive or maturity phase can negatively affect rice plants (Srivastava, 2011; Restrepo-Díaz and Garces-Varon, 2013).

Table 7. Predicted yield changes of early rice for different planting date across the Myaungmya Township

Scenarios	RCP4.5				RCP8.5			
Period	BD-10 days		BD+10 days		BD-10 days		BD+10 days	
	ton/ha	%	ton/ha	%	ton/ha	%	ton/ha	%
BL	3.99	-	3.99	-	3.99	-	3.99	-
NF	4.49	12.50	4.05	1.54	4.73	18.67	4.30	7.78
MF	4.76	19.35	4.30	7.86	3.71	12.94	4.18	4.73
FF	4.52	13.36	4.17	4.49	4.17	4.54	3.87	-3.00
VFF	4.55	14.11	4.18	4.88	3.86	-3.22	3.68	-7.64

BL = Observed year, NF = Near future, MF = Mid future, FF = Far future, and VFF = Very far future, BD = Baseline date

Table 8. Predicted yield changes of late rice for different planting date across the Myaungmya Township

Scenarios	RCP4.5				RCP8.5			
Period	BD+10 days		BD+20 days		BD+10 days		BD+ 20 days	
	ton/ha	%	ton/ha	%	ton/ha	%	ton/ha	%
BL	5.01	-	5.01	-	5.01	-	5.01	-
NF	4.80	-4.19	6.74	34.49	5.59	11.61	7.65	52.59
MF	5.12	1.95	7.33	46.05	4.38	-12.86	6.13	22.14
FF	4.26	-14.89	6.02	20.09	2.38	-52.56	3.91	-21.98
VFF	3.35	-33.12	5.06	0.98	1.62	-67.62	2.72	-45.80

BL = Observed year, NF = Near future, MF = Mid future, FF = Far future, and VFF = Very far future, BD = Baseline date

In order to investigate the impacts of climate change on crop yield, this study examined the temporal and spatial changes of rice in Myaungmya Township during the period from 2020-2099. Considering the impacts of climate change on rice production, the potential mean yield of early rice would increase up to 11.84% while the mean yield of late rice would lead to a massive drop up to 50.89% by the end of the 21st century. Our result is in agreement with the study of Shrestha (2014) in Myanmar using the AquaCrop model and two GCMs. He found that the early rice yield would increase under A2 and B2 scenarios; up to 40.3% and 20.4% respectively. Yin et al. (2015) observed that simulated rice yield would increase by 5 to 10% in China at the end of the 21st century. However, the rate of increase slightly varies from our result, possibly due to the differences in structure and external parameters of the crop model and GCMs (Bao et al., 2017).

On the other hand, the result showed a significant mean yield reduction of late rice in both scenarios which is also in good agreement with the studies of Candradijaya et al. (2014) in Indonesia using CROPWAT model, Gummadi et al. (2016) in India using EPIC model and Chunet et al. (2016) in Cambodia using CERES-Rice model. These results revealed that yield decreased more significantly under RCP8.5 than RCP4.5. The conclusion from the results across the world suggest that similar studies should be done in different parts of Myanmar, using different crop models and same GCMs or vice versa to access the uncertainties among GCMs and crop models as well.

Regarding the spatial variation of rice production, the farmers in the northern, eastern and south-central parts will benefit from the growing of early rice under climate change while the east-central part will be vulnerable by such impacts. In contrast, the majority of the late rice area will be very sensitive to climate change, especially by the period between 2060 and 2099.

4. CONCLUSIONS

The EPIC model can estimate rice yield in Myanmar reliably. There is a general increase in yield of early rice that can be estimated for all future periods with an increase of 11.84% under RCP4.5 and 7.56% under RCP8.5. However, the results show a significant decreasing trend of late rice yield with a predicted decrease of 37.32% under RCP4.5 and 50.89% under RCP8.5.

The study suggests that the sowing date is highly sensitive to rice yield. In order to maximize the early rice yield, it should be grown 10 days before from the current date, but the late rice should be grown at least 20 days after the current date. In addition, providing the farming machine, irrigation facilities, better infrastructure, improvement in cultivars that resist disease, pest and drought, good weather forecast and extension systems are needed to respond to climate change. In doing so, the farmers, especially resource-poor farmers, can adapt to the changing climate.

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