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Improving Rice Production Efficiency in Myanmar by Controlling for Environmental Production Factors

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Abstract

Rice is the dominant crop in Myanmar and central to the agricultural economy. To increase rice productivity, farmers' production performance is vital. This requires adjusting the availability of physical production inputs in response to environmental conditions. Very few studies have focused on the effects of relevant environmental conditions in Myanmar, including the impact of weather shocks during the rice production. This study aimed to improve rice production based on the present performance of rice farmers, while controlling the impact of adverse environmental conditions. Information on rice production was extracted randomly from in-depth interviews with rice farmers in the Ayeyarwady Delta region. The Cobb-Douglas stochastic production frontier function was applied to examine the effects of the underestimated environmental factors. Erratic rainfall and excessive temperature during early growth stage have a significant negative impact on monsoon rice productivity. During the 2018-2019 monsoon cropping season, different levels of yield loss due to weather shock negatively affected rice farmers' production efficiency. Controlling the environmental conditions improved technical efficiency from 88% to 93%. Based on these findings, policy makers and stakeholders should invest in climate services development, thus enhancing farmers' understanding of weather variability and upscaling the use of local climate adaptation strategies in accordance with the Myanmar Climate Smart Agriculture Strategy.

Keywords: rice farming, technical production efficiency, environmental conditions, weather-related hazards

1. Introduction

1.1 Background Information

The agricultural sector forms the backbone of Myanmar's economy and contributes one-third the national gross domestic product (GDP). The total export earnings from agriculture to in 2018-2019 was 18.1%. Rice is the dominant crop, not only for food security and subsistence but also for the nation's economic development. In 2018-2019, the total rice-cultivating area was 7.22 million hectares, comprising 6.10 and 1.12 million hectares under monsoon and summer rice, respectively, with the total rice production being > 28 million metric tons (MT) (MoALI, 2019). However, the rice productivity of Myanmar is lower than that of neighboring countries (Zorya, 2016). Myanmar's rice sector aims to ensure the nation's food security by increasing small-holders' household income from farming and building an internationally competitive rice sector. The government's ambitious target for milled rice exports is to reach at least 6 million MT by 2029-2030 (MoALI, 2015). The Ayeyarwady Delta is a major rice-producing region, comprising nearly 30% total rice production, and also vulnerable to flooding and

saltwater intrusion. These hazards damage thousands of hectares of farmland and lack adaptive capacity (Tun Oo et al., 2018). Two land types dominate Myanmar's rice-growing areas in the delta: favourable lowland (84.1% sown area) and unfavorable rain-fed systems (15.9% sown area, which includes flood-prone, drought-prone, and salt-affected areas) (MoALI, 2015). Three main soil types are used for rice production in the Ayeyarwady Delta: loamy, sandy loam, and clay loam (Shein, 2015; IFDC, 2018). Loamy and sandy loam soils are most suitable for rice production at neutral pH and inherently fertile.

1.2 Study Rationale

The agricultural sector strongly relies on environmental conditions and is highly sensitive to changing hydroclimatic conditions that affect crop yield stability (WFP, 2013). Recently, climate variability, including late or early monsoon onset, long dry spells, erratic rainfall, increasing temperature, heavy rains, strong typhoons, and flooding, have been occurring frequently worldwide and adversely affected the agricultural sector (MoALI, 2015). In 2015, the United Nations General Assembly established Sustainable Development Goals 13 (SDG 13) for urgent action to combat climate change and its impacts (A4ID, 2021). In light of these goals, strengthen resilience and adaptive capacity to climate-related hazards, integrating climate change measures into national policies, strategies and planning are key actions to contribute to the sustainable development agenda on climate action. Most farmers face serious damage to crop yield due to severe weather events during planting, vegetative growth, and harvesting, which affects farmers' allocation of farm inputs (Ali et al., 1994). Villano and Fleming (2006) have highlighted that seasonally variable and erratic rainfall, heterogeneous land type, soil type, and diverse socioeconomic characteristics in farm groups are important factors in the rain-fed lowland rice environment. Rainfall and temperature fluctuations substantially affect subsistence farming households and smallholder rice farmers, who mainly depend on rain-fed agriculture. Myanmar has suffered from various serious natural hazards and weather events. The Ayeyarwady and Rakhine Regions faced heavy rains and flooding in 2011, which reduced rice productivity by approximately 1.7 million tons (MoALI, 2015). In 2018, > 226,800 hectare of farmland across the country were destroyed owing to heavy rain in the early rainy season (FAO, 2019). The Ministry of Agriculture, Livestock and Irrigation (MoALI) developed Myanmar's Climate Smart Agriculture Strategy in 2015 in response to the adverse effects of climate hazards. Currently, some farmers use agricultural adaptation strategies in the study area, but adaptation options for rice farmers are still lacking. For example, most farmers lack knowledge of how to cope with the negative impacts of climate change using these climate adaptation practices. Moreover, no crop insurance program and relying heavily on agricultural loans; thus, farmers' debts easily increase when they face crop loss due to natural disasters. Crop insurance schemes that cover crop losses, and stabilize income in case of worst-case crop failures would provide an additional option. If unpredictable weather events occur during planting and early growth, some farmers can replant if production inputs are available and if it is not too late. Late sowing owing to a late rainy season can result in poor crop growth (Mar et al., 2018).

1.3 Literature Review

Several studies have focused on the technical efficiency of rice production and pointed out substantial inefficiencies and the potential to improve rice productivity. However, there has been limited empirical estimation considering the environmental production conditions that this omission leads to, resulting in biased parameter estimation of the production frontier, as well as the correlation of technical inefficiency. Sherlund et al. (2002) studied the technical efficiency of smallholders controlling for environmental conditions using the stochastic production frontier. Their findings indicate that controlling heterogeneous environmental conditions significantly changes inferences, particularly with respect to smallholder rice farmers' estimated technical inefficiency. Rahman and Hasan (2008) applied the Cobb-Douglas stochastic production frontier function to determine the Bangladeshi wheat production efficiency by considering the environmental factors. Their findings revealed that improved soil fertility, education promotion, strengthening research-extension link, and development of new varieties have significantly increased crop yield while controlling environmental conditions. Long and Yabe (2011) used both Cobb-Douglas and translog production functions to explore the impact of environmental factors on the productivity and efficiency of rice production in Vietnam's Red River Delta. Their study demonstrated that environmental factors, such as irrigation access and water pollution, but not soil fertility, affect rice yield. Little information is available on considering environmental factors in rice production of Myanmar. Mar et al. (2018) investigated the effect of erratic rainfall on pulse production efficiency in lower Myanmar. Their study found that erratic rainfall during planting and early growth pulse is an important parameter that influences pulse yield. Therefore, it is vital to consider the relevant environmental conditions in production efficiency studies. Although several studies have focused on the technical efficiency of rice production in Myanmar, very few studies have focused on rice production efficiency considering the relevant

environmental conditions, including the impact of weather-related hazards. To improve rice production efficiency by considering the dependence of crop yield on inter-farm heterogeneity in environmental conditions, this is the first study to explore the relationship between selected environmental production conditions and rice production efficiency during monsoon rice-growing season.

1.4 Research Objectives and Hypotheses

Therefore, this study aimed to examine the improvement in rice production and propose climate change adaptation measures based on the present performance of rice farmers in the Ayeyarwaddy Delta. Accordingly, this study first investigates the technical efficiency of rice farmers considering the relevant environmental factors, including weather-related hazards, land type, and soil type. Then, the influencing factors with and without environmental production conditions are analyzed.

Hypothesis 1: Adverse environmental factors such as heavy rain, high temperature, unfavorable land, and poor soil type negatively affect rice yield and technical efficiency of rice production.

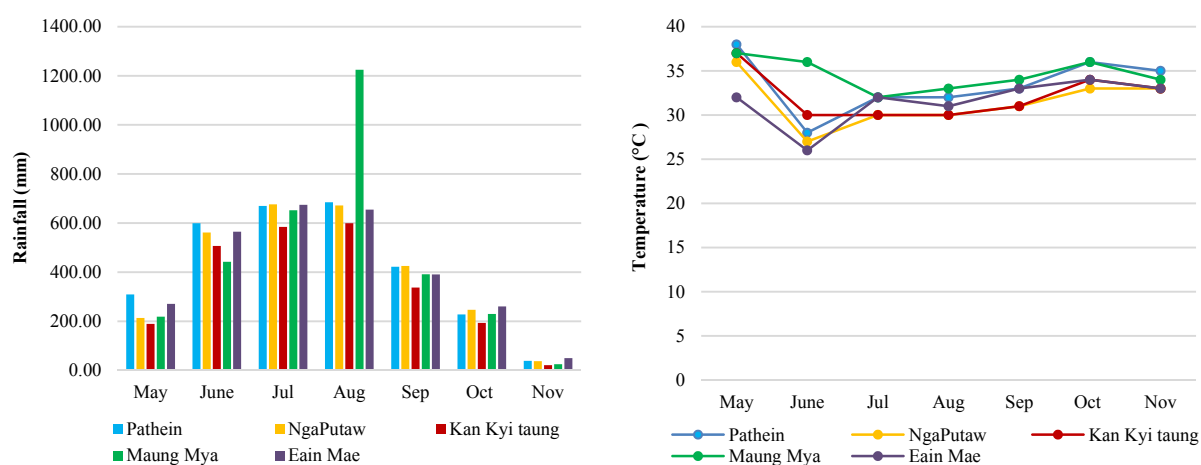
Hypothesis 2: Rice production inputs such as seed rate, fertilizer cost, and chemical cost are positively significant in increasing rice productivity.

Hypothesis 3: The education levels of farmers, weather information, farmers' perceptions of climate change, and climate adaptation practices significantly influence the technical efficiency of rice production.

2. Research Methodology

2.1 Research Area and Data Information

The Ayeyarwaddy Delta region, known as the rice bowl of Myanmar, comprises 2.89 million hectares of rice area and is also highly vulnerable to climate change impacts, particularly flooding and saltwater intrusion. Most farmers in this region depend on rice production for their livelihoods. This study focused on the Patheingyi and Myaung Mya Districts of the Ayeyarwaddy Delta because of the large share of monsoon rice production in this region (1.3 and 0.8 million MT, respectively) during the 2018-2019 cropping season. Patheingyi District comprises seven townships located in the capital city of the Ayeyarwaddy Delta region, Patheingyi City, and three townships in Myaung Mya District. The total rice-cultivated area of these two districts during the 2017-2018 cropping season was approximately 755,105 hectares, contributing to 36.87% rice-cultivating area in the Ayeyarwaddy Delta. Most areas in the study region are favorable for rice production and have a monsoonal climate, whereas some areas are prone to flooding during the monsoon, and salinity intrusion occurs at the end of the monsoon and during the summer season (MoALI, 2015). The average annual rainfall in Patheingyi District and Myaung Mya District is 2,583 and 2,910 mm, respectively, with a maximum temperature of approximately 38.2 and 29.5 °C, respectively (DOA, 2019). The average monthly rainfall and maximum temperature during the 2019 monsoon season in the study area are shown in Figures (1) and (2). The rice crop begins to grow in the third week of May and is harvested in the second week of November. The generalized cropping calendar for rice cultivation in the study area is presented in Appendix A1.



Figures 1 and 2. Average monthly rainfall (mm) and maximum temperature during the 2019 monsoon rice-growing season

Source: Department of Agriculture (DOA), Patheingyi District, Ayeyarwaddy Delta, MoALI (2019).

2.2 Sampling Procedures and Sample Size

Data were collected in June 2020 through a face-to-face questionnaire survey using a multistage sampling technique. Three townships from Patheingyi District (Patheingyi, Kangyidaunt and Ngapudaw) and two townships from Myaung May District (Myaung Mya and Einme) were selected because of their prime rice-cultivating areas and the high fluctuation of rainfall and temperature among the townships from each district. The next stage included the random selection of four or five villages from each township. A total of 160 rice farm households were selected using a simple random sampling. Among the two districts, 86 sampled farmers (56%) were from the Patheingyi District. After removing the missing data, 154 samples were valid for data analysis. In the study area, rice is cultivated in two seasons, monsoon and summer. However, this study focused on monsoon rice production because most farmers rely heavily on it. The survey covered the monsoon rice production period from May 2019 to October 2019.

Before starting the main survey, a pre-test was conducted in the study area. Based on the pre-test results, the questionnaire structure was modified to better capture the key necessary information. The final questionnaire contained detailed information on rice production in individual farms, including the yields obtained and the use of inputs such as seed rate, human labor rate, fertilizer cost, chemical cost (pesticides and herbicides), and land preparation cost, and rice cultivation area. Other information collected included farmers' perceptions of climate changes, severe weather incidences, and crop losses due to weather shocks at particular rice production stages during the 2018-2019 monsoon rice-growing season, and the farmers' managerial characteristics such as experience, education, and family labor ratio in total labor used in rice production. Data on access to weather information and current climate adaptation practices were also collected. Monthly rainfall and maximum temperature data during the 2018-2019 monsoon rice-growing season were collected from the respective survey areas of the township and division office of the Department of Agriculture (DOA).

2.3 Analytical Framework

A distinct feature of this study is that the omitted inter-farm heterogeneity in environmental conditions was incorporated into the empirical production function. Moreover, a set of critical managerial variables in rice production, including the impact of weather-related hazards, farmers' perceptions of weather variability, and current climate adaptation strategies of rice farm households, were used to evaluate the different efficiency levels of rice production.

Weather-related variables (monthly rainfall and temperature) are truly exogenous variables that influenced farmers' managerial performance in the production process. Moreover, the heterogeneous land and soil types are crucial parts of the rice production environment, which can cause wide fluctuations in crop yield. Therefore, relevant environmental production variables were included in the model in addition to the physical production inputs used in rice production. The environmental variables comprise not only the truly exogenous variables (rainfall quantity (mm) and maximum temperature (°C) that occurred during planting and early growth stage), but also the quasi-fixed characteristics in nature (land type and soil type) as described by Sherlund et al. (2002), Rahman and Hasan (2008), and Long and Yabe (2011) were included in the model.

This study applied the stochastic production frontier approach, first developed by Aigner et al. (1977) and Meeusen and Van Den Broeck (1977). The stochastic production frontier for the i th farmer is expressed as:

$$Y_i = f(X_i, W_i) - u_i + v_i \quad (1)$$

where, Y_i is the rice output, X_i is the physical input vector, W_i is the vector of relevant environmental factors that control rice production performance, and v_i is assumed to be independently and identically distributed $N(0, \sigma_v^2)$ two-sided random error, independent of the u_i , which is a non-negative random variable ($u_i \geq 0$) representing the technical inefficiency in rice production. This is assumed to be an independently distributed as truncations at zero of the normal distribution with a mean $-Z_i\delta$ and variance $\sigma_u^2 \left(\frac{1}{1 - \delta^2 Z_i^2} \right)$, where, Z_i is the correlation of inefficiencies on farm i . Most previous studies have estimated the following:

$$Y_i = g(X_i, W_i^*) - u_i^* + v_i^* \quad (2)$$

where, $W_i^* \subseteq W_i$ ignores some or all of the elements of W_i and leads to biased estimates of the parameters of the production function, overstatement of technical inefficiency, as well as biased estimates of the correlates of technical inefficiency (Sherlund et al., 2002).

This study applied the single-stage approach proposed by Battese and Coelli (1995) to determine the factors influencing production efficiency, wherein technical inefficiency is related to farm-specific managerial skills and farmer socioeconomic characteristics. The technical efficiency of the stochastic frontier production function for farm i is described as follows:

$$TE_i = E[\exp(-u_i) | \zeta_i] = E[\exp(-\delta_0 - \sum Z_i \delta | \zeta_i)] \quad (3)$$

where, E denotes the expectation operator. This is achieved by obtaining the expressions for the conditional expectation u_i for the observed value of ζ_i , where, $\zeta_i = v_i - u_i$. We defined a technical inefficiency model that includes dummy variables as follows:

$$u_i = Z_i \delta + D_i \tau + \zeta_i \geq 0 \quad (4)$$

where, δ and τ are the vectors of the parameters to be estimated, Z_i is the farm-specific managerial and socioeconomic characteristics of the rice farmer, D_i is a dummy variable representing yield loss due to weather shocks, and the error ζ_i is a random variable as $\zeta_i \sim N(0, \sigma_\zeta^2)$. As $u_i \geq 0$ when $\zeta_i \geq -Z_i \delta$, ζ_i distribution is assumed to be a truncation from below at the variable truncation point, $-Z_i \delta$. The maximum likelihood function was applied to estimate the unknown parameters, with the stochastic frontier and inefficiency effect function being estimated simultaneously. The likelihood function was defined in terms of the variance parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma^2$ (Battese & Coelli, 1995).

2.4 The Empirical Model

Among the functional forms of the production function, the Cobb-Douglas production frontier function and the translog model are widely used despite their own weaknesses (Okoruwa et al., 2009). Moreover, the choice of the functional form has a limited effect on technical efficiency (Kopp & Smith, 1980). Therefore, this study applied the Cobb-Douglas production frontier function to determine the influence of environmental production conditions on rice productivity and efficiency estimation.

To explore the effect of omitting environmental production conditions, the production frontier was estimated with and without the relevant environmental production conditions. The traditional specification that omits the four environmental variables is expressed as follows:

$$\ln Y_i = \alpha_0 + \sum_{j=1}^5 \alpha_j^* \ln X_{ij} + v_i^* - u_i^* \quad (5)$$

and,

$$u_i^* = \delta_0^* + \sum_{d=1}^9 \delta_d^* Z_{id} + \zeta_i^* \quad (6)$$

where, \ln is a natural logarithm; Y_i is the weighted amount of rice yield produced on the i th farm measured in kilograms (kg) per hectare; X_{ij} is the j th input used on the i th farm that had weighted values on a per hectare basis, such as the seed rate (kg), human labor (man-day), fertilizer cost (MMK), chemical cost (MMK) to control weeds, pests and diseases, and land preparation cost (MMK); v_i is the two-sided random error, and u_i is the one-sided half normal error. Z_{id} is the independent variable representing the farm-specific managerial and socioeconomic characteristics to justify the technical inefficiency of rice farms, ζ_i is the truncated random variable, and α_0 , α_j , δ_0 , and δ_d are the parameters to be estimated.

As previously mentioned, the full specification includes the four variables representing the environmental production conditions (rainfall and maximum temperature during the planting and early vegetative growth stages of the monsoon rice-growing season, land type, and soil type in the production function) and is given as follows:

$$\ln Y_i = \alpha_0 + \sum_{j=1}^5 \alpha_j \ln X_{ij} + \sum_{k=1}^4 \beta_k E_{ik} + v_i - u_i \quad (7)$$

and,

$$u_i = \delta_i + \sum_{l=1}^3 \tau_l D_{il} + \sum_{d=1}^9 \delta_d Z_{id} + \zeta_i \quad (8)$$

where, E_{ik} is the variable that represents the four environmental production factors and D_{il} is a dummy variable that depicts of yield losses (high, moderate, and slight yield loss) faced by the sampled farmers based on the impact of weather-related hazards during the last monsoon crop season. β_k and τ_l are the parameters to be estimated. All other variables were the same as those described previously. In the full specification of the production frontier model, five production inputs and four environmental production condition variables were used, and nine variables representing the managerial and socioeconomic characteristics of the farm household and three dummy variables for yield loss were organized into the technical inefficiency effect model.

2.4 Summary Statistics

The definitions, measurement units, and summary statistics of all the dependent and independent variables are presented in Table 1. In the study area, the generalized cropping calendar of monsoon rice production is from the third week of May to the mid-November. During the 2018-2019 monsoon rice-growing season, the average rainfall during planting and early growth (during the month of May and June) in the study area was 384.59 mm, with a range of 330.45 mm to 454.53 mm, while the mean sum of the maximum temperature during planting and early growth was approximately 32.92 °C. In the study area, most sampled farmland (68%) was favorable

lowland, most suitable for rice production, whereas the average soil type was loamy and sandy loam.

In the 2018-2019 monsoon rice-growing season, farmers faced yield loss owing to erratic weather conditions, particularly droughts and flooding. Approximately 84% sampled farmers faced erratic weather during planting and early growth. Regarding severe weather shocks, 45% encountered different levels of crop yield damage after harvesting the monsoon rice. Rice production inputs such as seed rate (kg ha^{-1}), human labor (man-days ha^{-1}), fertilizers cost (MMK ha^{-1}), chemical cost (MMK ha^{-1}), and land preparation cost (MMK ha^{-1}) were used to measure rice production efficiency. Average production on sampled farms is 2,753.24 kg ha^{-1} , with a range of 1,287.65-4,120.49 kg ha^{-1} . The average usage of rice seed is 103.85 kg ha^{-1} , with a range of 25.75-180.27 kg ha^{-1} . The mean amount of human labor used for all rice production activities, consisting of hired and family labor, was 71.34 man-days ha^{-1} , with a minimum and maximum of 24.69 and 130.86 man-days ha^{-1} , respectively. The mean fertilizer cost, including farmyard manure, was approximately 90,990 MMK ha^{-1} . The average expenditure on chemicals, including herbicides and pesticides, was approximately 13,530 MMK ha^{-1} , with a minimum and maximum of 2,470 and 74,070 MMK ha^{-1} , respectively. Therefore, the results showed a wide variation in chemical use. Regarding the land preparation cost, this study used the combined cost of animal and machinery services per hectare rice farm because only 24 sampled farmers used animal power to prepare their land. The average land preparation cost was approximately 62,250 MMK ha^{-1} , with a wide range from 12,350 MMK ha^{-1} to 154,320 MMK ha^{-1} . The average experience of respondents in rice production was 34 years, and the mean education level of the rice farmers was seven years. The average cultivation area of the sampled rice farmers was 3.86 hectares, ranging from 0.41 to 29.57 hectares. The average number of family laborers included in the total was 55%, indicating that half of the family members participated in their farm production activities. Approximately 48% respondents reported that they often observed weather information, such as the level of rainfall and temperature, and checked the notice of weather information from the media and extension officers from government and non-government organizations.

As the study area is vulnerable to climate variability, 43% rice farmers used crop calendar adjustments to manage sowing and harvesting times to adapt to heavy rain during the critical growth and harvesting stages. Approximately 47% respondents used flood-resistant varieties to reduce rice yield losses. The average index of rice farmers' perceptions of weather variability, pest and disease problems, and soil fertility was 38.25, showing that most farmers in the study area had limited awareness of environmental degradation (Appendix A2 describes the proposed and detailed questions of farmers' perceptions of 5-point Likert-like scale).

Table 1. Summary statistics of variables in the stochastic frontier production and inefficiency models (No. of observations = 154)

| Variable | Unit | Mean | STD | Min | Max |
|--|---|---------|--------|---------|---------|
| Yield | Kilograms per hectare | 2753.24 | 481.67 | 1287.65 | 4120.49 |
| Rainfall at early vegetative growth stage | Millimeter | 384.59 | 45.44 | 330.45 | 454.53 |
| Maximum temperature at early vegetative growth stage | Degree Celsius | 32.92 | 2.58 | 29.00 | 36.50 |
| Land type | Dummy variable (1 = Favorable lowland, 0 = otherwise) | 0.68 | 0.47 | 0.00 | 1.00 |
| Soil type | Dummy variable (1 = loamy and sandy loam, 0 = clay loam) | 0.58 | 0.49 | 0.00 | 1.00 |
| Seed rate | Kilograms per hectare | 103.85 | 29.51 | 25.75 | 180.27 |
| Fertilizer cost | '000 MMK per hectare | 90.99 | 62.49 | 12.35 | 320.99 |
| Chemical cost | '000 MMK per hectare | 13.53 | 12.52 | 2.47 | 74.07 |
| Human Labor Rate | Man-day per hectare | 71.34 | 27.73 | 24.69 | 130.86 |
| Land preparation cost ^a | '000 MMK per hectare | 62.25 | 20.24 | 12.35 | 154.32 |
| High yield loss by weather shocks ^b | Dummy variable (1 = Yes, 0 = No) | 0.05 | 0.22 | 0.00 | 1.00 |
| Moderate yield loss by weather shocks ^b | Dummy variable (1 = Yes, 0 = No) | 0.18 | 0.39 | 0.00 | 1.00 |
| Slight yield loss by weather shocks ^b | Dummy variable (1 = Yes, 0 = No) | 0.21 | 0.41 | 0.00 | 1.00 |
| No Loss by weather shocks | Dummy variable (1 = Yes, 0 = No) | 0.55 | 0.50 | 0.00 | 1.00 |
| Experience | Years | 33.53 | 11.99 | 5.00 | 60.00 |
| Education | Years | 7.03 | 3.21 | 2.00 | 14.00 |
| Cultivated Area for rice | Hectare | 3.86 | 3.33 | 0.41 | 29.57 |
| Family labor Ratio | Rate of no. of family labor and household size | 0.55 | 0.20 | 0.14 | 1.00 |
| Weather information | Dummy variable (1 = Yes, 0 = No) | 0.48 | 0.50 | 0.00 | 1.00 |
| Crop calendar adjustment | Dummy variable (1 = Yes, 0 = No) | 0.43 | 0.50 | 0.00 | 1.00 |
| Use the resistance varieties | Dummy variable (1 = Yes, 0 = No) | 0.47 | 0.50 | 0.00 | 1.00 |
| Farmer's perception of climate changes ^c | Measured | 38.25 | 2.81 | 30.00 | 45.00 |
| Location | 1 = Patheingyi District, 0 = Myaung Mya District | 0.56 | 0.50 | 0.00 | 1.00 |

Note. ^a) The combined cost of animal and machinery services for one hectare rice farm, because only 24 sampled farmers used animal power to prepare their land. Moreover, machinery services were paid per hectare, but animal power was counted on workdays.

^b) Figures based on farmer's response about their crop loss by weather shocks during 2018-2019 monsoon rice-growing season. A total of 45% sample farmers encountered different crop yield damage after harvesting the monsoon rice. *High yield loss* due to weather shocks indicate that farmers lost > 30%-≤ 50% average crop yield. A *moderate yield loss* and *slight yield loss* represent a loss of average crop yield from > 10% to ≤ 30% and ≤ 10%, respectively.

^c) Farmers' perceptions of how they perceived the climate to have changed in the last 10 years were measured as the sum of 10 five-point scale indicators, including weather variability, pest and disease problems, and soil fertility in the study area.

*1US\$ = 1,645 MMK (foreign exchange rates as of July 30, 2021, Central Bank of Myanmar).

3. Results

3.1 Correlation Between Environmental Conditions and Production Inputs

The results of correlations between production inputs and environmental variables are presented in Table 2. The strength of the correlation between environmental variables and production inputs such as seed rate, human labor, fertilizer, chemicals, and land preparation are generally weak but non-zero ($p < 0.01$ or 0.05). A similar strong correlation was reported by Sherlund et al. (2002) and Radman and Hasan (2008), who showed a valid case for the need to controlling environmental conditions in productivity and efficiency estimation. Exploring the relationship between environmental factors and rice production inputs should also be studied. In this study, the non-zero correlation indicates that environmental factors should be considered while estimating the rice production efficiency.

Table 2. Correlation matrix relating production inputs and environmental factors

| Environmental production conditions | Production inputs | | | | |
|-------------------------------------|-------------------|--------------------|-------------------|-----------------|-------------------------|
| | <i>Seed</i> | <i>Human labor</i> | <i>Fertilizer</i> | <i>Chemical</i> | <i>Land preparation</i> |
| Rainfall | 0.041 | 0.024 | -0.471 *** | 0.033 | -0.097 |
| Temperature | -0.065 | 0.090 | 0.282 *** | -0.300 *** | 0.166 ** |
| Land type | 0.437 *** | 0.134 | 0.066 | 0.208 ** | 0.065 |
| Soil type | 0.500 *** | 0.044 | 0.182 ** | 0.347 *** | 0.085 |

Note. ***, **, and * indicate significance at the 1% ($p < 0.01$), 5% ($p < 0.05$), and 10% ($p < 0.10$) levels, respectively.

Source: Own survey, 2020.

3.2 Stochastic Frontier Analysis and Productivity Effects of Environmental Production Conditions

The maximum likelihood estimates of the parameters for both the short (without environmental factors) and full (with environmental factors) specifications are described in Table 3 using STATA version 17. The variance inflation factor (VIF) values of all explanatory variables range from 1 to 2, indicating no multicollinearity in either specification. Rainfall and maximum temperature have a negative significant effect on the 1% level of significance as increased rainfall and temperature during planting and early growth increased crop damage and reduced crop productivity. Moreover, favorable lowland areas for rice production have a positive significant effect on rice productivity at the 1% level of significance whereas soil type has an insignificant positive effect on rice productivity. The positive relationship between rice productivity and environmental factors, such as land type and soil quality, indicates that favorable environmental conditions strongly increase crop productivity. The variables representing environmental conditions clearly affect production function estimation. Production inputs, such as seed rate, fertilizer cost, and chemical cost, have positive significant effects on rice productivity at the 1%, 5% and 10% levels, respectively, in both specifications. In both specifications, seed rate is the most dominant input influence on rice productivity, followed by chemical and fertilizer costs. Labor rate is positively related to rice productivity, but not statistically significant in both specifications. This results highlight that skillful and efficient human labor use is crucial for improving crop productivity in the study area.

The bottom part of Table 3 shows the estimated results of the technical inefficiency models for both specifications. The results show that the omission of environmental factors such as rainfall, temperature, land type, and soil type significantly affect the estimates of the relationship between the managerial characteristics of rice farmers and estimated technical inefficiency. The expected effects of variables representing high, moderate, and slight yield loss due to weather shocks during the cropping season are positively significant at the 1% and 5% levels. The results clearly reveal that the adverse effects of weather shocks decrease the technical efficiency of rice production.

The education of the household head and farmers' perceptions of climate change have a negatively significant effect on technical inefficiency in both specifications, implying that educated farmers who have knowledge about or pay attention to environmental degradation achieve excellent technical efficiency. In addition, using crop calendar adjustment and resistant varieties during the monsoon crop season had a positive significant effect on the technical efficiency of rice production in both specifications. Thus, these local adaptation practices have improved rice productivity and production efficiency. Access to weather information has a positive and significant effect on technical efficiency only for short specification. The result of this variable is insignificant in the full specification, revealing that the impact of weather shocks and environmental conditions is more dominant than the weather information received by farmers. Location has a positive relationship with technical inefficiency in both specifications, indicating that farmers in Pathein District are less efficient in rice production than those in Myaung Mya District.

Table 4 presents the results of the hypothesis testing. The null hypothesis that the environmental factors are jointly zero in the full specification is strongly rejected, indicating that rainfall, maximum temperature, land type, and soil type significantly affect rice productivity. The null hypothesis that there is no inefficiency effect is confidently rejected in both specifications using the likelihood ratio test. The γ value of both specifications in Table 3 also reject the null hypothesis. Thus, the variations in rice yields in both specifications are approximately 74% and 43% (Table 3), respectively, due to technical inefficiency rather than random variability among farmers, showing that most sampled rice farms operate below a technically efficient threshold.

The result of the null hypothesis that the managerial factors of rice farmers are jointly zero for both

specifications are rejected at the 1% level. This indicates that the technical efficiency of rice production relies significantly on the managerial factors of rice farmers. The null hypothesis of constant returns to scale in rice production is strongly rejected in both specifications, implying that the sampled rice farmers operate below the optimal scale. The linear combination of coefficients is significantly < 1 , indicating that the rice production in the study area runs under decreasing returns to scale.

The parameter estimates of the production inputs can be directly read as the elasticities of the rice production, because the Cobb-Douglas production function was applied. The elasticity of rice productivity with respect to seed rate and fertilizer cost under the full specification is 24.3% and 9.7%, respectively, lower than that under the short specification. This implies that seed input and fertilizer input are less responsive to rice productivity increases when environmental conditions controlled. This is consistent with the study by Radman and Hasan (2008), reporting 27.7% reduced elasticity of fertilizer input after controlling environmental conditions for Bangladeshi wheat farmers.

Table 3. Maximum likelihood estimates for parameters of the Cobb-Douglas production function

| Variables | Without environmental conditions | | | With environmental conditions | | |
|--|----------------------------------|------------|---------|-------------------------------|------------|---------|
| | Coefficients | Std. Error | t-ratio | Coefficients | Std. Error | t-ratio |
| <i>Production Function</i> | | | | | | |
| Constant | 6.4967 *** | 0.1526 | 42.57 | 7.3238 *** | 0.2145 | 34.14 |
| Rainfall at planting & early vegetative stage | - | - | - | -0.0006 *** | 0.0002 | -3.24 |
| Maximum temperature at planting & early vegetative stage | - | - | - | -0.0100 *** | 0.0032 | -3.09 |
| Land type | - | - | - | 0.0781 *** | 0.0139 | 5.62 |
| Soil type | - | - | - | 0.0236 | 0.0176 | 1.34 |
| Seed rate | 0.2063 *** | 0.0248 | 8.31 | 0.1561 *** | 0.0208 | 7.51 |
| Fertilizer cost | 0.0185 ** | 0.0093 | 1.98 | 0.0167 ** | 0.0083 | 2.01 |
| Chemical cost | 0.0322 *** | 0.0084 | 3.85 | 0.0261 *** | 0.0090 | 2.91 |
| Human labor rate | 0.0140 | 0.0159 | 0.88 | 0.0144 | 0.0136 | 1.06 |
| Land preparation cost | 0.0084 | 0.0194 | 0.43 | -0.0074 | 0.0166 | -0.45 |
| <i>Variance Parameter</i> | | | | | | |
| $\sigma^2 = \sigma_u^2 + \sigma_v^2$ | 0.0089 | 0.0016 | 5.58 | 0.0039 | 0.0006 | 6.50 |
| $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$ | 0.7385 | 0.0792 | 9.33 | 0.4293 | 0.1553 | 2.76 |
| Log Likelihood Function | 187.730 | | | 224.720 | | |
| <i>Technical Inefficiency Effects Function</i> | | | | | | |
| Constant | 0.7063 *** | 0.1929 | 3.66 | 0.5008 *** | 0.1369 | 3.66 |
| High yield loss by weather shocks | - | - | - | 0.2524 *** | 0.0325 | 7.67 |
| Moderate yield loss by weather shocks | - | - | - | 0.0724 *** | 0.0241 | 3.00 |
| Slight yield loss by weather shocks | - | - | - | 0.0568 ** | 0.0265 | 2.14 |
| Experience of household head | -0.0011 | 0.0010 | -1.09 | -0.0002 | 0.0007 | -0.34 |
| Education of household head | -0.0159 *** | 0.0046 | -3.48 | -0.0078 ** | 0.0031 | -2.54 |
| Family labor ratio | 0.0179 | 0.0529 | 0.34 | 0.0171 | 0.0360 | 0.47 |
| Rice area | 0.0035 | 0.0035 | 1.00 | -0.0003 | 0.0028 | -0.12 |
| Farmer's perception of climate changes | -0.0131 ** | 0.0052 | -2.53 | -0.0114 *** | 0.0037 | -3.07 |
| Weather information | -0.0956 ** | 0.0477 | -2.00 | -0.0243 | 0.0288 | -0.84 |
| Crop calendar adjustment | -0.1359 *** | 0.0502 | -2.70 | -0.0611 * | 0.3221 | -1.90 |
| Use the resistance varieties | -0.1232 *** | 0.0333 | -3.70 | -0.0539 ** | 0.0211 | -2.56 |
| Location | 0.2138 *** | 0.0388 | 5.50 | 0.1374 *** | 0.0258 | 5.33 |
| Total Number of Observations | 154 | | | 154 | | |

Note. ***, ** and * indicate significance level at 1% ($p < 0.01$), 5% ($p < 0.05$) and 10% ($p < 0.10$) respectively.

Source: Own survey, 2020.

Table 4. Tests of hypothesis

| Hypothesis | Critical Value of χ^2 (d.f., 0.99) | Without environmental variables | | With environmental variables | |
|--|--|---------------------------------|----------|------------------------------|----------|
| | | LR statistic | Decision | LR statistic | Decision |
| No effect of environmental variable in productivity $H_0: \beta_1 = \beta_2 = \dots = \beta_4 = 0$ | 13.28 | - | - | 44.75 *** | Reject |
| Presence of inefficiency $H_0: \gamma = 0$ | 6.64 | 42.62 *** | Reject | 12.91 *** | Reject |
| No effect of managerial variables on inefficiency $H_0: \alpha_1 = \alpha_2 = \dots = \alpha_9 = 0$ | 21.67 | 46.41 *** | Reject | 33.95 *** | Reject |
| Constant returns to scale in production $H_0: \delta_1 + \delta_2 + \dots + \delta_5 = 1$ | 15.09 | 563.14 *** | Reject | 909.13 *** | Reject |

Note. ***, ** and * indicate significance level at 1% ($p < 0.01$), 5% ($p < 0.05$) and 10% ($p < 0.10$) respectively.

Source: Own survey, 2020.

3.3 Distribution of Rice Production Efficiency in the Study Area

The frequency distribution of the estimated technical efficiency scores of rice farmers for both specifications is plotted in Figure 3, and the descriptive statistics of the technical efficiency levels for both specifications are described in Table 5. Interestingly, the improvement feature where the environmental variables are included in the full specification appears at a decreased level of technical efficiency distribution. The minimum technical efficiency score with and without environmental conditions were 69.9% and 56.1%, respectively, indicating a 13.8% improvement (Figure 3 and Table 5). The mean technical efficiency improved by five points after considering environmental conditions. Under the full specification, only 4% farmers run below the 75% efficiency level, whereas 9% farmers operate at that level under the short specification. In other words, most sampled rice farmers (96.1%) under the full specification operate at the highest efficiency level (0.80-1.00) when compared to those under the short specification (82.5%). Moreover, the mean technical efficiency level in rice production is 93% in the full specification, indicating that production can be improved by 7.53% $\{[(0.93 - 1)/0.93] \times 100\}$. This result is consistent with those of previous studies on technical efficiency under the control of environmental variables (Sherlund et al., 2002; Rahman & Hasan, 2008; Mar et al., 2018).

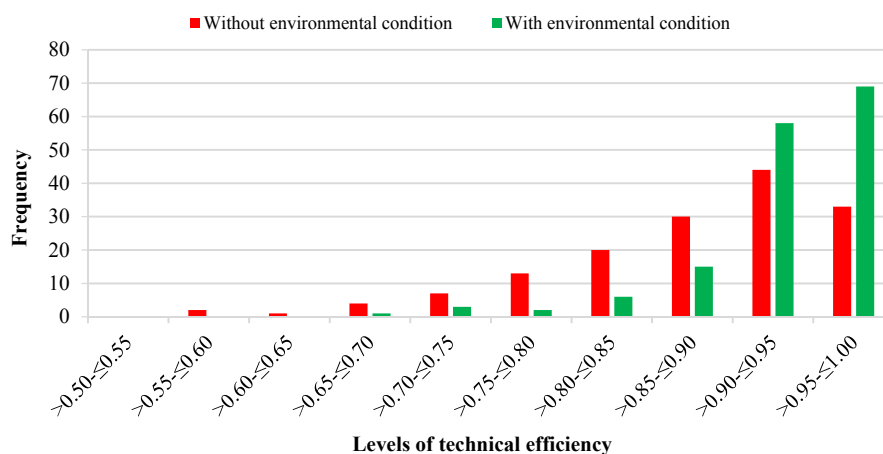


Figure 3. Technical efficiency scores with and without environmental conditions

Source: Own survey, 2020.

Table 5. Technical efficiency estimates with and without environmental conditions

| Items | Without environmental production factors | With environmental production factors |
|-----------------------|--|---------------------------------------|
| Mean efficiency score | 0.876 | 0.930 |
| Standard deviation | 0.086 | 0.053 |
| Minimum | 0.561 | 0.699 |
| Maximum | 0.979 | 0.983 |

Source: Own survey, 2020.

4. Discussion

This study aims to understand the impact of environmental conditions on rice production in the Ayeyarwaddy Delta. Environmental conditions are vital for production performance but have often been omitted in previous productivity and efficiency studies, causing biased inferences of production parameters, efficiency scores, and correlations of technical inefficiency.

Rice farmers in the study area utilizing current production inputs with full efficiency may improve technical efficiency by 12% under the current situation. However, severe weather shocks or unpredictable climate variability beyond human control, including flood, drought, cyclones, and saline water intrusion, will reduce yield and technical efficiency in rice production. Farmers in the study area lack knowledge about climate change and have limited access to weather information to adjust farming activities. Local climate adaptation strategies should be developed to reduce the negative impacts of climate change. This was also noted by Tun Oo et al. (2018).

Other environmental factors, such as favorable lowland and good soil type, increase rice productivity and improve the technical efficiency of rice production. Thus, the government should widely support suitable varieties and agricultural practices related to unfavorable land for rice production. Furthermore, soil conservation programs should be emphasized to improve soil fertility. The production efficiency of rice cultivation in the study area increased by 5% from 88% to 93% while controlling for environmental conditions.

Seed is the most dominant factor for increasing rice productivity in both specifications and effective use of quality and certified seeds improves the rice productivity and profit. Linn and Maenhout (2019) have also reported the important role of high-quality seeds and varieties in high yield and better-quality rice. In addition, the efficient and effective use of fertilizers and agrochemicals would improve not only rice productivity, but also the environmental conditions of rice farms. Policy makers should encourage efficient agrochemical use and pay attention to safety in accordance with integrated pest management and site-specific management. Efficient agrochemical use could also have widespread environmental benefits (such as water quality).

The impact of farmers' managerial practices on production efficiency revealed that education, knowledge, and concern about climate change significantly improved production efficiency. Moreover, current climate adaptation practices, such as crop calendar adjustment and changes to flood-resistant varieties, are technically efficient for rice production in the study area. Gutu et al. (2012) also reported that changing the varieties, crop diversification, and crop calendar adjustments are significant agricultural adaptation options to help reduce climate stress. Improving farmers' access to accurate weather forecasts would help them to utilize more specific climate adaptation strategies. However, other environmental conditions, such as heterogeneous land type, soil quality, and vulnerability to extreme weather events, influence the technical efficiency of rice production in the study area. Moreover, suitable and effective agricultural adaptation options must be developed for various environmental conditions. This factor was also highlighted the study by Hein et al. (2019).

5. Conclusions and Policy Implications

The findings of this study show that controlling measurable environmental production conditions could allow for significantly improve technical efficiency and precisely estimate the sources of technical inefficiency. Policymakers and stakeholders should understand the impact of current managerial practices on rice production performance to improve rice development strategies. The effective and efficient use of high-quality seeds in the study area is important for increasing rice productivity. Therefore, the government should promote access to high-quality seeds throughout rice-growing regions and suggest optimal seed rates for individual rice varieties. Recommendations should be grounded in area-specific research and effective extension activities. Moreover, the government should focus on developing local climate-smart varieties for flood- and drought-prone areas by collaborating with International Rice Research Institute (IRRI), non-government organizations, and private seed production companies, and also provide seed and capital to subsidize replanting after a quick assessment of the damage level. Research on local climate-smart varieties and the development of crop management options for stress-prone areas should be enhanced to improve the effective use of seeds.

Farmer education level is crucially important based on the results of the inefficiency models. Farmers with high education levels may adopt new agricultural technologies and innovation and can easily learn efficient farming practices through extension and training services from public and private organizations. Most of respondents were not fully aware of the impact of climate variability impacts on crop production. Farmers who are highly aware of environmental variability, including current climate-related hazards, can improve their technical efficiency and crop productivity more easily. This study reported that current climate adaptation strategies can reduce crop yield losses due to erratic weather and improve the technical efficiency of rice production. Therefore,

policy makers and stakeholders should invest in climate services development, enhance farmers' understanding of weather variability, and upscale the use of local climate adaptation strategies in accordance with the Myanmar Climate Smart Agriculture Strategy. An appropriate crop insurance program should be developed to protect farmers from unexpected weather shocks and crop failures. In the study area, farmers need to be aware of climate change and understand the appropriate climate adaptation strategies to increase the efficiency of rice production. The findings of this study will contribute to the development of the rice production sector by controlling the adverse environmental production factors and help to provide the better climate adaptation strategies. Moreover, the findings of this study may provide important information for planning and applying more effective policies to build sustainable development in the rice sector by controlling the adverse effects of environmental production factors.

The results of this study were based on the Ayeyarwaddy Delta, which might not be representative of Myanmar's overall rice production efficiency. However, this approach can be used in future research by considering other important environmental production conditions with a larger sample size. Investigations can also be extended to other rice production areas in Myanmar. Furthermore, future studies could determine the necessary level of environmental performance to conserve the farm environment by estimating the environmental efficiency of rice production.

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References

- A4ID (Advocates for International Development). (2021). *The Legal Guide to the Sustainable Development Goals (SDGs)*. London, United Kingdom. Retrieved from https://www.a4id.org/wp-content/uploads/2021/11/SDG-Legal-Guide_Chapter-13_Final.pdf
- Aigner, D. J., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and Estimation of Stochastic Production Function Models. *Journal of Econometrics*, 6, 21-37. [https://doi.org/10.1016/0304-4076\(77\)90052-5](https://doi.org/10.1016/0304-4076(77)90052-5)
- Ali, F., Parikh, A., & Shah, M. (1994). Measurement of profit efficiency using behavioral and stochastic frontier approach. *Applied Economics*, 26(2), 181-188. <https://doi.org/10.1080/00036849400000074>
- Battese, G. E., & Coelli, T. J. (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics*, 20, 325-332. <https://doi.org/10.1007/BF01205442>
- DOA (Department of Agriculture). (2019). *Data Sources from Regional Offices*. Department of Agriculture, Ministry of Agriculture, Livestock and Irrigation, Patheingyi, Myanmar.
- FAO. (2019). *Handbook on climate smart agriculture in Myanmar* (p. 192). Nay Pyi Taw, Myanmar.
- Gutu, T., Bezabih, E., & Mengistu, K. (2012). Econometric analysis of local level perception, adaptation and coping strategies to climate change induced shocks in North Shewa, Ethiopia. *International Research Journal of Agricultural Science and Soil Science*, 2(8), 347-363.
- Hein, Y., Vijitsrikamol, K., Attavanich, W., & Janekarnkij, P. (2019). Economic assessment of climate adaptation options in Myanmar rice-based farming system. *Journal of Agricultural Science*, 11(5), 35-48. <https://doi.org/10.5539/jas.v11n5p35>
- IFDC (International Fertilizer Development Center). (2018). *Soil fertility and fertilizer management strategy for Myanmar* (p. 95). Muscle Shoals, AL, USA.
- Kopp, R. J., & Smith, V. K. (1980). Frontier production function estimates for steam electric generation: A competitive analysis. *Southern Economic Journal*, 47, 1049-1059. <https://doi.org/10.2307/1057240>
- Linn, T., & Maenhout, B. (2019). Measuring the efficiency of rice production in Myanmar using data envelopment analysis. *Asian Journal of Agriculture and Development*, 2-16. <https://doi.org/10.22004/ag.eco.298422>
- Mar, S., Nomura, H., Takahashi, Y., Ogata, K., & Yabe, M. (2018). Impact of Erratic Rainfall from Climate Change on Pulse Production Efficiency in Lower Myanmar. *Sustainability*, 10(2), 402. <https://doi.org/>

10.3390/su10020402

- Meeusen, W., & van den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, 18, 435-444. <https://doi.org/10.2307/2525757>
- MoALI (Ministry of Agriculture, Livestock and Irrigation) (2019). *Myanmar Agriculture at a Glance*. Department of Planning, Ministry of Agriculture, Livestock and Irrigation (MoALI): Naypyidaw, Myanmar.
- MoALI (Ministry of Agriculture, Livestock and Irrigation). (2015). *Myanmar Climate-Smart Agriculture Strategy* (p. 64). Ministry of Agriculture, Livestock and Irrigation (MoALI), Naypyidaw, Myanmar.
- MoALI (Ministry of Agriculture, Livestock and Irrigation). (2015). *Myanmar Rice Sector Development Strategy* (p. 112). Department of Planning, Ministry of Agriculture, Livestock and Irrigation (MoALI): Naypyidaw, Myanmar.
- Okoruwa, V. O., Akindeinde, A. O., & Salimonu, K. K. (2009). Relative economic efficiency of farms in rice production: A profit function approach in north central Nigeria. *Journal of Tropical and Subtropical Agroecosystems*, 10, 279-286.
- Rahman, S., & Hasan, M. K. (2008). Impact of environmental production conditions on productivity and efficiency: A case study of wheat farmers in Bangladesh. *Journal of Environmental Management*, 88, 1495-1504. <https://doi.org/10.1016/j.jenvman.2007.07.019>
- Shein, H. A. (2015). *The soil type and Characteristics of Myanmar*. Department of Agriculture, Ministry of Agriculture, Livestock and Irrigation (MoALI). Retrieved from <https://www.landusedivision.gov.mm/wp-content/uploads/2020/03/Soil-Types-and-Characteristics-of-Myanmar.pdf>
- Sherlund, S. M., Barrett, C. B., & Adesina, A. A. (2002). Smallholder technical efficiency controlling for environmental production conditions. *Journal of Development Economics*, 69, 85-101. [https://doi.org/10.1016/S0304-3878\(02\)00054-8](https://doi.org/10.1016/S0304-3878(02)00054-8)
- Tun, O. A., Van Huylenbroeck, G., & Speelman, S. (2018). Assessment of climate change vulnerability of farm households in Pyapon District, a delta region in Myanmar. *International Journal of Disaster Risk Reduction*, 28, 10-21. <https://doi.org/10.1016/j.ijdrr.2018.02.012>
- Van Long, H., & Yabe, M. (2011). The impact of environmental factors on the productivity and efficiency of rice production: A study in Vietnam's red river delta. *European Journal of Social Sciences*, 26(2), 218-230.
- Villano, R., & Fleming, E. (2006). Technical inefficiency and production risk in rice farming: Evidence from Central Luzon Philippines. *Asian Economic Journal*, 20(1), 29-46. <https://doi.org/10.1111/j.1467-8381.2006.00223.x>
- WFP (World Food Programme). (2013). *Food security focus in dry zone, regional integrated multi-hazard early warning system (RIMES)*. 9th Monsoon Forum, Nay Pyi Taw, Myanmar. Retrieved from <http://www.wfp.org>
- Zorya, S. (2016). *Unleashing Myanmar's Agricultural Potential*. Retrieved June 13, 2017, from <http://blogs.worldbank.org/eastasiapacific/unleashing-myanmar-agricultural-potential>

Appendix A

Table A1. Generalized cropping calendar of monsoon rice production in Ayeyarwaddy Delta

| May | | Jun | | | | Jul | | | | Aug | | | | Sept | | | | Oct | | | | Nov |
|---------------------------------|---|--|---|---|---|---|---|---|---|---|---|---|---|------------------------------------|---|---|---|-----|--|---|---|-----|
| 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 |
| Seedbed preparation for nursery | | Land preparation for the field, application of farmyard manure and uprooting the seedlings and transplanting | | | | Fertilizer application, herbicide and pesticide application, irrigation | | | | Drainage, fertilizer application and manual weeding | | | | Pesticide application and drainage | | | | | Harvesting, threshing, drying and transporting | | | |

Source: Department of Agriculture (DOA), Patheingyi District, Ayeyarwaddy Delta, MoALI (2019).

Table A2. Farmers' perceptions and attitudes on the climate changes

| No. | Impact |
|-----|--|
| 1. | The temperature has changed over the last 10 years. (Hotter or cooler) |
| 2. | The number of dry day has increased over the last 10 years. |
| 3. | Erratic rainfall conditions have faced over the last 10 years. |
| 4. | The level of precipitation has increased over the last 10 years. |
| 5. | Unpredictable storm/cyclone has suffered over the last 10 years. |
| 6. | The event of flooding has increased over the last 10 years. |
| 7. | Saline water intrusion has increased over the last 10 years. |
| 8. | The soil fertility is more degrading over the last 10 years. |
| 9. | Pest and disease infestation are increased over the last 10 years. |
| 10. | The crop productivity has decreased over the last 10 years. |

Note. Please read the following statements and indicate to what extent do you agree with each statement (1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree).

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