Measuring the Efficiency of Rice Production in Myanmar Using Data Envelopment Analysis

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Abstract

Rice production in Myanmar is constrained by biophysical and socioeconomic factors. Nonetheless, efficient farm practices can enhance productivity, farmers' profit, and the price and quality of marketed rice. This study analyzed the profitability and efficiency of rice production in the Ayeyarwaddy Region of Myanmar and identified the influencing socioeconomic characteristics and farm-specific characteristics. Primary data from 130 randomly sampled farmers in the Ayeyarwaddy Region were collected. Data were analyzed using descriptive statistics, data envelopment analysis (DEA), and Tobit regression analysis. According to the average overall technical efficiency, farmers have an additional rice yield potential of 25 percent that can be attained by improving input utilization. The best practices benchmarked in the region showed that technical inefficiency is caused by excessive use of inputs, especially herbicides and animal power. Most rice farms in this study suffer from allocative and economic inefficiencies resulting from wrong combinations of input usages. The average economic efficiency level indicates that farmers can increase their profitability by 57 percent if they adapted to reduce input costs. Moreover, efficiency was significantly higher for farmers who were younger, better educated, more experienced, had access to agricultural extension services, and cultivated the Aye Yar Min variety. Efficiency can be improved by setting up farmers' cooperatives to increase the scale of operations. Moreover, the government should intervene to reduce input prices, control the quality of input seeds, and install an appropriate financial crop insurance mechanism. Effective and systematic agricultural extension services should be widespread to improve the efficiency and decision-making skills of rice farmers in the study area.

Keywords: rice production, farmers, efficiency, DEA, Myanmar, Ayeyarwaddy Region

JEL Classification: D61, L66, Q10, Q12

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Introduction

Agriculture plays a major role in Myanmar's society by ensuring food security, at both the community and national levels, as well as providing employment and income for a growing population. Among agricultural crops, rice plays an essential role not only in food security but also in the nation's economic development. In 2016–2017, rice production was reported at more than 19 million MT, and the country's exports were 1.5 million MT (USDA 2017), which was worth about USD 439 million in 2016 (WTO 2018). The country's average rice yield amounted to about 3.84 MT per hectare (MT/ha), while the yield of Southeast Asian countries like Vietnam was about 5.58 MT/ha in 2016 (FAO 2017). In 2016, Myanmar was ranked seventh among paddy-producing countries in the world (Statista 2017). However, rice yield and production in Myanmar remain low compared to neighboring countries, which poses a high potential for productivity increases (Zorya 2016). According to Saysay (2016), rice production and supply are sensitive to profitability, and improving profitability provides incentives to increase production and marketable surplus. Improving productivity through more efficient utilization of scarce resources is the best and most effective way.

Variations in rice yields reflect the current uneven distribution of agricultural inputs and skills. Farmers have different resource availabilities, input and output prices, and optimal operating points (Ali and Flinn 1989; Wang, Wailes, and Cramer 1996). Aung (2012) determined several major factors that may increase rice productivity, including types of rice varieties, fertilizers, agricultural chemicals, irrigation techniques, and rural institution policies that support the agriculture sector.

According to Amos (2007), efficiently utilizing the limited resources by smallholder farmers in developing countries is a prerequisite to increase farm income and improve food security. Improving the productivity of the rice industry could contribute to poverty reduction, leading to hunger eradication, national food security, and economic development (FAO 2004).

In this study, we first analyzed the profitability of rice production using the enterprise budget. Second, we measured the technical, scale, allocative, and economic efficiency of rice production via data envelopment analysis (DEA) to assess the potential for increasing rice production in the Ayeyarwaddy Region in Myanmar. Lastly, we identified the socioeconomic and farm-specific characteristics that influence the efficiency of rice production in the study area. Our contribution is threefold—this is the first study to analyze technical, scale, allocative, and economic efficiency of rice production in Myanmar using the DEA approach. This study identified the most efficient farmers whose practices can be applied as a benchmark for other farmers in the area to improve their utilization of scarce resources. The results of this study also provide relevant recommendations for the farmers to better control their resource usage and improve their operational decision making in rice production, toward food security and rural development in Myanmar.

Benchmarking Efficiency Using Data Envelopment Analysis

Efficiency can be understood in terms of a firm's ability to convert input to output and respond optimally to economic signals or prices in production economics. When measuring efficiency, we need to know the benchmarking between companies that operate in the same industry. The most popular techniques used to measure farm efficiency are DEA, using mathematical programming methods, and the stochastic frontier analysis (SFA), applying econometric methods (Sivarajah 2017).

DEA is a non-parametric, deterministic procedure for evaluating the frontier and employs the best-practice frontier (Bates et al. 1996). SFA is a parametric approach that requires the assumption of a specific function a priori even though it can estimate parameters for the function that incorporates error components: statistical noise associated with data measurement errors and a non-negative component that measures the inefficiency in production (Coelli et al. 2005). Therefore, the DEA approach is less sensitive to misspecification relative to SFA (Watkins et al. 2014). This study used DEA approach to measure the different types of efficiency in rice production.

DEA, originally developed by Charnes, Cooper, and Rhodes (1978), is a very powerful service management and benchmarking technique to evaluate nonprofit and public sector organizations. Linear programming is the methodology that makes DEA particularly powerful compared with other productivity management tools. DEA has been widely studied, used, and analyzed by academics to evaluate firm (the decision-making unit) performance using efficiency measurements.

In the literature, a distinction is made between input-oriented and output-oriented DEA models that measure efficiency. The input-oriented DEA model tries to determine the minimum inputs required for a firm to obtain the same level of output. In other words, the outcome of the input-oriented DEA model indicates how much a firm can decrease its input for a given level of output. The output-oriented DEA model tries to determine the maximum output a firm can realize for a given level of input. The output-oriented DEA model indicates how much a firm can increase its output for a given level of input (Banker, Charnes, and Cooper 1984).

Thirteen empirical studies published between 1999 and 2017 investigated the farm efficiency of rice production in developing countries and are summarized in Table 1. All of these studies applied cross-sectional data. For each of these studies, we listed the country, the type of efficiency measured, and the DEA model used (input-oriented vs. output-oriented). All the studies investigated technical efficiency. Based on the types of analysis, nine studies used an input-oriented DEA; two studies applied an output-oriented DEA; and two studies employed both input-oriented and output-oriented DEA, depending on their objectives in rice production and their input and output variables.

Table 1. Empirical studies on efficiency measurement of rice production using DEA approach in selected developing countries

Authors	Country	Efficiency Measurement	Type of Analysis
Linh et al. (2017)	Vietnam	Technical scale	Input-oriented
Sivasankari et al. (2017)	India	Technical scale	Input-oriented
Khan, Baten and Ramli (2016)	Malaysia	Technical scale	Input-oriented
Ogunniyi et al. (2015)	Nigeria	Technical	Input-oriented
Mailena et al. (2014)	Malaysia	Technical scale	Output-oriented
Tipi et al. (2010)	Turkey	Technical scale	Input-oriented
Kiatpathomchai (2008)	Thailand	Technical allocative Economic	Input-oriented
Brázdik (2006)	Indonesia	Technical	Input-oriented
Chauhan, Mohapatra, and Pandey (2006)	India	Technical	Input-oriented
Dhungana, Nuthall, and Nartea (2004)	Nepal	Technical allocative Economic	Input-oriented Output-oriented
Krasachat (2004)	Thailand	Technical	Input-oriented
Coelli, Rahman, and Thirtle (2002)	Bangladesh	Technical allocative Economic	Input-oriented
Wadud (1999)	Bangladesh	Technical allocative Economic	Input-oriented Output-oriented

Note: Authors' compilation based on literature

Impact of Socioeconomic and Farm-Specific Characteristics on Efficiency

The estimation of efficiency without clearly identifying important socioeconomic and demographic, institutional, and policy variables, has limited importance for policy and management purposes (Saysay 2016). According to Rahman (2013), the determinants of farm production efficiency are categorized into three aspects based on the nature of the relationship that exists between a farm and some factors within or outside the farm: (1) farm-farmer relationship (i.e., the influence of the farmer's socioeconomic characteristics on farm production); (2) farm-institution relationship (i.e., the influence of agricultural extension, credit, research, infrastructure, etc.); and (3) farm-production relationship (i.e., the factor-product relationship to determine the most profitable mix of resources to produce a given output level or to determine the most profitable amount of output to produce at a given level of input). Most of the studies in the literature focus on the farmer-farm relationship. Linh et al. (2017); Ogunniyi et al. (2015); Mailena et al. (2014); and Dhungana, Nuthall, and Nartea (2004) indicated that the education of farmers impacted on the technical efficiency of rice production. Moreover, Dhungana, Nuthall, and Nartea (2004) found out that education had a positive impact on economic, allocative, and scale efficiency. Linh et al. (2017); Ogunniyi et al. (2015); Tipi et al. (2009); and Kiatpathomchi (2008) found out that total farm size and the age of the farmers influenced the technical efficiency of rice production. According to Dhungana, Nuthall, and Nartea (2004), age of farmers had a negative impact on the technical, scale, and economic efficiency of rice production. Wadud (1999) observed that family size had a negative impact on technical and economic efficiency, while Ogunniyi et al. (2015) found that farming experience had a positive impact on technical efficiency. However, Kiatpathomchi (2008) and Wadud (1999) indicated that farming experience has a negative impact on the economic efficiency of rice production. According to Kiatpathomchi (2008), the rice variety as an element of the farm-production relationship impacts negatively on technical efficiency and economic efficiency. On the other hand, Aung (2012) identified that farmers in Myanmar with higher educational level have higher economic efficiency.

Methodology

Data Collection and Sampling Technique

Both primary and secondary data were collected on rice production in two townships, Myanaung and Kyangyin in the Ayeyarwaddy Region, the largest rice production area in Myanmar (Appendix 1). Primary data were collected through random sampling, the sample size of which was calculated as a direct proportion[1] compared to the (finite) population (Appendix 2). A sample of 130 farmers was selected and in-depth interviews and key informant interviews were conducted (Umberger 2014) to collect sociodemographic data (i.e., age, education level, farmer's experience in rice production and marketing, family size); production data (i.e., material inputs, family labor and hired labor, animal power, machine power, and their prices and wages); financial data (i.e., credit sources and interest rates); and other related primary data. The Department of Agriculture (DOA), Ministry of Agriculture, Livestock, and Irrigation (MOALI), FAOSTAT, and other relevant sources provided secondary data.

Research Method: Benefit-Cost Analysis

The concept of enterprise budget (Olson 2009) was used to evaluate the profitability of rice production by farmers. This enabled evaluating the cost and return of value-adding activities. In order to estimate the return above variable cost (RAVC) or gross margin, the average yield and average price were used. To calculate variable costs, material costs, hired labor costs, family labor costs, and the interest on cash costs were taken into

[1] This is based on Yamane's (1967) the equation (i.e., $n = \frac{N}{1+N(e^2)}$ where N is the population, e^2 is the standard error, and n is the sample size).

account by means of Equation 1.

$$\textit{Return above variable cost (RAVC)} = \textit{Total gross benefit} - \textit{total variable cost} \quad (1)$$

Research Method: Data Envelopment Analysis (DEA)

Technical Efficiency and Scale Efficiency

Technical efficiency (TE) is defined as the ability of a farm to either produce the maximum feasible output from a given bundle of inputs or to produce the given level of output using minimum amount of inputs (Basanta, Nuthall, and Nartea 2004). TE can be measured under the assumption of constant returns-to-scale (CRS), which hypothesizes that the output will change in the same proportion as the inputs change. If TE is measured under the assumption of variable returns-to-scale (VRS), the production technology is assumed to exhibit increasing and/or decreasing returns-to-scale (Kumar and Gulati 2008). TE with constant returns-to-scale (TE_{CRS}), which is further referred to as the overall technical efficiency, helps to determine inefficiencies due to input/output arrangement as well as the size of operations. It is composed of two components: pure technical efficiency and scale efficiency (SE) (Sharma, Leung, and Zaleski 1999). Pure technical efficiency, also known as TE with variable returns-to-scale (TE_{VRS}), is achieved by estimating the efficient frontier under the assumption of variable returns-to-scale. Pure technical efficiency allows abstraction of the scale effect and reveals the ability of the business unit to organize its inputs efficiently in the production process. Hence, pure technical efficiency can be used as an index to capture the managerial performance of a decision-maker. The ratio of overall technical efficiency vs. pure technical efficiency provides SE. When overall technical efficiency is equal to pure technical efficiency, the business unit is called a scale-efficient unit. SE expresses whether a firm is operating at its optimal size. SE gives one an idea of a farmer's managerial ability that will allow him or her to select the optimal resource input size and scale of production to achieve the expected production level (Kumar and Gulati 2008). Scale inefficiency is the result of decreasing returns-to-scale (DRS) or increasing returns-to-scale (IRS). DRS implies that a firm is too large to take full advantage of its scale and has a supra-optimum scale size. In contrast, a firm that is experiencing IRS is too small for its scale of operations and, thus, operates at sub-optimum scale size. A firm is scale efficient if it operates at CRS.

The TE score for a given farm n is obtained by solving the following input-oriented DEA model:

$$TE_n = \min \theta_n \quad (2)$$

subject to

$$\sum_{i=1}^{I} \lambda_i x_{ij} - \theta_n x_{nj} \leq 0 \qquad \forall_j \quad (3)$$

$$\sum_{i=1}^{I} \lambda_i y_{ik} - y_{nk} \geq 0 \qquad \forall_k \quad (4)$$

$$\sum_{i=1}^{I} \lambda_i = 1 \quad (5)$$

$$\lambda_i \geq 0 \quad (6)$$

where:

Sets

I set of farms (index i)

J set of inputs (index j)

K set of outputs (index k)

Parameters

x_{ij} amount of input j used on farm i

x_{nj} amount of input j used on farm n

y_{ik} amount of output k produced on farm i

y_{nk} amount of output k produced on farm n

Decision variables

λ_i nonnegative weights for farm i

θ_n technical efficiency of farm n

The objective function (Equation 2) of the input-oriented DEA model minimizes the inputs, while the outputs are kept at their current levels. If θ_n is equal to 1, the business unit is technically efficient. When θ_n is smaller than 1, the business unit is technically inefficient, with the inefficiency level equal to $1 - TE_n$ (Coelli 1995). Equation (3) is the input constraint formulated for every input *j*. This constraint stipulates that the input used by farm *n*, weighted by its efficiency level θ_n, must exceed or be equal to a weighted combination of inputs used by the other farms. Equation (4) is the output constraint formulated for every output *k*. This constraint stipulates that the output obtained by farm *n* must be lower than or equal to the weighted combination of outputs obtained by other farms. Equation (5) sets the sum of all weights given to other farms equal to 1 and ensures that the technical efficiency TE_n is calculated under the assumption of VRS (Coelli 1995). The model defined by equations (2) to (6) is the formulation proposed by Banker, Charnes, and Cooper (1984) to calculate pure technical efficiency ($TE_n = TE_{VRSn}$). When Equation (5) is omitted, CRS is assumed, and the model reflects the formulation proposed by Charnes, Cooper, and Rhodes (1978) to calculate the overall technical efficiency ($TE_n = TE_{CRSn}$).

The scale efficiency of farm *n* (SE_n) can be calculated using the following equation:

$$SE_n = \frac{TE_{CRS_n}}{TE_{VRS_n}} \tag{7}$$

When SE_n, a farm is scale-efficient, and its combination of inputs and outputs is efficient both under CRS and VRS. If $SE_n = 1$, the combination of inputs and outputs is not scale-efficient. When a firm does not operate under scale efficiency, the returns-to-scale may be increasing or decreasing. IRS is happening if a proportional increase in all the inputs results in more than proportional increase in the output. In that case, the operational scale of a farm is labelled as too small. A firm is operating under IRS if the sum of the dual weights of the dual model corresponding to Model (2) to Model (6) is less than 1. When firms are operating at DRS, a proportional increase in all the inputs results in less than proportional increase in the output. In that case, the operational scale of the firm is labelled as too large. A firm is operating under DRS if the sum of the dual weights of the dual model corresponding to Model (2) to Model (6) turns out to be larger than 1. If a farm operates under IRS or DRS, the efficiency might be improved by changing its scale of operation (Coelli et al. 1998). We refer to Banker and Morey (1986) or Banker and Thrall (1992) for an in-depth analysis.

Economic Efficiency

Economic efficiency (EE) is also known as cost efficiency and is calculated as the ratio of the minimum feasible costs and the actually observed costs for a decision-making unit (Farrell 1957). If a decision-making unit is both technically and allocatively efficient, it is said to be economically efficient. The EE score for a given farm *n* is obtained by solving the following linear programming model (EE input-oriented DEA model) to find the minimum cost:

$$MC_n = min_{\lambda_i x^*_{nj}} \sum_{j=1}^{J} P_{nj}\, x^*_{nj} \tag{8}$$

Subject to

$$\sum_{i=1}^{J} \lambda_i\, x_{ij} - x^*_{nj} \leq 0 \quad \forall_i \tag{9}$$

$$\sum_{i=1}^{I} \lambda_i\, y_{ik} - y_{nk} \geq 0 \quad \forall_k \tag{10}$$

$$\sum_{i=1}^{I} \lambda_i = 1 \tag{11}$$

$$\lambda_i \geq 0 \tag{12}$$

where:

Sets

I	=	set of farms (index *i*)
J	=	set of inputs (index *j*)
K	=	set of outputs (index *k*)

Parameters

x_{ij}	=	amount of input *j* used on farm *i*
y_{ik}	=	amount of output *k* produced on farm *i*

y_{nk} = amount of output k produced on farm n

P_{nj} = price for input j on farm n

Decision variables

λ_i = non-negative weights for farms i

x^*_{nj} = cost-minimizing level of input j on farm n given its input price and output levels

The objective function (Equation 8) of the input-oriented model used to measure economic efficiency minimizes the costs of rice production, while the outputs are kept at their current levels. Equation (9) is the input constraint for every input j, which stipulates that the inputs of farm n must exceed or be equal to the weighted combination of inputs used by other farms. Equation (10) is the output constraint formulated for every output k, which stipulates that the output obtained by farm n must be lower than or equal to the weighted combination of outputs obtained by other farms. Equation (11) sets the sum of all weights given to other farms equal to 1 and ensures that the minimum cost in Equation (8) is calculated under the assumption of VRS (Fletschner and Zepeda 2002; Wu and Prato 2006). The economic efficiency of farm n (EE_n) can then be calculated based on Equation (13):

$$EE_n = \frac{\sum_{j=1}^{J} P_{nj}\, x^*{}_{nj}}{\sum_{j=1}^{J} P_{nj}\, x_{nj}} \tag{13}$$

where the numerator is the minimum total cost obtained for farm n based on Model (8) to Model (12), and the denominator is the actual total cost observed for farm n. $EE_n = 1$ indicates that the farm is economically efficient and $EE_n < 1$ indicates that the farm is economically inefficient.

Allocative Efficiency

Allocative efficiency (AE) or price efficiency is defined as the ability of a farm to use inputs in optimal proportions, given their respective prices and the production technology (Farrell 1957). In other words, allocative efficiency is the ability to select a combination of inputs to produce a set of outputs at minimum cost. AE can be calculated by the following equation:

$$AE_n = \frac{EE_n}{TE_n} \tag{14}$$

where:

EE_n = the economic efficiency calculated for farm n using Equation (13); and

TE_n = the technical efficiency calculated for farm n using the model defined by equations (2) to (6).

AE_n = 1 means that the farm is price efficient, while $AE_n < 1$ means that the farm is price inefficient.

Research Method: Tobit Regression Model

The Tobit regression model was used to perform a regression analysis to determine the significant socioeconomic and farm-specific characteristics that hinder rice production efficiency obtained via DEA. Tobit analysis assumes that the dependent variable has a number of factors clustered at limiting values (Tobin 1958). Efficiency scores lie between zero and one (unity) or are equal to these boundary values. There are usually one or several values at 1, but often, none at or close to zero. As a result, the two-limit Tobit model was used in this analysis (McDonald 2009), and the following regression model was employed:

$$y_i^* = x_i\,\beta_i + \mu_i \quad i=1,2,\ldots,n \tag{15}$$

$$yi = 1, \text{ if } y_i^* \geq 1 \tag{16}$$

$$y_i = y_i^* \text{ if } 0 < y_i^* < 1 \tag{17}$$

$$y_i = 0, \text{if } y_i^* \leq 0 \tag{18}$$

where

$\mu_i \sim N(0, \sigma^2)$ = the error term;

x_i = explanatory variables;

β_i = estimated parameter coefficients;

y_i^* = a latent variable; and

y_i = the efficiency scores for the i^{th} production unit obtained via the DEA model.

Empirical Results

Production and Profitability of Rice Farmers in the Ayeyarwaddy Region

In the study area, rice is cultivated in two seasons, monsoon and summer. This study investigates the rainfed Emata varieties that are grown during the monsoon production season when fields are tilled around the beginning of June (Table 2). Land preparation activities (e.g., plowing and harrowing) together with the application of farmyard manure (at 2 tons/ha) and compound fertilizer (at 42.39 kg/ha) are mainly done using animal power and human labor, although some farmers use tractors. Before land preparation, seedbeds are prepared by sowing rice seeds (104.48 kg/ha) in nurseries in the last week of May. The rice seedlings are transplanted in the rice fields between 15 and 21 days after sowing. After planting, the application of herbicides (3.44 kg/ha or 0.21 L/ha); fertilizers (104.92 kg/ha of urea, 4.87 kg/ha of potash, and 9.51 kg/ha of T-super); pesticides (0.04 kg/ha or 0.35 L/ha); weed control; and irrigation are all done by human labor. Urea fertilizer and pesticides are normally applied three times before harvesting. Harvesting and threshing are done by human labor in late October and at the beginning of November. Combine harvester machines are rarely used to harvest and thresh the rice in the study area. After threshing, the rice is dried by human labor and transported mainly by animal power. On the average, total labor used for all rice production activities is 5.82 animal-days/ha for animal power, 7.18 machine-days/ha for machine power, and 68.12 man-days/ha for both family and hired human labor.

The results shown in Table 3 provides insights into farmers' production system and the costs and profits from monsoon rice production for Emata varieties. The farmers in the study area obtain an average paddy yield of 3,000.11 kg/ha. The average total gross benefit

Table 2. Rice cultivation steps (transplanting method) practiced by farmers in the study area

Month	Week	Activities
May	3	Seedbed preparation for nursery, herbicide application
	4	Seed broadcasting on the seedbeds
June	1	Land preparation for the field, application of farmyard manure and Compound fertilizers
	2	
	3	Uprooting the seedlings and transplanting them to the field
	4	
July	1	Herbicide application, pesticide application
	2	
	4	Application of urea fertilizer and Potash, irrigation
August	1	Drainage
	3	Application of urea fertilizer and T-super, and herbicide application
	4	Manual weeding
September	1	Pesticide application and urea fertilizer application
	2	Pesticide application, irrigation
	4	Drainage
October	4	Harvesting, threshing, transporting and drying
November	1	

Source: Own survey (2017)
Note: These cultivation steps are general. Farmers manage their rice cultivation depending on the local conditions.

Table 3. Enterprise budget and benefit-cost analysis of 2016 monsoon rice production for Emata rice (N=130)

Items	Level	Effective Price (MMK)	Total Value (MMK)
1. Gross benefit			
Yield of paddy (kg/ha)	3,000.11	236	
Total gross benefit (MMK/ha)			**708,026**
2. Variable cost			
(a) Material cost			
Seed (kg/ha)	104.48	336	35,105
FYM (ton/ha)	2.00	7,487	14,974
Urea fertilizer (kg/ha)	104.92	481	50,467
Potash (kg/ha)	4.87	950	4,627
T-super (kg/ha)	9.51	960	9130
Compound fertilizer (kg/ha)	42.39	520	22,043
Pesticide (powder) (kg/ha)	0.04	25,461	1,018
Pesticide (liquid) (L/ha)	0.35	17,500	6,125
Herbicide (powder) (kg/ha)	3.44	7,919	27,241
Herbicide (liquid) (L/ha)	0.21	17,172	3,606
Fuel (gal/ha)	1.51	2,943	4,444
Total material cost(a) (MMK/ha)			**178,780**
(b) Family labor cost			
Land preparation (machine) (machine-day/ha)	2.24	9,439	21,143
Land preparation (Amd/ha)	4.18	4,288	17,924
Manure application (Md/ha)	2.57	3,157	8,113
Picking (Md/ha)	1.94	2,228	4,322
Seeding (Md/ha)	2.34	2,527	5,913
Transplanting (Md/ha)	0.51	3,558	1,815
Irrigation and drainage (Md/ha)	2.47	3,083	7,615
Manual weeding (Md/ha)	0.65	2,186	1,421
Fertilizer application (Md/ha)	4.43	2,544	11,270
Pesticides application (Md/ha)	1.06	2,641	2,799
Herbicide application (Md/ha)	1.96	2,587	5,071
Harvesting (Md/ha)	0.27	3,946	1,065
Drying (Md/ha)	0.74	3,206	2,372

Continued on next page

Table 3 continued

Items	Level	Effective Price (MMK)	Total Value (MMK)
Total family labor cost (b) (MMK/ha)			**90,844**
(c) Hired labor cost			
Land preparation (machine) (machine-day/ha)	3.94	9,439	37,190
Land Preparation (Amd/ha)	1.64	4,288	7,032
Picking (Md/ha)	3.80	2,280	8,664
Seeding (Md/ha)	1.22	2,527	3,083
Transplanting (Md/ha)	21.31	3,558	75,821
Manual weeding (Md/ha)	7.62	2,186	16,657
Fertilizer application (Md/ha)	0.46	2,544	1,170
Pesticide application (Md/ha)	0.21	2,641	555
Herbicide application (Md/ha)	0.23	2,587	595
Harvesting (Md/ha)	14.33	3,946	56,546
Harvesting and threshing by combine harvester (MMK/ha)	0.42	42,850	17,997
Threshing by machine (machine-day/ha)	0.58	20,573	11,932
Transportation (MMK/ha)			7,500
Drying (Md/ha)	0.11	3,206	353
Total hired labor cost (Md/ha)			**245,096**
(d Interest on cash cost			
Material cost (MMK/ha)	178,780	0.27	48,270
Hired labor cost (MMK/ha)	245,096	0.27	66,176
Interest on cash cost (MMK/ha)			**114,446**
Total variable costs (a + b + c + d)			629,166
Return above variable costs			78,860
Return per unit of capital invested (B/C ratio)			1.13
Break-even price (MMK/kg)			210
Break-even yield (kg/ha)			2,665.96

Source: Own survey (2017)
Notes:
kg = kilogram, ha = hectare, MMK = Myanmar Kyat, L = liter, gal = gallon, Md = man-days
Amd = Animal-days
USD 1 = MMK 1,350 (2017)

is Myanmar Kyat (MMK) 708,026/ha, and the average total variable cost is MMK 629,166/ha. Hence, the RAVC amounts to MMK 78,860/ha. For every MMK 100 invested in Emata rice, farmers receive a profit of MMK 13. The total variable costs are covered if the sample farmers receive a price of MMK 210/kg. Results show that rice farmers achieve a very low profit, which just about covers their costs.

Technical, Allocative, and Economic Efficiency of Rice Farmers

Descriptive statistics of inputs and outputs at farm level

To measure farm efficiency, we used the types of inputs applied by the majority of the farmers in rice production. Table 4 presents the statistics of the input and output variables to analyze the technical, allocative, and economic efficiency.

The output was measured as kilograms of rice yield. The average rice yield of the sampled farms is 3,000.11 kg/ha, with a minimum yield of 516.44 kg and a maximum yield of 5,164.39 kg. The standard deviation of the paddy yield is quite high, which indicates a large variability among the sampled farms. The inputs are seeds; urea fertilizer; herbicides; animal, machine, and human labor; and their corresponding price information. Among the inputs, mean total man labor used is 68.12 man-days/ha with a standard deviation of 25.33 man-days/ha, which means that rice production in the study area is labor-intensive (Ogunniyi et al. 2015). The data in Table 4 are used as input for calculating the input-oriented technical efficiency using Model (2) to Model (6), the economic efficiency using Model (8) to Model (13), and the allocative efficiency using Equation (14). The results are shown in Table 5.

Table 4. Descriptive statistics of input, output, and prices of the variable inputs of sampled farms (N=130)

	Variables	Mean	Minimum	Maximum	Std. Deviation
Output variables	Rice yield (kg/ha)	3,000.11	516.44	5,164.39	818.49
Input variables	Seed rate (kg/ha)	104.48	77.47	180.75	17.27
	Urea fertilizer (kg/ha)	104.92	0.00	247.10	52.47
	Herbicide (kg/ha)	3.44	0.00	7.41	4.62
	Animal power (animal-day/ha)	5.82	0.00	22.24	6.13
	Machine power (machine-day/ha)	7.18	1.00	15.83	4.04
	Human labor (man-day/ha)	68.12	7.41	155.67	25.33
	Price of seed (MMK/kg)	336.26	143.54	542.25	85.82
	Price of urea fertilizer (MMK/kg)	480.80	340.00	960.00	73.31
	Price of herbicide (MMK/kg)	7,919.23	3,000.00	40,000.00	7,709.81
	Wage of animal power (MMK/animal-day)	4,288.46	3,500.00	5,000.00	603.17
	Price o machine power (MMK/machine-day)	20,575.00	2,000.00	65,000.00	13,286.51
	Wage of human labor (MMK/man-day)	2,856.91	2,000.00	3,428.57	283.99

Source: Own survey (2017)

Table 5. Frequency distribution of rice farms on technical, allocative, and economic efficiency indexes

Efficiency Level	Technical Efficiency						Allocative Efficiency		Economic Efficiency	
	TE_{CRS} (Overall TE)		TE_{VRS} (Pure TE)		Scale Efficiency (SE)		(AE)		(EE)	
	No.	%	No.	%	No.	%	No.	%	No.	%
0.01–0.10	0	0.00	0	0.00	0	0.00	0	0.00	1	0.77
0.11–0.20	4	3.08	0	0.00	3	2.31	0	0.00	6	4.62
0.21–0.30	1	0.77	0	0.00	1	0.77	1	0.77	15	11.54
0.31–0.40	3	2.31	0	0.00	3	2.31	7	5.38	43	33.08
0.41–0.50	5	3.85	0	0.00	3	2.31	26	20.00	32	24.62
0.51–0.60	15	11.54	1	0.77	6	4.62	50	38.46	19	14.62
0.61–0.70	24	18.46	3	2.31	8	6.15	36	27.69	11	8.46
0.71–0.80	24	18.46	30	23.08	23	17.69	8	6.15	2	1.54
0.81–0.90	16	12.31	23	17.69	26	20.00	1	0.77	0	0.00
0.91–1.00	38	29.23	73	56.15	57	43.85	1	0.77	1	0.77
Median		0.76		0.93		0.88		0.57		0.41
Mean		0.75		0.90		0.83		0.57		0.43
Minimum		0.15		0.59		0.15		0.28		0.07
Maximum		1.00		1.00		1.00		1.00		1.00
IRS		-		-		73.08%		-		-
DRS		-		-		6.15%		-		-
CRS		-		-		20.77%		-		-

Source: Own survey (2017) and DEAP 2.1 (1996)

Technical Efficiency and Scale Efficiency

Technical efficiency

As shown in Table 5, the average overall TE_{CRS} is 0.75. This means that most of the farmers in the study area do not utilize their production resources in the most efficient manner, and farmers do not obtain optimum output from the given level of inputs. The sample farmers can still increase their technical efficiency by 25 percent via the adoption of best practices in efficient farms (i.e., farmers with an efficiency score θ_n equal to 1). This result is consistent with TE_{CRS} in other countries: Sri Lanka at 0.75 (Thibbotuwawa, Mugera, and White 2012); South Korea at 0.77 (Nguyen, Hoang, and Seo 2012); India at 0.76 (Sivasankari, Vasaanthi, and Prema 2017) and 0.77 (Chauhan, Mohaptra, and Pandey 2006); and Nepal at 0.76 (Dhungana, Nuthall, and Nartea 2004).

The TE_{VRS} is 0.90, which indicates that about 10 percent of the inefficiency can be addressed by improving farmers' managerial skills so that they are able to use their inputs more efficiently. This result is very close to the findings of Chauhan, Mohaptra, and Pandey (2006) in India.

Scale efficiency

SE provides useful information for farmers to evaluate whether the scale of production should be changed in order to improve efficiency. The average scale efficiency score is 0.83 (calculated as TE_{CRS}/TE_{VRS} or 0.75/0.90). Hence, the technical efficiency can be improved by 17 percent by adapting the scale of their farms. The average scale efficiency score obtained in our study is similar to the findings of Ogunniyi et al. (2015); Khan, Baten, and Ramli (2016); and Chauhan, Mohaptra,

Table 6. Distribution of input slacks for achieving optimum (technically efficient) paddy yield

Inputs	Mean Slack	Mean Input Used	Excess Input Used out of Mean Input Used (%)	Number of Farmers
Seed rate (kg/ha)	2.61	104.48	2.50	16
Urea fertilizer (kg/ha)	8.26	104.92	7.87	29
Herbicide	1.21	3.44	35.17	47
Animal power (animal-day/ha)	0.98	5.82	16.84	38
Machine power (machine-day/ha)	0.48	7.18	6.69	29
Human labor (man-day/ha)	2.45	68.12	3.60	23

Source: Own survey (2017) and DEAP 2.1 (1996)

and Pandey (2006). However, results of this study differ from that of Sivasankari, Vasaanthi, and Prema (2017); Linh et al. (2017); Ogunniyi et al. (2015); Khan, Baten, and Ramli (2016); Tipi et al. (2009); Dhungna et al. (2004); Krasachat (2004); Coelli, Rahman, and Thirtle (2002); and Wadud (1999) who observed that the scale efficiency was larger than TE_{VRS}. Further analysis of the scale efficiency reveals that 43.9 percent of the farmers score more than 0.9, showing that these farms are operating quite close to the optimal rate given their scale.

The observed returns-to-scale of the sampled rice farms are presented in Table 5. Out of 130 farms, about 20.8 percent operate at CRS. About 73.1 percent of the farms show increasing returns-to-scale, indicating that most of the farms in the sample are too small and, therefore, these rice farms would benefit from an increase in scale. Only 6.2 percent of the farms operate at decreasing returns-to-scale (i.e., operating above their optimal scale). Hence, the majority of the farms in the study area should operate on a larger scale in order to achieve more efficient and higher production. The scale of operations can be increased by setting up cooperatives in rice production and exploiting economies of scale.

Input slacks and excessive input use

The optimum solution of the DEA model provides input and output slacks corresponding to the input and output constraints. Slacks exist only for inefficient farms and indicate how these farms can improve their operations and their technical efficiency (Jacobs, Smith, and Street 2006). From the concept of an input-oriented DEA efficiency analysis, the technical efficiency can be improved by the proportional reduction of one or multiple inputs while still attaining the same output (Kiatpathomchai 2008). Table 6 provides insight into the input slacks, given the VRS assumption. Since slack indicates the excess of an input, expenditures can be reduced by decreasing the inputs by the amount of slack, without reducing its output (Sivsankari 2017). Almost all the inputs are used excessively. The mean slacks for seed rate and urea fertilizer are 2.61 kg/ha and 8.26 kg/ha, respectively, which means that these excess amounts of seed and fertilizer are wasted in the production process. The percentage of herbicide slack is the highest (35.2%) among all inputs used in rice production. Moreover, the mean slack for animal power, machine power, and human labor are 0.98 animal-days/ha, 0.48 machine-days/ha, and 2.45 man-days/ha, respectively. The largest input excess of labor used in rice production is animal labor (16.5%).

Allocative Efficiency and Economic Efficiency

Allocative efficiency

An analysis of the allocative efficiency reveals that most rice farmers employ an inefficient input mix, given the input prices (Table 5). As a result, their costs are, on average, 43 percent higher

Table 7. Distribution of excess input used for achieving minimum (economically efficient) costs of rice production

Inputs	Mean Cost Minimizing Input Used	Mean Input Used	Excess Input Used	Excess Input Used out of Mean Input Used (%)
Seed rate (kg/ha)	86.04	104.48	18.44	17.65
Urea fertilizer (kg/ha)	103.85	104.92	1.07	1.02
Herbicide (kg/ha)	3.01	3.44	0.43	12.50
Animal power (animal-day/ha)	4.52	5.82	1.30	22.41
Machine power (machine-day/ha)	2.73	7.18	4.45	61.92
Human labor (man-day/ha)	14.90	68.12	53.22	78.12

Source: Own survey (2017) and DEAP 2.1 (1996)

compared to the most efficient farm and they can reduce their costs by carefully considering the relative input prices when selecting input quantities. The mean allocative efficiency of rice production in the study area is very low compared to the United States (Watkins 2014); Malaysia (Khan, Baten, and Ramli 2016); Sri Lanka (Thibbotuwawa, Mugera, and White 2012); Thailand (Kiatpathomchai 2008); Nepal (Dhungana, Nuthall, and Nartea 2004); and Bangladesh (Coelli, Rahman, and Thirtle 2002; Wadud 1999), which range between 0.71 and 0.91. Thus, rice farmers in Myanmar need better guidance and information in selecting the appropriate combination of inputs given input prices.

Economic efficiency

According to the results shown in Table 5, only one farm (0.77%) is economically efficient and about 24.6 percent of the farms have acceptable economic efficiency, ranging between 0.51 and 0.90. Majority of the farms (74.63%) are not economically efficient and have a score lower than 0.51. These results confirm that the rice farmers are economically inefficient and that the total cost of rice production for each farm could be reduced by 57 percent, on average, to achieve the same level of output. The economic efficiency of rice production in the study area is very low compared to other countries (i.e., United States, Sri Lanka, Thailand, Nepal, and Bangladesh) with mean economic efficiency, ranging from 0.52 to 0.78.

Excess input use and economic efficiency

Table 7 indicates the distribution of excess inputs given the economic efficiency as well as the optimal input combination that minimizes input costs. Since the percentages of excess use (prices of inputs are taken into account in the cost minimization) in machine power (61.92%) and human labor (78.12%) are very high compared to other inputs, rice farmers should carefully manage their excess use of labor.

Best Practices for Rice Production

According to Table 5, only one farmer among the sampled rice farmers is efficient on technical, allocative, and economic aspects. The remaining 129 farmers are not economically efficient in their rice production. Table 8 represents the percentage of the farmers who achieve the same output level or have the same input level as this efficient farmer. The purpose of this description is to set a best practice and to allow other farmers to learn how they can improve their efficiency. The efficient farmer yields 3,098.63 kg/ha of paddy. In total, 21 other farmers (16.28%) have the same or a higher production level. Most of the other farmers use the best practice level of seeds (75.19%) and

Table 8. Distribution of farmers following the best practice farmer in achieving optimal output and using optimal input level

Output and Inputs	Best Practice Level	Frequency of Farmers Who Followed the Best Practice Level (N=129)	Percentage of Farmers Who Followed the Best Practice Level (N=129)
Rice yield (kg/ha)	3,098.63	21	16.28
Inputs			
Seed rate (kg/ha)	103.29	97	75.19
Urea fertilizer (kg/ha)	123.55	90	69.77
Herbicide (kg/ha)	0.37	2	1.55
Animal power animal-day/ha	9.88	9	6.98
Machine power machine-day/ha	1.00	23	17.83
Human labor man-day/ha	22.24	1	0.78
Prices			
Seed rate MMK/kg	334.93	20	15.50
Urea fertilizer MMK/kg	460.00	26	20.16
Herbicide MMK/kg	6,000.00	49	37.98
Animal power MMK/animal-day	5,000.00	47	36.43
Machine power MMK/machine-day	50,000.00	0	0.00
Human labor MMK/man-day	2,300.00	0	0.00

Source: Own survey (2017) and DEAP 2.1

urea fertilizer (69.77%). However, the benchmark found that only a few other farmers are as efficient with respect to other resources, such as herbicide (1.55%), animal power (6.98%), machine power (7.83%), and human labor (0.78%). Table 8 further reveals the input prices paid by the most efficient farmer for seed, urea fertilizer, herbicide, animal power, machine power, and human labor. Other farmers pay the best practice prices for herbicides (37.98%), animal power (36.43%), urea fertilizer (20.16%), and seed rate (15.50%) compared to the most efficient farmer except for machine and human labor.

Farm-Specific Factors Related to Farm Efficiency

In this section, we attempt to examine factors affecting efficiency by following a two-step approach, as suggested by Coelli and Battese (1996). To determine the influencing factors, the Tobit model is applied to regress the efficiency scores on the farm characteristics. The dependent variables are the efficiency scores calculated in the previous sections. Table 9 describes the summary statistics of the independent farm-specific variables. These independent variables are farm-farmer variables such as age, family size, education, and experience; farm-production variables such as farm size and rice variety; and farm-institution variables such as extension services received.

Among these variables, the rice variety used is an important input for achieving a high yield (Ataboh, Umeh, and Tsue 2014). The varieties used by the farmers in the study area are Aye Yar Min, Sin Thu Kha, Shwe War Tun, Yadanar-toe, Kayin Ma, Shwe Wa Ti, and Pale Thwe. In our analysis, the farmers were grouped into two (i.e., those who grow the Aye Yar Min variety and those who do not). Farmers that grow the Aye Yar Min variety obtain a higher profit since they receive a higher price due to its high quality and yield (Linn and Maenhout 2019).

Table 9. Descriptive statistics of socio-economic variables for the sample farms (N=130)

Variables	Unit	Mean	Minimum	Maximum
Age	Year	51.09	27.0	85.00
Family size	Number	4.00	2.00	8.00
Education	Schooling year	6.58	2.00	15.00
Experience	Year	27.07	3.00	54.00
Farm size	ha	3.07	0.40	15.78
Variety used		1 = Aye Yar Min, 0 = others		
Received extension services		1 = Yes, 0 = No		

Source: Own survey (2017)

Table 10. Results of Tobit regression coefficients (N=130)

Independent Variables	TE_{CRS}	TE_{VRS}	SE	AE	EE
Constant	0.6225*** (0.0917)	0.8825*** (0.0531)	0.6987*** (0.0855)	0.5599*** (0.0514)	0.3361*** (0.0606)
Age	-0.0041** (0.0017)	-0.0009 (0.0009)	-0.0035** (0.0015)	-0.0021** (0.0009)	-0.0038*** (0.0011)
Family size	-0.0028 (0.0131)	-0.0035 (0.0076)	-0.0006 (0.0122)	0.0089 (0.0073)	0.0021 (0.0087)
Education	0.0174*** (0.0065)	0.0014 (0.0014)	0.0189*** (0.0061)	0.0056 (0.0008)	0.0162*** (0.0043)
Experience	0.0023 (0.0016)	0.0003 (0.0009)	0.0019 (0.0015)	0.0019** (0.0038)	0.0027*** (0.0011)
Farm size	-0.0000 (0.0069)	-0.0028 (0.0227)	0.0017 (0.0064)	-0.0055 (0.0220)	-0.0039 (0.0045)
Variety used	0.1479*** (0.0392)	0.0598*** (0.0185)	0.1115*** (0.0366)	0.0135 (0.0179)	0.0978*** (0.0259)
Received extension services	0.1135*** (0.0319)	0.0418** (0.0185)	0.0885*** (0.0298)	0.0033 (0.0514)	0.0697*** (0.0211)
SE of regression	0.1852	0.1072	0.1726	0.1038	0.1224
Wald Chi-Square	47.3736***	13.7616*	41.4958***	12.4492*	61.2085***
Log likelihood	39.4354	110.4767	48.5859	114.6713	93.2603
Likelihood ratio (LR) test	40.3928***	13.0804***	36.0119***	11.8880*	50.1563***

Source: Own survey (2017) and Eviews 9
Note:
Dependent variables are TE_{CRS} index, TE_{VRS} index, SE index, AE index and EE index.
Figures in the parentheses are standard error.
* = significant at 10% level, ** = significant at 5% level and *** = significant at 1% level

Another independent variable is the agricultural extension services received by the farmers (Taraka et al. 2011), which implies a knowledge information transfer from extension agents to farmers. In effect, farmers can make better decisions based on their own objectives and possibilities. This independent variable is a binary variable (i.e., farmers participate in the extension program or do not participate).

Table 10 indicates the results of the Tobit regression analysis for technical efficiency, scale efficiency, allocative efficiency, and economic efficiency of the rice farmers. All independent variables, except family size and farm size, are significant factors impacting the efficiency of a farm in one way or another. In our discussion, we only indicate significant relationships.

The age of the farmers negatively impacts technical efficiency under the assumption of CRS, which confirms the findings of Ogunniyi et al. (2015) and Tipi et al. (2009). The age of the farmers also has a negative and significant impact on scale efficiency, allocative efficiency, and economic efficiency, which implies that younger farmers are more efficient than older farmers. In-depth interviews revealed that younger farmers accept new technologies in rice production more easily, while older farmers are less willing to adopt new practices and modern inputs and would, therefore, need more contact with extension agents.

Education is an important factor, indicating the ability of farmers to receive and understand information on modern technologies. More educated farmers perform better in terms of technical, scale, and economic efficiency as a result of their access to information and good farm planning (Linn and Maenhout 2018b). This result confirms the studies of Linh et al. (2017); Mailena et al. (2014); and Dhungana, Nuthall, and Nartea (2004) but is not consistent with the findings of Ogunniyi et al. (2015).

Experience in rice farming has a positive impact on allocative efficiency and economic efficiency, which indicates that experienced farmers are more efficient in their use of input resources. Thus, experience improves the decision making of farmers. This study contradicts with the findings of Kiatpathomchai (2008) and Wadud (1999).

The farmers that grow the Aye Yar Min variety are more efficient compared to those that do not. However, the type of variety cultivated is not related to allocative efficiency (i.e., the allocation of inputs in rice production at given prices of inputs). This result is consistent with the findings of Kiatpathomchai (2008), but not with Watkins et al. (2014) who found that variety choice had a significant and positive impact on allocative efficiency.

The extension services received by the farmers have a positive and significant impact on all types of efficiency except for allocative efficiency. This implies that even if rice farmers receive extension services, farmers are unable to improve their input allocation of resources and better management of costs. Farmers who receive or participate in the extension services provided by agricultural extension agents are more efficient as a result of the technical assistance to the farmers, information sharing, and the training courses supported by the DOA and by private agrochemical companies. This finding confirms the results of Jaforullah and Whiteman (1999) and Backman, Islam, and Sumelius (2011).

Discussion

The profitability of rice production in the Ayeyarwaddy Region of Myanmar is very low. Rice farmers get low price for their produce, especially during the harvesting period, yet they pay high price for the inputs that they use. The benefit-cost ratio of rice production (1.13) in Myanmar is lower than in Thailand (1.61) (Kiatpathomchai 2008). Furthermore, the average yield in Thailand is higher than that in Myanmar. In addition, according to Kiatpathomchai (2008), rice farmers in Thailand utilize mostly machine power and human labor than animal power. Considering that the profitability of rice farmers is highly related to their efficiency, they can earn more profit from rice production if they can manage their inputs effectively and efficiently.

Kiatpathomchai (2008); Dhungana, Nuthall, and Nartea (2004); Coelli, Rahman, and Thirtle (2002); and Wadud (1999) also analyzed the technical, allocative, and economic efficiency of rice production (Table 11). This study included many more inputs in the analysis, particularly herbicide input, which has not been considered as an input variable in previous studies. Pure technical efficiency in this study is higher than the results found by Dhungana, Nuthall, and Nartea (2004); Coelli, Rahman, and Thirtle (2002); and Wadud (1999), but is slightly lower than that found by Kiatpathomchai (2008). These benchmarking studies have been proven useful to gain insight into the input resource mix decision of efficient

Table 11. Information of input and output variables and results of efficiency scores via DEA in rice production in some developing countries

Country	Authors	Mean Efficiency Results	Output Variable	Input Variables
Myanmar	This study (2019)	TE (VRS) = 0.90 AE (CRS) = 0.57 EE (CRS) = 0.43 SE = 0.83 CRS = 20.77% DRS = 6.15% IRS = 73.08%	Rice yield (kg/ha)	Seed rate (kg/ha) Urea fertilizer (kg/ha) Herbicide (kg/ha) Animal power (animal-day/ha) Machine power (machine-day/ha) Human labor (man-day/ha) Price of seed (MMK/kg) Price of urea fertilizer (MMK/kg) Price of herbicide (MMK/kg) Wage of animal power (MMK/animal-day) Price of machine power (MMK/machine-day) Wage of human labor (MMK/man-day)
Thailand	Kiatpathomchai (2008)	TE (VRS) = 0.92 AE (VRS) = 0.78 EE (VRS) = 0.68	Rice yield (kg/ha)	Labor (man-hr/ha) Machine (THB/ha) Seed (Kg/ha) Fertilizers: DAP (kg/ha) Urea (kg/ha) N-fertilizer (kg/ha) P-fertilizer (kg/ha)
Nepal	Dhungana et al. (2004)	TE (VRS) = 0.82 AE (CRS) = 0.87 EE (CRS) = 0.66 SE = 0.93 CRS = 10.52% DRS = 42.12% IRS = 47.36%	Rice yield (kg/farm)	Land (ha) Seed (kg/farm) Labor (Person days/farm) Mechanical labor costs (NPR/farm) Fertilizer costs (NPR/farm)
Bangladesh	Coelli et al. (2002)	TE (VRS) = 0.69 AE (VRS) = 0.81 EE (VRS) = 0.56 SE = 0.95 CRS = 10.90% DRS = 58.06% IRS = 31.04%	Rice output (kg)	Land cultivated (ha) Animal power (pair-days) Fertilizer (kg) Seed (kg) Labor (day) Land rent (BDT/ha) Fertilizer price (BDT/kg) Seed price (BDT/ha) Labor wage (BDT/ha) Animal wage (BDT/pair)
Bangladesh	Wadud (1999)	TE (VRS) = 0.85 AE (VRS) = 0.87 EE (VRS) = 0.79 SE = 0.93 CRS = 16.67% DRS = 62.66% IRS = 20.67%	Output (Maund/ac) (1Maund = 37.32 kg)	Land (ac) Labor (man-day/ac) Irrigated land (ac) Fertilizer applied (kg/ac) Pesticides used (ml)

Notes: THB - Thai Baht; NPR - Napalese Rupee; BDT - Bangaladeshi Taka farms and find weaknesses in current cultivation techniques (Dhungana, Nuthall, and Nartea 2004).

In this study, technical inefficiency results largely from the high use of herbicides and animal power. It can be inferred from the use of herbicides that weed problem in the study area is serious and can cause low rice yield. Farmers use herbicides unsystematically and carelessly, negatively affecting yield. The inefficient mix of input resources results from a perceived uncertainty by the decision-maker on one hand (Linn and Maenhout 2018), and operational constraints imposed on the other (Linn and Maenhout 2019). In Linn and Maenhout (2018), climate uncertainty was revealed as the major source of uncertainty impacting the rice supply chain. When making decisions under high uncertainty, it is much more difficult to select the most efficient mix of resources. In response, an appropriate financial insurance mechanism should be implemented by the government or private partners to buffer the financial implications of unexpected crop failures for farmers.

According to Linn and Maenhout (2019), crop cultivation in Myanmar is still carried out the traditional way, and most farmers lack the appropriate level of mechanization required to increase efficiency. Myanmar farmers do not have the knowledge nor financial resources to invest. The government should develop a farm mechanization and cultivation program in cooperation with private institutions and provide the appropriate (public) infrastructure, teach farmers how to adapt their farm and farming techniques, and help them acquire farm machinery via low-interest loans.

On average, the rice farms in the study area are scale inefficient. Scale efficiency in this study is lower than those in Dhungana, Nuthall, and Nartea (2004); Coelli et al. (2002); and Wadud (1999) (Table 11) because of the small scale of many farms operating in Myanmar. In order to achieve economies of scale, the organization of small-scale cultivations into comparatively larger collective systems consisting of multiple farmers should be promoted through the collaboration of government, farmer organizations, and the private sector (Thibbotuwawa, Mugera, and White 2012). Establishing cooperatives among farmers will increase the scale of operations.

Allocative and economic inefficiency of rice production can be attributed largely to the abundant use of labor and input seeds. In Thailand, the economic inefficiency of rice production resulted from the overuse of fertilizers (Kiatpathomchai 2008); in Bangladesh, it was from the abundant use of labor (both animal power and human labor) and fertilizer (Coelli, Rahman, and Thirtle 2002); and in Sri Lanka, it was from the inefficient use of human labor, machinery, and input seeds (Thibbotuwawa, Mugera, and White 2012). Labor unit price is high, which is associated with the high demand for labor. Agricultural production in Myanmar is largely labor-intensive. While farm mechanization plays an important role in improving the quality of paddy and in reducing postharvest losses, the acquisition of the required machinery is too expensive for farmers in Myanmar. Meanwhile, labor scarcity during transplanting, weeding, and harvesting results in losses, both in the quantity and quality of the rice produce. Raising farm efficiency, lowering unit costs, and reducing postharvest losses will increase rice production and, thus, the profits of farmers. To solve the labor scarcity problem, farm mechanization extension programs and affordable loans should be granted.

The quality of input seeds and variety used are important factors impacting on the efficiency of rice farming. The use of high-quality and pure seed is of high importance to maximize paddy quality and the resulting profit. However, most farmers use impure seeds, which they produce on their own farms, using traditional methods (Wong and Wai 2013; Linn and Maenhout 2019). In addition, uncertainty related to production inputs impacts managerial decision making and related farming efficiency (Linn and Maenhout 2018). The availability of high-quality and pure seed is a necessary condition for higher yield and better quality rice, and this should be controlled by the government. How (state) seed production companies function should be revised so that all farmers are able to access high-quality input seeds at the least possible cost. On the other hand, managerial skills can be further improved by investments in the formal school system and the extension system. Better education of farmers enhances their decision making and communication skills via support service providers, such as extension officers and other stakeholders in the business. In line with the research of Dhungana, Nuthall, and Nartea (2004), government initiatives in collaboration with private partners should be set up to educate farmers so they can learn efficient farming practices by applying extension tools, such as field day visits to efficient farms (Dhungana, Nuthall, and Nartea 2004). Extension services need to be reformed to increase the mobility of extension officers; improve links among farmers, researchers, and extension staff; and promote the use of modern technologies for agricultural extension. New skills are needed for a new era of global agricultural engagement. Thus, an efficient agricultural extension system has to be implemented by the DOA-MOALI in cooperation with international and local non-government organizations and private agrochemical companies.

Conclusion and Recommendations

This study investigated the profitability of rice production in the Ayeyarwaddy Region in Myanmar. In order to evaluate the performance of rice production, we estimated the technical, scale, allocative, and economic efficiency scores by using an input-oriented DEA model. Tobit analysis was used to explore the factors influencing the efficiency scores of rice farmers. The study attempts to address the lack of empirical studies that focus on efficiency performance using DEA and the factors impacting efficiency in Myanmar rice farms.

The empirical results reveal a substantial potential to increase the efficiency of rice farms in Myanmar. Various inefficiencies limit the profitability of rice production for farmers in the study area. Analysis of best practices of more efficient rice farms showed that technical inefficiency is caused by excessive application of inputs, especially of herbicides and animal power. In addition, most rice farmers in the region produce rice at increasing returns to scale, indicating that increasing the scale of operations would improve their efficiency and profitability. Moreover, allocative efficiency and economic efficiency are very low due to inappropriate management (i.e., wrong input combinations) and high input costs. In particular, the high costs for machine power and human labor are causes of economic inefficiency. A regression analysis provided insights into the determinants of the inefficient performance of the farmers. Farm-farmer related variables (i.e., age, education, and experience) impact on farm efficiency, while the farm-production related variable (variety used) and farm-institution related variable (extension services received by farmers) were found to impact on their technical scale and economic efficiency.

Our findings pose several important policy implications toward reducing the variation in actual output from the maximum potential output in rice production.

Low economic efficiency reveals the potential for increasing output levels considerably, which will further enhance farm income and the welfare of farm households. Improving the allocative and economic efficiency of rice production would require appropriate price policies for inputs and outputs. Moreover, agricultural mechanization could further lower costs, and should be realized with the cooperation of private and public organizations. The most efficient farms could be encouraged to disseminate their best practices and share their experience with other farms to improve the average farm efficiency in the study area. It would also be beneficial to increase the scale of farming operations by organizing cooperatives among farmers, similar to those in other Southeast Asian countries. In this way, farmers could have a stronger bargaining position, which may lead to lower input prices and higher output prices, price fluctuations will be less volatile, and more accurate market information and better market orientation could be obtained. In addition, best practices and extension programs will be transferred to more farmers in a more efficient manner.

The education of farmers is an important determinant of rice farm efficiency. In the long run, better performance in the agricultural sector can be achieved by increasing private and public investments in education in rural areas. In the immediate future, farmers may learn agricultural technologies from benchmarking with the practices of relatively efficient farms. These practices can be spread formally via extension services, or informally via setting up cooperatives among different parties. Moreover, farmer field schools supported by various development agencies cooperating with the DOA may be rigorously implemented to help farmers improve their analytical and decision-making skills.

Using high-quality input seeds and growing the Aye Yar Min helped widely maximize efficiency. Government could play a role in ensuring that pure and high-quality seeds are accessible to rice farmers. The input seeds currently used by most farmers are impure because they produce the seeds on their own farms using traditional methods. Growing high-quality Aye Yar Min variety would help to increase farmers' profit.

Lastly, extension programs need to be widened and strengthened to help farmers to optimize the mix of farming inputs and production methods. In this regard, the country's extension policy needs to be reformed to reorganize the duties of extension officials, enabling them to spend more time on field visits with the rice farmers.

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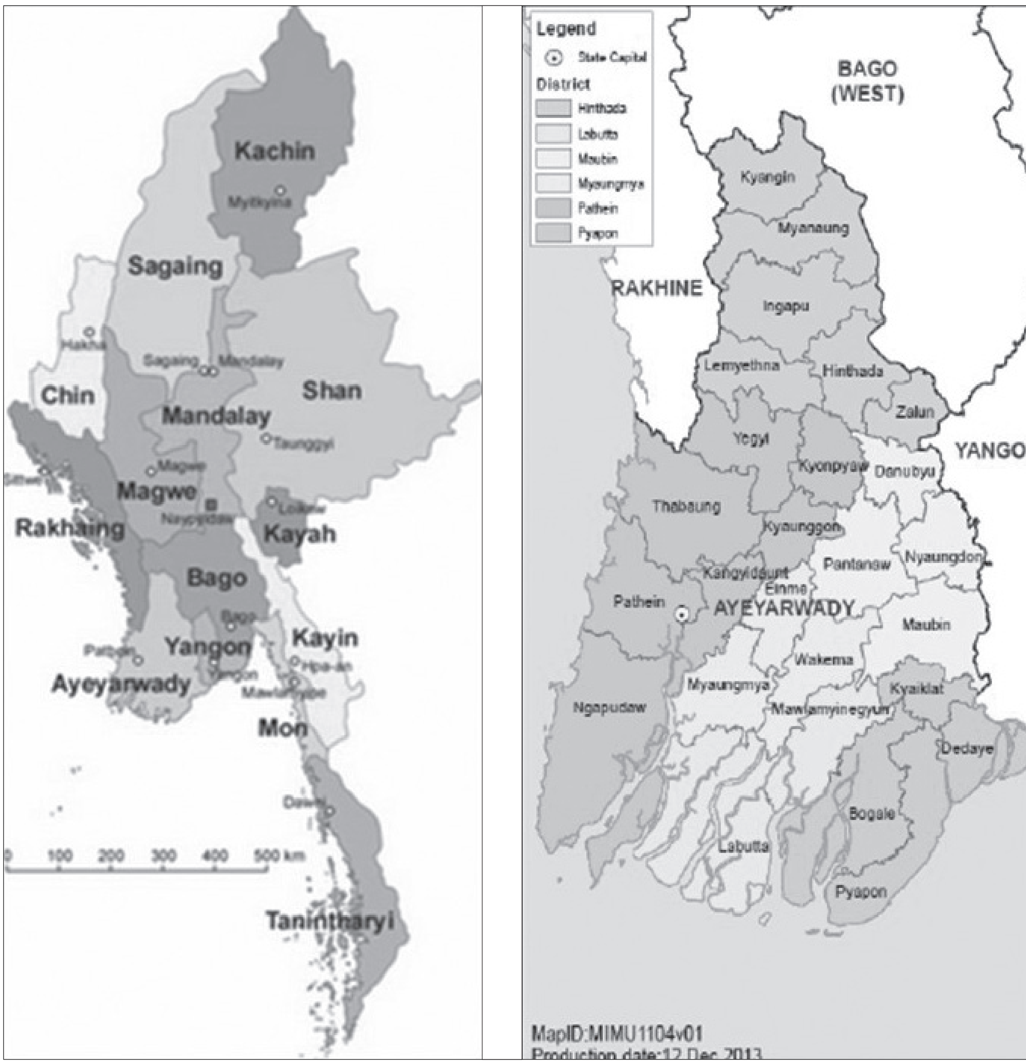
Appendices

Appendix 1. Map of Myanmar (left) and the Ayeyarwaddy Region (right) showing the study areas



Appendix 2. Sampled respondents along the rice value chain in the study area

Townships	Total Population	Sampled Respondents
Myanaung (Laharpauk village)	399	30
Myanaung (Htanthonepin village)	327	30
Kyangin (Kyantaw village)	663	35
Kyangin (Sonehele village)	630	35
Total		**130**

Source: DOA (2017)