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Research Article

An Application of Stochastic Nonparametric Envelopment of Data to Estimate the Efficiency of Rice Milling Industry in Sri Lanka

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Abstract

The Rice milling industry is the biggest agro-based processing industry in Sri Lanka which convert the paddy into a consumable form. The present study utilized the StoNED method to estimate the technical efficiency (TE) of the rice milling industry in the *Ampara* district. The data of rice mill's inputs, outputs, cost of production, and availability of modern machinery were mainly collected from 102 randomly selected commercial rice mills with aid of a structured questionnaire. The significant factors that influence the TE of rice milling were estimated by employing Tobit regression analysis. The results of the TE indicated that this industry achieved more than 90% efficiency in rice milling with productive operational size. The estimated TE scores by input-output and cost functions were significantly ($p<0.05$) different. The empirical results reveal that the experience of owners and labours in rice milling, availability of paddy dryers, weighing bridge, parboiling units, auto paddy feeders, paddy separators, and own transports were the significant ($p<0.05$) factors that impacted the efficiency of producing rice. The present study recommends that providing practical oriented training and increasing capital investment by rice millers or providing credit facilities to implement modern processing units would improve the TE of rice mills.

Introduction

The measurement of efficiency in the agricultural industry is the productive approach to increase the productivity of countries where the Gross Domestic Production (GDP) is primarily supported by Agricultural sector. The Sri Lankan economy is widely dependent on Agriculture sector, 9.01% of GDP contributed by this sector (Department of Agriculture, 2020). Improved efficiency is one of the vital components for a firm's growth, which in turn is the primary driver of economic welfare. Firm-level efficiency analyses are essential for macro-level productivity. There were two competing paradigms in the field of efficiency analysis; Data Envelopment Analysis (DEA) (Charnes et al., 1978; Farrell, 1957) and Stochastic Frontier Analysis (SFA) (Aigner et al., 1977; Meeusen & van Den Broeck, 1977).

DEA is a mathematical programming technique that uses some axioms of production theory such as free disposability (monotonicity), convexity (concavity), and constant returns to scale (homogeneity) to estimate the technical efficiency (TE) and no particular functional form are assumed for the frontier or the distribution of inefficiency (Cooper et al., 2011). However, the primary weak point of DEA is that it attributes all deviations from the frontier to inefficiency (Cooper et al., 2011). On the other hand, SFA employs parametric regression approaches, which necessitate ex-ante descriptions of the frontier and inefficiency distribution functional forms. The strength of SFA is estimating composite error terms from the predefined production function. The composite error term can be decomposed into an inefficiency term and noise term that accounts for omitted factors such as unobserved heterogeneity of firms, random errors of measurement and data processing, specification errors, and other sources of noise (Kumbhakar & Lovell, 2003).

In the trade-off between DEA and SFA, DEA can apply axiomatic properties and estimate the frontier

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nonparametrically, however, it does not model noise. On the other hand, SFA cannot impose axiomatic properties but can model inefficiency and noise. These limitations in DEA and SFA have persisted for a long time within a context of efficiency analysis. Therefore, Kuosmanen (2008), Kuosmanen and Johnson (2010), and Kuosmanen and Kortelainen (2012) worked on the consolidation of non-parametric and parametric approaches known as convex nonparametric least squares (CNLS). This is a unified framework of efficiency analysis, which can be referred to as Stochastic Nonparametric Envelopment of Data (StoNED). StoNED's development is more than technical innovation, it's a fundamental leap in efficiency analysis. It could be used to model noise while imposing axioms of production. The unified framework of StoNED offers deeper insights into the economic intuition and foundations of DEA and SFA.

Rice plays a vital part in guaranteeing food security because it contributes 41.8% of total calories and 35.5% total protein requirement of an average Sri Lankan diet (FAOSTAT, 2013). A majority of consumers spend a considerable portion of their income on purchasing the rice. According to the Household Income and Expenditure Survey 2016, the average household spent Rs. 2,452 per month for rice consumption, which 12.8% of the monthly food budget. Per capita consumption of rice was 109 kg/ year in 2009, gradually the annual consumption increased up to 190 kg per person/year in 2021 (FAO, 2022). It indicates that the demand for rice steadily increasing annually in Sri Lanka. Further, Rice Research and Development Institute (2016) predicted that the annual demand for rice grows at 1.1% per year meanwhile the annual production should grow at a rate of 2.2% per year to meet the demand in near future.

The rice milling industry has an important link in converting paddy into rice is required to contribute provision of rice to the nation in terms of quantity and quality. This industry increases the value-addition of paddy. This industry processes paddy produced by farmers into ready-to-cook or stored rice. The quality and quantity of rice production has a significant impact on the rice market in general. Improving the quality of rice in each subsystem is decided by a few factors. For instance, farming techniques and input factors used in the on-farm subsystem influence the paddy output both in quality and quantity. In addition, the milling machine condition also affects both the quality and quantity of rice produced. Ideally, the current milling rate for rice was 66.7% in 2023 (FAO, 2022) and Senanayake and Premaratne (2016) reported that, in the milling process of paddy, it takes slightly under 1.5 kg of paddy to produce one kilogram of rice in Sri Lanka. The quantity and quality of rice produced would have an effect on the market supply of staple food in Sri Lanka. Further the efficiency estimation informs the significance of the factors of production on the rice productivity in rice milling sector and the influential factors on TE of rice milling. Therefore, it is very important to estimate TE and explore determinants of TE of the rice milling industry. Hence, this research applied the newly innovated TE paradigm known as StoNED to estimate the TE of the rice milling industry in Sri Lanka taking *Ampara* District as a case study. *Ampara* district is the highest paddy yielding district in Sri Lanka and total production was 267,017 metric tons in the 2023/2024 *Maha* season (Department of Census and Statistics, 2024). *Ampara* is one of the major paddy milling regions in the country where all conventional and commercial millers exist. There are 330 commercial rice mills including all large, medium and small scale have been identified by the Institute of Post-Harvest Technology (IPHT) survey in 2014. The existing millers produce both raw and parboiled rice. Therefore, this region has huge potential for rice milling and marketing.

Estimating the efficiency of rice production exists in a large body of literature over the years in Sri Lanka. Gedara et al. (2012), Gunarthne & Thiruchelvam (2002), Herath (1989), Shantha, Asan Ali, & Bandara (2012), Warnakulasooriya & Athukorale (2016), and Wijesinghe & Wijesinghe (2015) estimated the TE by Maximum Likelihood Estimation (MLE) using SFA with Cobb Douglas production function. These studies found that farmland size, capital availability, the experience of farmers and inputs such as fertilizer and agrochemical usage significantly impacted the TE of rice farms. (Thibbotuwawa et al., 2013) used DEA to estimate TE of irrigated and rainfed rice farms in different regions of Sri Lanka. Further, the application DEA and SFA approaches are found in studying TE of rice milling sector. Wijesinghe and Weerahewa (2017) studied the TE of rice mills during the study of Structure Conduct and Performance (SCP) of the rice milling industry of Sri Lanka. TE was estimated through the DEA approach. Results revealed that the TE of different categories of rice mills in the sample was about 90%. However, the researchers did not study the factor influencing the TE of mills. The profit efficiency of rice processors was investigated by employing the DEA approach in Nigeria, the researcher found that profit efficiency in transportation was 14%, hiring of operating space was 10%, pay for duties and taxes was 28%, communication was 13%, rice paddy was 21%, maintenance and repairs was 21%, transportation was 28% and fuel was 35% (Obisesan et al., 2017).

The TE of rice milling was compared between Thailand and Taiwan. DEA was used to estimate the TE and Tobit regression model was used to explore the factors affecting TE in both countries (Wongkeawchan et al., 2017). The results showed that the total TE and pure TE of rice mills in Thailand on average are less than in Taiwan. Further, the milling capacity was the only factor that impacts the TE of rice mills in Thailand. Apriande (2013) studied the characteristics and relative efficiency of the rice milling industry in Java, Indonesia. Variable Return to Scale (VRS) and Constant Return to Scale (CRT) TE were estimated through the DEA approach. Nevertheless, the study did not investigate the factor influencing the TE of mills. In contrast (Wijesinghe and Weerahewa (2013) investigated TE of rice mills in the *Gampaha* district, Sri Lanka using SFA. The study found that the mean TE of the sample was 97.8% and no significant difference in TE between the millers with advanced machinery such as dryer, elevator and colour separator, and millers without such machinery. However, this field has a dearth of applying StoNED in any field of study, especially the rice milling industry since it is an essential industry converting paddy into rice.

Given the critical role of the rice milling sector in agricultural value chains and food security, and the potential for efficiency gains through technological advancements, this study is justified in its aim to rigorously assess the technical efficiency (TE) of this sector using the novel StoNED paradigm. The main objective of this study was to measure the TE of rice milling sector using newly innovated TE paradigm known as StoNED. The specific objective of the research as follows: Estimating (1) Significant factors of production on rice milling output. (2) Significant influential cost on the paddy milling process cost. (3) Core influential factors on TE of rice milling industry.

Methodology

Study area and data collection

This study was carried out in the *Ampara* District located Southeastern region of Sri Lanka. First, the details of rice millers were collected from 17 *pradeshiya sabhas*. Based on the details, there were more than 350 registered rice mills. A survey of rice mills was conducted from 102 randomly selected rice millers. The survey was conducted from January 2024 to April 2024 when the rice mills utilized the paddy produced under the *Maha* season. The survey collected information related to outputs and inputs from the mill records. Monthly rice output and the monthly production of rice byproducts such as broken rice, bran, and husk were considered as outputs. The input information such as labour hours, electricity, and paddy usage to produce the above outputs were also collected. Apart from the inputs and outputs details, the monthly cost of paddy, electricity and labour were gathered from the mill records. The capital expenditure was calculated as 5% annual depreciation of the cost of machines, and it was calculated for monthly expenditure. The TE scores of each rice mill were estimated separately for both input-output function and cost function. using GAMS software. The mean TE scores differences between these two functions were tested by an unpaired t-test. In addition, contextual variables such as milling capacity, land area of rice mill, and size of the mill were collected. Further, the socio-economic variables related to rice millers and the availability of additional rice processing units were also collected.

Estimation of TE scores

The present study estimated the efficiency of each mill using the input-output frontier (equation 1) and cost frontier (equation 2). The StoNED method of efficiency estimation was performed via two stages. In the first stage, parametric regression methods with Convex Nonparametric Least Squares (CNLS) were used to estimate the average inefficiency. Secondly, de-convoluted noise and inefficiency terms were used to estimate firm-specific inefficiencies. First, the CNLS regression was carried out to find the composite residual (ε_i^{CNLS}) by solving a multiplicative model of finite-dimensional quadratic programming (QP) proposed by Kuosmanen and Kortelainen (2012). Further, the contextual variables (z) was also directly incorporated into the objective functions (equation 1 and 2) as suggested by Johnson and Kuosmanen (2011).

$$
\begin{aligned}
&\min_{\alpha,\beta,\varepsilon} \sum_{i=1}^{n} (\varepsilon_i^{\text{CNLS}})^2 \\
&\text{subject to} \\
&y_i = \alpha_i + \beta_i^{'} x_i + \delta z_i + \varepsilon_i^{\text{CNLS}} \forall_i \qquad (1) \\
&\alpha_i + \beta_i^{'} x_i \le \alpha_h + \beta_h^{'} x_i \forall h,i \\
&\beta_i \ge 0 \forall_i
\end{aligned}
$$

where y_i *and* x_i are the output and inputs of the i^{th} rice mill. α_i, β_i are the intercept and slope parameters of inputs of rice of the rice mills[1]. Similarly, the linearized cost frontier model with contextual variables (z) of the rice mill was estimated via CNLS estimation (equation 2). The cost frontier model was linearized by taking the natural logarithms for both sides of the cost equation.

[1]The notation $\beta_i^{'} x_i = \beta_{i1} x_{i1} + \beta_{i2} x_{i2} + \dots\dots\dots + \beta_{im} x_{im}$, where β_{im} and x_{im} are parameter and m[th] input of i[th] rice mill.

$$\min_{\gamma,\beta,\delta,\varepsilon} \sum_{i=1}^{n} \varepsilon_i^2$$

$$s.t.$$

$$\ln x_i = \ln \gamma_i + \delta z_i + \varepsilon_i \forall i \quad (2)$$

$$\gamma_i = \beta_i' y_i \forall i$$

$$\gamma_i \geq \beta_h' y_i \forall h, i$$

$$\beta_i \geq 0 \forall i$$

Following the estimation of ε_i^{CNLS}, the expected value of inefficiency (μ) was estimated using two parametric approaches namely, the method of moments (MM) introduced by Aigner et al. (1977) and quasi-likelihood estimation developed by Fan et al. (1996). However, the present study used the MM approach where the estimators are unbiased and consistent (Greene, 2008). In the MM approach, the distribution for inefficiency term is assumed in half-normal distribution [$u_i \sim N^+(0, \sigma_u^2)$] and the noise is a standard normal distribution [$v_i \sim N(0, \sigma_v^2)$]. Based on the assumptions, the second and third central moments of the ε_i^{CNLS} distribution are given by

$$M_2 = \left[\frac{\pi - 2}{\pi}\right]\sigma_u^2 + \sigma_v^2$$

$$M_3 = \left(\sqrt{\frac{2}{\pi}}\right)\left[\frac{4}{\pi} - 1\right]\sigma_u^3 \quad (3)$$

After estimating the average inefficiency (μ) function using CNLS, the frontier of the production function can be estimated as the sum of $f(x_i) = g(x_i) + \mu$.

$$\hat{\phi}_{\min}^{StoNED}(x) = 1$$

$$\min_{\alpha,\beta}\{\alpha + \beta' x \mid \alpha + \beta' x_i \geq \hat{f}(x_i) \forall i = 1, \ldots.. n\} \quad (4)$$

Under the assumption of a normally distributed error term and a half-normally distributed inefficiency term, Jondrow et al. (1982) derived a formula for the conditional distribution of inefficiency u_i, given ε_i, and propose the inefficiency estimator as the conditional mean E(u_i | ε_i). Therefore, given the parameter estimate $\hat{\sigma}_u$ and $\hat{\sigma}_v$, we calculate the conditional expected value of inefficiency in equation 5.

$$E(u_i|\hat{\varepsilon}_i) = \frac{\hat{\sigma}_u\hat{\sigma}_v}{\sqrt{\hat{\sigma}_u^2 + \hat{\sigma}_v^2}}\left[\frac{\rho\left(\dfrac{\hat{\varepsilon}_i\hat{\sigma}_u}{\hat{\sigma}_v\sqrt{\hat{\sigma}_u^2+\hat{\sigma}_v^2}}\right)}{1-\Phi\left(\dfrac{\hat{\varepsilon}_i\hat{\sigma}_u}{\hat{\sigma}_v\sqrt{\hat{\sigma}_u^2+\hat{\sigma}_v^2}}\right)} - \frac{\hat{\varepsilon}_i\hat{\sigma}_u}{\hat{\sigma}_v\sqrt{\hat{\sigma}_u^2+\hat{\sigma}_v^2}}\right] \quad (5)$$

where ρ is the density function of the standard normal distribution N (0,1), Φ is the corresponding cumulative distribution function and $\hat{\varepsilon}_i$ is the error estimator of composite error term that can be defined as follows.

$$\hat{\varepsilon}_i = \hat{\varepsilon}_i^{CNLS} - \hat{\sigma}_u\sqrt{2/\pi} \quad (6)$$

The present study estimated the efficiency for two scales for both frontiers (input-output and cost frontier) known as TE for constant return to scale (TE_{CRS}) and TE for variable return to scale (TE_{VRS}) using GAMS software. The estimated mean TE scores from both input-output frontier and cost frontier were compared using an unpaired t-test to check the TE scores differences at a 5% significant level. Further, the factors influencing TE of rice mills were estimated using the following Tobit regression equation since the TE scores are truncated at zero and one.

$$TE_i = TE^* = \beta_0 + \beta_i Z_{ij} + v_i$$

$$if \;\; TE_i > 0 \; (or) \;\; TE_i = 0, if \;\; TE \leq 0 \quad (7)$$

Where, TE_i is the technical efficiency of the ith rice mill, TE^* is the latent variable. Z_{ij} expresses the jth factors influence TE of ith rice mill and v_i is the error term.

Results and Discussion

The mean outputs, inputs and cost of production for milling rice in the *Ampara* District is illustrated in Table 1. Monthly, 61% of rice were milled out of 15,081.45 kg of paddy, where the remaining included by broken rice (17%), bran (6%), and paddy husk (3%). Milling 100 kg of paddy could produce 65 kg of consumable rice and this finding is supported by Wijesooriya and Priyadarshana (2013) who conducted the study in the North-central, Central, and Southern provinces of Sri Lanka. Apart from the paddy input, millers consumed 2,900 units of electricity and 660 labour hours that was used to produce 123,467 kg of rice output every month. Considering the average monthly cost of production, 75% of the cost was accounted for paddy purchasing.

Table 1. Inputs, outputs and cost summary statistics of rice mills in Ampara districts

Variables	Mean	SE	Max	Min
Outputs				
Rice (kg/Month)	10,346.70	929.85	18,649.36	9,050.00
Brocken rice (kg/Month)	2,563.85	148.48	5,164.44	139.58
Bran (kg/Month)	904.89	61.87	2,008.39	79.76
Paddy husk (kg/Month)	452.44	37.12	1,147.65	49.85
Aggregated output (kg/Month)	14,267.88	1,177.32	26,969.84	9,319.19
Inputs				
Paddy (kg/Month)	15,081.45	1,237.37	28,691.33	997.00
Electricity usage (Unit/Month)	2,888.58	93.60	4,872.00	609.20
Labour (hours/Month)	662.35	32.84	1,560.00	240.00
Cost				
Cost of paddy (LKR/Month)	626,460.23	51,398.45	1,191,793.71	41413.84615
Electricity charge (LKR/Month)	36,107.24	11,816.83	60,900.00	7,615.00
Labour charge (LKR/Month)	68,672.12	34,377.06	163,800.00	23,364.00
Capital expenditure (LKR/Month)	55,916.67	49,266.08	208,333.33	3,750.00
Total cost (LKR/Month)	787,156.26	146,858.42	1,624,827.04	76,142.85

(Source: Survey Data, 2024)

In terms of the demographics, age of the rice millers was around 46 years with 12 years of experience. They attended a maximum of 3 training programs related to rice milling. Rice millers in this region were able to earn Rs. 107,529.00 per month. In addition, the land area for the rice mill was almost one acre with a building size of 5,450 square feet. The average milling capacity of rice mills in the *Ampara* District was 1,400 kg per hour (Table 2).

Table 2. Socio-economic characteristics summary statistics of rice millers in Ampara District

Variables	Mean	SE	Max	Min
Age (Years)	46.46	1.00	70.00	27.00
Rice milling experience (Years)	12.38	0.81	41.00	1.50
Number of trainings attended related to rice milling	0.76	0.08	3.00	0.00
Income from rice milling (LKR/Month)	107,529.41	6,776.71	325,000.00	40,000.00
Income from other sources (LKR/Month)	3,093.14	1,145.09	52,000.00	0.00
Milling capacity (kg/hour)	1432.55	39.28	700.00	2600.00
Area of rice mill (Acres)	0.94	0.05	0.1	2.5
Building area of rice mill (Square feet)	5,446.47	285.99	500.00	12,600.00

(Source: Survey Data, 2024)

Table 3 depicts the correlation between contextual variables and input variables. It revealed that there was no significant correlation between inputs and selected contextual variables. The milling capacity showed a significantly lower correlation with paddy input, electricity and capital expenditure. The significant positive correlation with electricity usage is consistent with studies highlighting energy consumption as a major input in rice milling, particularly for machinery operation and processing (Jittanit, et al., 2010) Similarly, the strong positive correlation with capital expenditure reflects the need for larger machinery, storage facilities, and overall infrastructure for higher capacity mills (Dawe, 2002). The insignificant correlation with labor might suggest that while larger mills process more, they may also employ more automated processes, leading to a less direct linear relationship with the total workforce compared to other inputs. Similarly, the land area of the mill showed a significantly lower relationship with capital expenditure.

Table 3. Correlation among contextual variables and input variables

Contextual variables	Inputs			
	Paddy Input	Electricity Usage	Labour Usage	Capital Expenditure
Milling Capacity	0.362**	0.223*	0.130	0.500**
Land area of Mill	0.193	0.045	0.115	0.461**
Size of the Mill	0.128	-0.125	0.151	0.171

(Source: Analyzed Survey Data, 2024; *, **, and *** indicate significance at 10%, 5% and 1% level respectively)

Table 4 discloses the efficiency measures estimated through input-output function and cost function. The estimated efficiency scores from the two functions were above 0.90 thus, the milling industry in the *Ampara* District was 90% efficient in producing rice and its byproducts from the optimum level of inputs. However, the mean efficiency scores estimated through both input-output function and cost function were significantly ($p<0.05$) different (Table 5). Therefore, the present study estimated the efficiency factors separately (Table 6 and 7). The scale of efficiency results revealed that on an average, rice mills were operated under the most productive size.

Table 4. Descriptive statistics for efficiency measures estimated from StoNED

Efficiency criteria	Input-output function			Cost function		
	Mean	Min	Max	Mean	Min	Max
CRS	0.93±0.003	0.84	0.98	0.91±0.004	0.82	0.96
VRS	0.95±0.004	0.86	1.00	0.93±0.004	0.84	0.98
Scale efficiency (TE_{CRS}/TE_{VRS})	0.98±0.000	0.97	0.98	0.98±0.000	0.97	0.98

(Source: Analyzed Survey Data, 2024)

Table 5. Mean Comparisons for TECRS and TEVRS Scores

TE estimation methods	Unpaired t- statistic (p-value) for TE_{CRS} score	Unpaired t- statistic (p-value) for TE_{VRS} score
(a) Input output function	4.059 (0.0001)	4.077 (0.0001)
(b) Cost function	Between (a) and (b)	Between (a) and (b)

(Source: Analyzed Survey Data, 2024)

Table 6. Factors affecting technical efficiency of rice milling: Input-output function

Variables	Input-output function					
	TE_{CRS}			TE_{VRS}		
	Coefficient	SE	p-value	Coefficient	SE	p-value
Age (Years)	0.0003	0.0003	0.394	0.0003	0.0004	0.380
Educational level (years)	0.004	0.004	0.303	0.004	0.004	0.426
Professional qualification (yes/No)	0.006	0.007	0.412	0.002	0.008	0.791
Experience in rice milling (Years)	0.0008**	0.0004	0.045	0.0008*	0.0005	0.091
Number of trainings attended	0.003	0.003	0.387	0.003	0.004	0.472
Other sources of income (Yes/No)	-0.009	0.011	0.369	-0.005	0.012	0.694
Area for paddy drying (feet square)	0.0001	0.0000	0.343	0.0001	0.0001	0.320
Average labour experience (Years)	0.003***	0.001	0.004	0.003***	0.001	0.001
Availability of dryer (Yes/No)	0.026***	0.006	0.000	0.030***	0.007	0.000
Availability of polisher (Yes/No)	0.008	0.007	0.269	0.013	0.009	0.159
Availability of weighing bridge (Yes/No)	0.015**	0.007	0.025	0.012	0.008	0.131
Availability of rice grader (Yes/No)	0.019	0.012	0.125	0.019	0.014	0.190
Availability of husk removing funnel (Yes/No)	0.004	0.008	0.629	0.008	0.009	0.385
Availability of transformer (Yes/No)	-0.005	0.006	0.400	-0.005	0.007	0.447
Availability of rice parboiling unit (Yes/No)	0.016***	0.006	0.009	0.021***	0.0068	0.004
Availability of auto paddy feeder (Yes/No)	0.012*	0.006	0.069	0.010	0.007	0.160
Availability of paddy cleaner (Yes/No)	-0.003	0.009	0.773	-0.007	0.104	0.488
Availability of paddy separator (Yes/No)	0.018**	0.008	0.023	0.018**	0.009	0.045
Availability of bucket elevator (Yes/No)	-0.016	0.017	0.355	-0.018	0.019	0.346
Availability of dryer own transport (Yes/No)	0.019***	0.007	0.004	0.023***	0.008	0.004
Constant	0.884***	0.026	0.000	0.896***	0.029	0.000
Log-Likelihood		256.87***			195.19***	
Likelihood ratio chi^2 (20)		127.30			131.56	
Prob> Chi^2		0.000			0.000	

(Source: Analyzed Survey Data, 2024)

Table 7. Factors affecting technical efficiency of rice milling: Cost function

Variables	Cost function					
	TE_{CRS}			TE_{VRS}		
	Coefficient	SE	p-value	Coefficient	SE	p-value
Age (Years)	0.0002	0.0003	0.486	0.0003	0.0003	0.394
Educational level (years)	0.004	0.004	0.306	0.004	0.004	0.303
Professional qualification (yes/No)	0.004	0.007	0.518	0.006	0.007	0.412
Experience in rice milling (Years)	0.001*	0.003	0.059	0.001**	0.0004	0.045
Number of trainings attended	0.003	0.003	0.373	0.003	0.003	0.387
Other sources of income (Yes/No)	-0.009	0.010	0.382	-0.010	0.010	0.369
Area for paddy drying (feet square)	0.0001	0.0001	0.332	0.0001	0.0001	0.343
Average labour experience (Years)	0.002***	0.0007	0.003	0.002***	0.0008	0.004
Availability of dryer (Yes/No)	0.026***	0.005	0.000	0.026***	0.006	0.000
Availability of rice polisher (Yes/No)	0.007	0.007	0.331	0.005	0.007	0.269
Availability of weighing bridge (Yes/No)	0.015**	0.006	0.019	0.015**	0.007	0.025
Availability of rice grader (Yes/No)	0.018	0.012	0.136	0.019	0.012	0.125
Availability of husk removing funnel (Yes/No)	0.003	0.008	0.672	0.004	0.008	0.629
Availability of transformer (Yes/No)	0.006	0.006	0.328	0.005	0.006	0.400
Availability of rice parboiling unit (Yes/No)	0.017***	0.006	0.003	0.157***	0.006	0.009
Availability of auto paddy feeder (Yes/No)	0.013**	0.006	0.049	0.012*	0.006	0.069
Availability of paddy cleaner (Yes/No)	-0.003	0.009	0.778	-0.003	0.009	0.773
Availability of paddy separator (Yes/No)	0.018**	0.008	0.021	0.183**	0.008	0.023
Availability of bucket elevator (Yes/No)	-0.016	0.016	0.339	-0.016	0.168	0.355
Availability of own transport (Yes/No)	0.018***	0.006	0.007	0.192***	0.007	0.004
Constant	0.867***	0.025	0.000	0.884***	0.026	0.000
Log-Likelihood		260.02***			256.87***	
Likelihood ratio chi^2 (20)		131.49			127.30	
Prob> Chi^2		0.000			0.000	

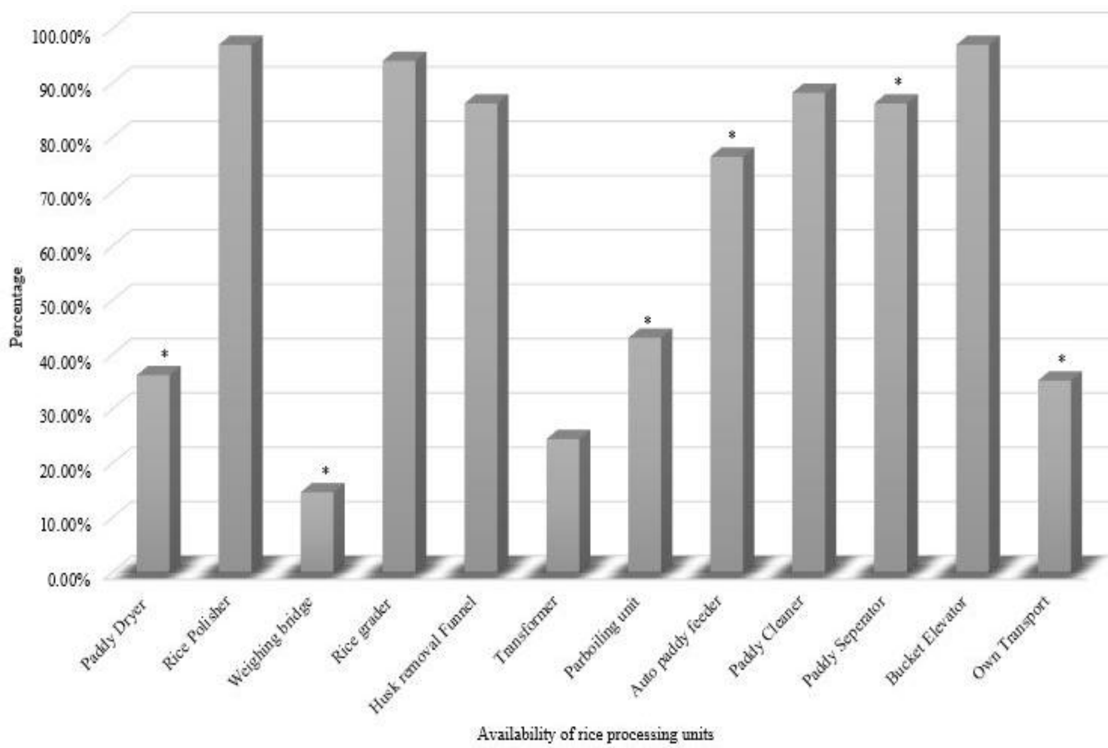
(Source: Analyzed Survey Data, 2024)

The level of significance and the factors which determine the TE of rice milling were comparatively similar based on the results shown in Tables 6 and 7. However, the level of significance varies according to the scale (TE_{CRS} and TE_{VRS}) used in the functions. Considering the socio-economic characteristics of rice millers, the experience of rice millers and the labours significantly ($p<0.05$) influenced the TE scores estimated from the input-output and cost functions. The TE scores of rice milling were positively increased by 0.001 and 0.003 through the marginal increment of the aforementioned socio-economic factors. Vitally the availability of additional processing units had a significant impact on the TE of rice mills. Thus, the availability of paddy dryer, weighing bridge, parboiling unit, paddy feeder, paddy separator, own transport was the important rice milling processing units that influence the TE.

The rice mills with paddy dryers had significantly increased (~0.03) TE than the miller without paddy dryers. This is obvious as millers without paddy dryers used cement flour, which requires more time for drying paddy up to 8 to 12 % moister content. Similarly, the mills owned weighing bridge had significantly ($p<0.05$) increased TE by 0.02. Since the rice mills do not have weighing bridges, they need to send their transport vehicle to the weighing bridge before and after loading paddy to measure the weight of paddy. This activity could delay the rice milling process and incur high cost. Parboiling is the hydro-thermal treatment for improving the self-life and organoleptic properties of rice.

Similarly, this process reduces the nutrient loss during rice polishing and the breakage of rice (Arendt & Zannini, 2013). Those who used parboiling units were technically more efficient than the millers who practiced the manual parboiling process. The TE was higher in rice mills that used auto feeders and paddy separating devices, at 0.01 and 0.02 respectively. Importantly, the availability of own transportation facilities provided increased TE scores by 0.02. Rather than renting out a vehicle for rice distribution and paddy supply, the availability of own vehicles increases the efficiency of the paddy input supply chain and rice distribution to wholesale and retailers.

Less than 40 % of the rice millers used paddy dryers, weighing bridges, and own vehicles for paddy supply and rice distribution (Figure 1). Because capital and maintenance costs for paddy dryers, weighing bridges, and vehicles are higher for small and medium scale rice mills. In the case of large-scale mills, the marginal cost for rice production is low as their rice production rate is higher. About 50% of the rice millers owns parboiling units and it caused a significant positive impact on TE. More than 75 % of rice millers utilized auto paddy feeders and paddy separators during rice milling.



Conclusion

This paper investigated the efficiency levels of the Sri Lankan rice milling industry by applying a new approach called Stochastic Nonparametric Envelopment of Data (StoNED), which is a combined method of non-parametric and parametric approaches. The results of the technical efficiencies indicate that the rice milling industry achieved more than 90% efficiency in rice milling. The estimated efficiency scores by input-output function and cost function were significantly different from each other. However, the factors impacting the efficiency of the rice milling industry via Tobit regression were similar in both functions. The empirical results show that the experience of owners and labours in rice milling were the significant socio-economic factors in determining the rice milling efficiency. Further, the availability of paddy dryers, weighing bridge, parboiling units, auto paddy feeders, paddy separators, and own transports were the important technical aspects that significantly influence the efficiency of producing rice. Most of these millers used auto paddy feeders and paddy separators in rice milling. However, a considerable amount of rice millers used to weigh bridges and own transportation while only half of the millers utilize paddy dryer and parboiling units. The present study recommends that providing practical oriented training to rice millers and the workers would increase the exposure and familiarity in rice milling could raise the efficiency. Further, the increasing capital investment by rice millers or providing credit facilities to implement processing units were identified as significant technical aspects in improving the TE of rice mills.

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