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Research article

How productive are rice farmers in Sri Lanka? The impact of resource accessibility, seed sources and varietal diversification☆

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ABSTRACT

This paper assesses the impact of resource accessibility, seed sources and varietal diversification on the production efficiency of Sri Lankan rice growers using farm and household level survey data. The empirical results show that there are opportunities for average Sri Lankan rice farmers to further improve production efficiency by up to 30%. Among the variables, those related to resource accessibility, age, migration, income sources and agricultural training are all found to affect production efficiency. Furthermore, we find that households relying only on their own saved seeds are less efficient compared to those who had purchased seeds from markets. In addition, this study indicates that varietal diversification significantly reduces production efficiency.

1. Introduction

Agricultural development is one of the most powerful tools used in the battle for self-subsistence, poverty alleviation and employment generation in many developing countries and is typically the cornerstone of such economies (Aryal and Marenya, 2021; Maïga et al., 2020). In 2019, approximately 884 million of the global population was employed in agricultural activities including fishing, and this percentage contributed to 4% of global GDP (FAO, 2020; World Bank, 2020). According to the projection of the Food and Agriculture Organization (FAO, 2020), food insecurity will affect 26% of the global population in 2021 compared to the 9% affected in 2019. In addition, the share of the agricultural sector's contribution to global GDP has declined from 4.3% to 3.3% for the period 1970 to 2013 (FAO, 2015). According to the Central Bank of Sri Lanka (CBSL, 2020), there has been a noticeable decline in the contribution of the agricultural sector to GDP, which has fallen from 47% to 7% between 1950 and 2019 in Sri Lanka. According to the FAO (2020), subsistence farmers are the most affected due to climate change and are also likely to be severely affected by the COVID 19 pandemic. Moreover, poor performance is associated, in particular, with crop diversity, adoption of new technology, post-harvest losses and inefficient use of resources and underutilized crop varieties – all evident in the agricultural sectors of developing countries (FAO, 2020).

A growing body of literature has revealed that productivity can be enhanced either by adopting new technology or by improving the efficiency of crop production (Alauddin et al., 2021; Lampach et al., 2021; Idiong, 2007; Mahama et al., 2020). Studies show that technical efficiency (TE) is one of the key elements in determining agricultural production (see, Adom and Adams, 2020; Battese and Coelli, 1995; Ho et al., 2017; O'Donnell et al., 1999). According to Farrell (1957), the TE of a firm is its ability to produce the maximum output from a given set of inputs and technology (an output-oriented approach). Alternatively, the TE of a firm can be described as the ability to minimize the use of inputs to produce a given level of specific output (input oriented).

The determinants of small holder farmers TE identified in the literature are broadly related to human capital, physical capital, institutional capital and environmental characteristics. Farmers' human capital includes variables such as farmers' age, education and family size. The effects of these variables on TE have been extensively studied and have resulted in mixed findings (Lampach et al., 2021; Tesfaye and Tirivayi,

☆ The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy and/or ethical restrictions.

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2020). Rahman and Rahman (2009) in a Bangladeshi study reported a positive impact of age, education and family size on rice farmers' TE. Tan et al. (2010) found that age and education have positive effects on the TE of rice production in South East China. Diverse crop cultivation associated with age suggest that experienced farmers are more likely to choose diverse crops (Tesfaye and Tirivayi, 2020). In addition, experienced farmers are more open to the adoption of multiple technologies and are technically more efficient. A similar finding shows a positive impact of education on the TE of rice farmers in Vietnam (Khai and Yabe, 2011). Small family size was shown to have a negative impact on TE. Moreover, the elements of physical capital such as farm size and household assets have also been revealed to have influenced farmers' TE variations (Chen et al., 2010; Manjunatha et al., 2013).

Efficiency variations between farms can also be explained by the farming household's institutional capital such as access to credit (Chiona et al., 2014; Tan et al., 2010) and extension services (Solis et al., 2009). A study by Ahmad et al. (2021) reveals that timely and appropriate use of inputs received by farmers positively improves farm efficiency. Furthermore, a few studies have revealed that environmental characteristics such as climatic conditions and land quality are the determinants of farmers' TE. Over the long term, environmental and technical efficiency can be improved by the use of high-quality inputs (Lampach et al., 2021).

An issue that has received much less attention in the literature is the link between farmers' TE and variables such as seed sources and varietal diversification. Several studies have found that implementing crop diversity in the face of repeated climate shocks[1] is an efficient risk management and consumption smoothing technique (Tesfaye and Tirivayi, 2020; Lampach et al., 2021). A limited number of studies that touch on this relationship include that of Chiona et al. (2014) who found a positive impact of the use of hybrid seed on maize producers' TE in Zambia and that of Manjunatha et al. (2013) who reported that varietal diversification is positively and significantly associated with the efficiency of Indian farms. A study in Ghana shows that multi-crops are more efficient than single crops in coco farming (Ofori-Bah and Asafu-Adjaye, 2011). Other studies show that crop diversification improves efficiency and minimizes the impacts of climate change (Hossain et al., 2019; Khanal et al., 2018).

Given the above background, this study aims to examine smallholder farmers' technical efficiency in rice production in Sri Lanka. More than 25% (1.8 million) of the total labor force is engaged in agricultural activities in Sri Lanka (CBSL, 2020) where rice is one of the most important cereal crops accounting for about 16% of the total land area and contributing 7% to agricultural GDP (CBSL, 2020). Rice is generally produced in two cropping seasons, the 'Yala' and the 'Maha' which are related to the dry and wet seasons. The majority of the cultivation is based on irrigated agriculture. Approximately 45% of this cultivated area is fed by major irrigation schemes, 25% by minor irrigation schemes and 30% is rain-fed. The total production of rice was 4.1 million metric tons in 2019/2020 (Ayoda and Mark, 2020). It is important to note that cultivation of rice is not just an economic activity but a way of life that has shaped Sri Lankan society and culture for centuries (see, Figure 1). The per capita consumption of rice is 107kg per person per annum, and this provides 45% of the total calories and 40% of the total protein requirements for Sri Lanka's population (Liu et al., 2020; Senanayake and Premaratne, 2016). Given the increasing demand for rice in the country, increased rice productivity can, potentially, improve Sri Lanka's food security situation and the standard of livelihoods of a large percentage of the country's population. At present, Sri Lanka imports 0.7 million metric tons of rice (US$400 million) annually due to the growing demand for rice (Rathnayake et al., 2020).

[1] Jawid and Khadjavi (2019) show that one of the adaptation measures employed by farmers in Afghanistan due to climate change is the use of improved seed varieties.

A number of studies have assessed agricultural productive efficiency in Sri Lanka (Athukorala and Wilson, 2012; Gedara et al., 2012; Karunarathna and Wilson, 2017). However, very little is known about the impact of resource accessibility, seed sources and varietal diversification on farmers' technical efficiency in crop production. The resource accessibility here is defined as the farmers' access to agricultural income sources, education, training, markets and credit sources. It is assumed that easy access to such resources and services would increase TE. This study, therefore, contributes to the existing literature in two ways. First, it extends the literature on agricultural productive efficiency and provides empirical evidence for policy makers on ways to improve efficiency in rice production. In this way, this study supports the country's nutritional and food security policies. Second, this study investigates the impact of resource accessibility, seed sources and varietal diversification on rice farmers' TE.

2. Methodology

2.1. Study area and data collection

The data used for this study were collected in a face-to-face survey in the Batticaloa district of Sri Lanka (see, Figure 2). This district is located in the Eastern province of the country and comprises of 14 Divisional Secretariats (DS). Batticaloa is the third largest rice producer in the country contributing to around 5% of the national production (CBSL, 2020). Agriculture is the most important source of livelihood for the majority of the people in this district. Out of the 14 DS divisions in Batticaloa, farmers in 10 DS divisions are involved in rice cultivation. The district is positioned in the country's dry zone where the mean annual temperature and rainfall are 27 °C and 1,756 mm, respectively. Such conditions are particularly conducive to rice cultivation (CBSL, 2020). Moreover, rice cultivation is mainly carried out under rain-fed conditions since only about 35% of the total cultivatable area has year-round irrigation water. The dominant soil type in the Batticaloa district is the alluvial soil in the flat terrain that is suitable for rice cultivation. However, the lack of water in the soil is one of the constraints for rice production in the region. According to Sugirtharan et al. (2013) land degradation has had both direct and indirect effects on farming communities in Sri Lanka, including the reduction of crop yields, and increasing soil erosion and sedimentation. Besides, a study by Detruck et al. (1993) found that the sulfate-rich soils in Sri Lanka reduces paddy yields. However, the study suggests that crop management could potentially mitigate the conditions that cause reductions in rice yields. The dry zone of Sri Lanka is most vulnerable to poor organic C which influences soil fertility (Nayakekorale, 2020). Moreover, salinity reported in coastal areas in Sri Lanka results in large reductions in productivity and also increases soil degradation (Mapa, 2020; Pavithra et al., 2019).

The data for this study were collected utilizing three methods viz: a pilot study, a focus group discussion, and a household survey. The pilot

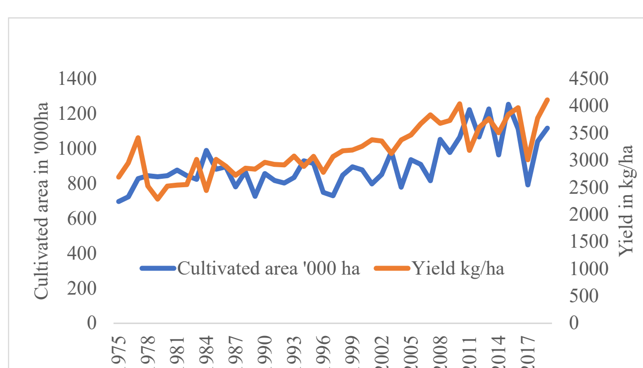

Figure 1. Trends in rice cultivated areas and yields in Sri Lanka.

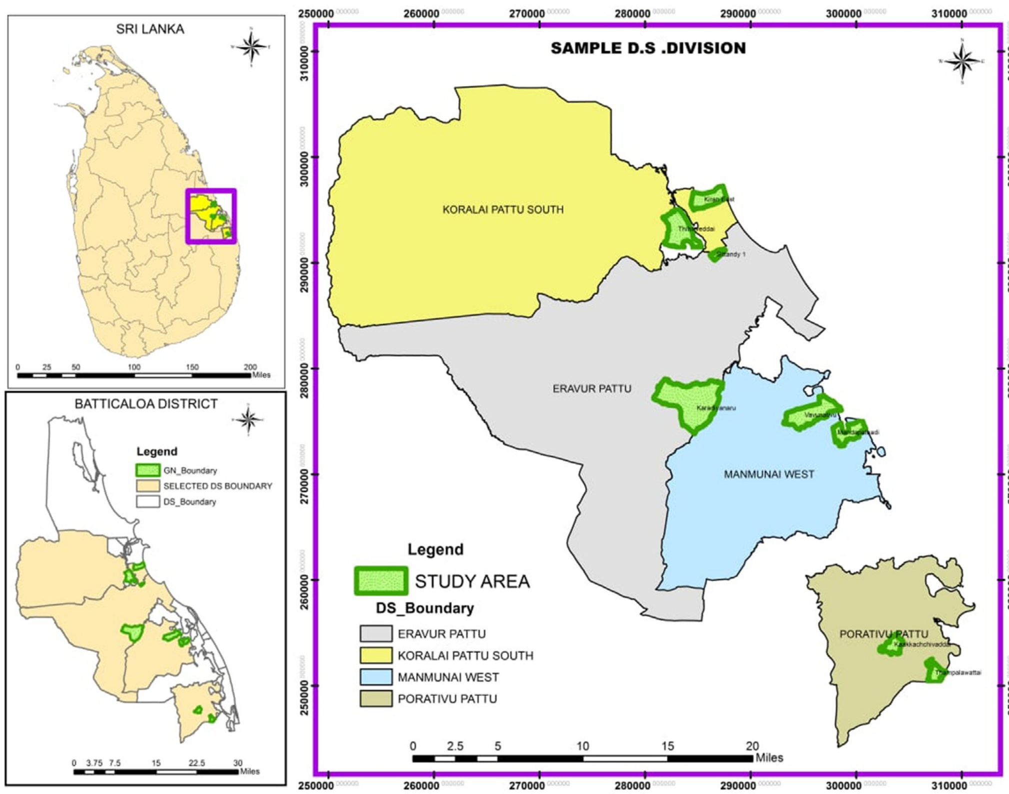

Figure 2. Map of Sri Lanka showing the study areas. Source: Authors' compilation, 2021.

survey was conducted with 54 farming households in the study area. We used two focus group discussion with farmers (6–8 farmers including male and female farmers) to examine the farming practices of the region. The selection of farming households for this study involved three stages. First, we selected four intensive rice producing DS divisions, namely, Koralaipattu South, Earvurpattu, Manmunai West and Porativupattu. Selection was based on secondary data available at the district secretariat in Batticaloa.

In the second step, we selected two (2) rice producing villages from each DS division based on the number of farming households involved in rice production. The respondents for the final survey were chosen by randomly selecting 250 rice growing farming households from the four selected DS divisions. The survey comprised of a semi-structured questionnaire consisting of three sections. Section one covered background information and the respondents' socio demographic characteristics. Section two sought household level information on the use of inputs and outputs of farming. Section three consisted of questions related to institutional support for farming. The field survey was conducted using five well-trained enumerators who were university undergraduates. A half-day of training was provided to familiarize them with the questionnaire. The interview was conducted in the local Tamil language and took approximately 40 min to complete. From the 250 survey respondents, we received 238 useable responses for our analysis.

2.2. Technical efficiency estimation

We used stochastic frontier analysis (SFA) framework to estimate technical efficiency. The SFA model was first developed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) and has been increasingly used to estimate TE (Kompas and Che, 2006). SFA has the ability to separate the effect of noise from the effect of inefficiency compared to other efficiency measures. Moreover, SFA generates good results for a single output and multiple inputs. In a meta-analysis of TE in the agricultural practices of developing countries Thiam et al. (2001) found that when comparing stochastic and deterministic frontiers, there was no significant difference in their estimates of TE across studies. In this study, we use SFA, given that rice production is an example of a single output and multiple input production and given that rice production in Sri Lanka is subject to heterogeneous environmental factors such as weather which are beyond the control of farmers. Moreover, given that farmers are comparatively less educated, it is accepted that respondents may not answer some of the questions correctly leading to measurement errors affecting estimated efficiency scores. Hence, we employed SFA to measure the TE of rice farmers in Sri Lanka.

Many studies have used a second stage regression method to determine farm specific attributes in an attempt to explain the observed differences in efficiency among farms. However, Battese & Coelli (1995) directly incorporated farm specific characteristics in their efficiency model. This model allows the estimation of farm specific sources and the factors explaining efficiency differentials among farms in a single procedure. We adopted this model and used Frontier 4.1 software (Coelli 1996) for the analysis. The general form of the model is:

$$Y_i = x_i\beta + (V_i - U_i) \quad i = 1, 2, \ldots N \tag{1}$$

where,

- Y_i is the logarithm of the production of farm i
- x_i is the vector of the logarithm of input quantities used by farm i
- β is the vector of unknown parameters to be estimated
- V_i are normally distributed random variables with zero mean and variance σ^2 and which represent random shocks such as exogenous factors, measurement errors, omitted explanatory variables, and statistical noise.
- U_i are non-negative random variables associated with inefficiency in production, which are assumed to be independently distributed as truncations at 0 of the N (mi, σ^2u) distribution; where:

$$m_i = z_i\delta \tag{2}$$

- mi is the inefficiency of farm i
- z_i is the vector of variables which may influence the inefficiency of a farm, and
- δ is a vector of parameters to be estimated.

The maximum likelihood method is used to estimate the unknown parameters of the stochastic production frontier and the inefficiency effects. Following Battese and Coelli (1995), the likelihood function is expressed in terms of the variance parameters, $\sigma^2 = \sigma^2 v + \sigma^2 u$ and $\gamma = \sigma^2 u/\sigma^2 v$.

The measures of TE relative to the production frontier are defined as:

$$EFFi = E(\exp(Yi^*)|Ui,Xi)/E(\exp(Yi^*)|Ui = 0,Xi), \tag{3}$$

where EFF_i is the technical efficiency of the farm i. and Yi* is the production of farm i. In the case of the production frontier, EFF_i will take a value between zero and one. The efficiency of production of farm i, given the level of inputs, is defined by exp (-Ui), which is a log form dependent variable.

A functional form for the production function must be selected to estimate the stochastic production model represented by Eq. (1). The most commonly used functional forms of production efficiency for agricultural farms are Cobb-Douglas and transcendental logarithmic (Thiam et al., 2001) forms. In this study, we employed the Cobb-Douglas functional form to characterize agricultural technology due to its computational feasibility. Moreover, several studies have employed the Cobb-Douglas production function in analyzing technical efficiency in agriculture (Battese and Coelli, 1992; Binam et al., 2004; Khanal et al., 2021; Mayen et al., 2010).

The Cobb-Douglas functional form is expressed as:

$$lnY_i = \beta_0 + \sum_{j=1}^{5} \beta_j \, lnX_{ij} + V_i - U_i \tag{4}$$

where, Y is the output variable, Xij are the 5 input variables included in the study, Vi is the random noise and Ui is the inefficiency term.

Selection of variables related to inputs, output and inefficiency followed the existing literature (Adom and Adams, 2020; Chen et al., 2010; Gedara et al., 2012; Rahman and Rahman, 2009). Moreover, the selected variables were based on the study site context. The variables were discussed in the pilot study and focus group discussions to check their importance in the study site context. The output variable is measured as the total rice produced by households expressed in kilograms (kg). Thus, the output included the quantity of rice that is both consumed and sold by the individual households. To better estimate production, we asked the respondents to report inputs and outputs separately for each plot of rice they cultivate. The plot specific inputs and outputs were added to obtain the total inputs and outputs for the household. Inputs included the area of land under rice cultivation measured in hectares, labour used in rice production measured in man-days, the quantity of fertilizers used measured in kg, the quantity of seed used measured in kg and the duration of tractor use in numbers of hours.

The study's inefficiency effects model included a number of variables representing resource accessibility, seed sources and varietal diversification. These variables are defined in Table 1. Variables related to resource accessibility include age of the head of the household - which is taken as a proxy for farming experience - educational attainment, family members' out-migration status, income sources, distance to the market, access to credit and seed sources. Similarly, variables related to varietal diversification include varietal richness (measured as the number of rice

Table 1. Descriptive statistics of the variables included in the model.

Variable		Definition	Mean ± Standard deviation
Production		Rice production (kg/ha)	3876.235 ± 1169.092
Land		Area under rice cultivation in hectares	5.227 ± 4.250
Labour		Labour used per hectare (days)	30.172 ± 23.229
Tractor		Duration of tractor use per hectare (hours)	9.885 ± 13.515
Seed		Seed used per hectare (kg)	268.055 ± 175.609
Fertilizer		Chemical fertilizers used per hectare (kg)	230.284 ± 287.814
Resource accessibility	Age	Age of farmer in years	51.640 ± 10.771
	Education	Household heads' education in number of years of schooling	8.180 ± 3.352
	Migration	Dummy = 1 if any member of the family had migrated to other places for work for more than 3 months in the previous year, 0 otherwise	0.630 ± 0.492
	Income source	Dummy = 1 if the household had only agriculture as their source of income, 0 if they had multiple sources	0.710 ± 0.455
	Market distance	Distance from house to market (km)	10.508 ± 6.024
	Credit	Dummy = 1 if the household had access to credit, 0 otherwise	0.450 ± 0.498
	Training	Dummy = 1 if any member in the household had received training related to agriculture in the last five years, 0 otherwise	0.810 ± 0.284
Varietal diversification	Varieties	Number of rice varieties cultivated last year	2.360 ± 1.903
	Hybrid/improved	Dummy = 1 if household also cultivated hybrid/improved rice varieties, 0 otherwise	0.460 ± 0.530
Seed sources	Seed source	Dummy = 1 if household had only used their own saved seed, 0 if seeds were purchased from the market	0.180 ± 0.389

Number of observations ($n = 238$).

varieties cultivated by the household) and the adoption of hybrid or improved varieties by the household. In addition, we included a variable ‘seed source’ measured as a dummy variable which takes the value 1 if the household uses its own saved seed only and 0 if seeds are purchased from the market.

Several variables pertaining to biophysical factors such as soil type, rainfall, and temperature were employed in the model. However, very low variability was observed among the sample households for those variables. In addition, some other explanatory variables were included in the questionnaire such as access to agricultural extension services and membership in agricultural related local institutions. However, in our sample data we found a strong correlation between extension services and training, membership and access to credit. Extension and membership were, therefore, excluded in the analysis in favour of training and credit.

Once the stochastic production frontier is estimated, we compare the technical efficiency scores between different groups of farmers. For this purpose, we performed the Kruskal-Wallis test (Kirkley et al., 1995; Le et al., 2017) and examine the statistical significance differences between the distributions of variables that are found to significantly affect technical efficiency.

3. Results and discussion

3.1. Descriptive statistics

Table 1 presents descriptive statistics for the surveyed households. The average land area under rice cultivation was 5.23 ha and on average, a household produced 3,876 kg of rice per hectare using, on average, 30 days of labour, 10 h of tractor time, 268 kg of seed and 230 kg of chemical fertilizer. The average age of the head of the household was 52 years with an average of 8 years of formal schooling. The average distance from house to input market was 10km, which means that farmers need to travel a long distance to buy their inputs and sell their output. As a result, they have to bear considerable transportation costs in their production process. In addition, less than half the farmers (45%) have access to credit facilities, indicating that rice farmers in Sri Lanka face difficulties in accessing financial capital. This lack of finance has been reinforced by financial institutions requiring farmers who wish to obtain loans to provide guarantees from two people receiving a monthly salary. Hence, tough conditionality imposed by these institutions has further hampered access to cultivation loans.

Some 63% of the households had at least one family member working away from their home district. This provides the prospect that farming households could obtain state-of-the-art farming information and off-farm working opportunities through this family member. Only 18% of farmers used their own saved seeds, whereas the rest purchased their seed inputs from the market. This finding is supported by a research study that indicates that the majority of farmers in developing countries have limited storage facilities (Bhanot et al., 2021). About 46% of the respondents reported that they had cultivated hybrid and/or modern rice varieties in addition to traditional varieties. On average, households cultivated more than 2 varieties of rice in the sample area. The results show that 71% of households relied only on agriculture for household income. 81% reported that at least one of their family members had received training related to agriculture in the last five years.

Table 2. Maximum likelihood estimates of the stochastic production frontier with technical inefficiency determinants.

Production frontier	Coefficient (Standard error)
Constant	4.851*** (0.322)
Land	0.192*** (0.049)
Labour	0.470*** (0.074)
Tractor	0.102*** (0.035)
Seed	0.132*** (0.036)
Fertilizer	0.173*** (0.047)
Scale elasticity	1.069
Technical inefficiency determinants	
Age	-0.095*** (0.026)
Education	-0.065 (0.066)
Migration	1.192*** (0.137)
Income source	-2.736*** (0.204)
Market distance	0.046 (0.034)
Credit	-1.045 (0.771)
Training	-1.772* (1.008)
Seed source	1.825** (0.825)
Varieties	0.475*** (0.095)
Hybrid/improved	-2.394*** (0.268)
Sigma-squared	4.190*** (0.732)
Gamma	0.790*** (0.002)
Observations	238
Log likelihood	-163.064
LR test of the one-sided error	253.078

Note: Standard Errors are reported in parenthesis. ***, ** and * denotes 1%, 5% and 10% statistically significant levels.

3.2. Technical efficiency estimates

The maximum likelihood estimates for the estimated Cobb Douglas model are presented in Table 2. The results show that the estimated mean output elasticities of all five inputs in the model were positive and significantly different from zero ($P < 0.01$), indicating a positive relationship between the input variables and rice production. Results indicate that labour is the most important of the five factors considered. They reveal that a 1% increase in labour raises rice production by 0.47%. This is equivalent to an increase in rice production by 60 kg/ha by increasing an additional labour day. Similarly, a 1% increase in land and fertilizer could increase rice production by 0.19% and 0.17%, respectively. The sum of the first-order coefficients of the five inputs - which is referred to as the scale elasticity - reveals increasing returns to scale. This suggests that for the farming households under study, an increase in all inputs of a certain proportion would result in a more than proportionate increase in output. The variance parameter γ is 0.79, which is significantly different from zero and indicates that 79% of the error variation in the production function was due to inefficiency.

Table 3 shows the summary of statistics for TE. We found the mean TE score to be 0.71 with a standard deviation of 0.22. These findings indicate that by increasing TE, rice farmers in Sri Lanka can increase their production by 29% (i.e. about 1125 kg/ha) at the existing level of inputs and technology. The results also show that only 40% of the households attained an efficiency level of more than 80%, indicating that a large percentage of farmers can increase their rice production by improving efficiency (see, Table 3). The mean TE of rice farms in this study is low, but comparable to those from other studies in Asian countries. For instance, the mean TE of rice farmers is found to be 81% in Vietnam (Khai and Yabe, 2011), ranges from 80% to 91% in South-East China (Tan et al., 2010), is 83% in India (Tadesse and Krishnamoorthy, 1997), between 74% and 67% in urban and rural areas in Nepal (Piya et al., 2012) and is 72% in Sri Lanka (Gedara et al., 2012). In the next section, the variables affecting technical efficiencies are discussed.

3.3. Technical efficiency determinants

The results indicate that the variables included in the TE model are important in explaining the levels and variations in agricultural production in Sri Lanka (see, Table 4). The Battese and Coelli (1995) model used technical inefficiency scores (i.e. 1 – TE) as the dependent variable and regressed this against the explanatory variables included. Thus, the

Table 3. Technical efficiency distribution.

Range of technical efficiency	Frequency	Percent (%)
<0.30	20	8.41
0.30–0.40	03	1.26
0.40–0.50	07	6.94
0.50–0.60	16	10.72
0.60–0.70	17	7.14
0.70–0.80	69	24.99
0.80–0.90	93	35.08
0.90–1.0	13	5.46
Total	238	100
Mean of TE scores	0.71	
Standard deviation of TE scores	0.22	

negative coefficient (in Table 2) indicates a positive effect on technical efficiency. Among these variables, those related to resource accessibility, education, distance to the market and access to credit services do not seem to have a significant role in improving efficiency. The age of the head of the household has a negative effect on inefficiency, which indicates that older farmers are more efficient at rice production. This is consistent with the other findings that older farmers are more experienced and hence contribute positively to technical efficiency (Tan et al., 2010; Piya et al., 2012). The results corroborate the findings of Tesfaye and Tirivayi (2020) and Anang and Asante (2020) in their Ugandan and Ghanan study, which indicated that older farmers are technically more efficient than their younger counterparts.

The effect of migration status on technical inefficiency is found to be positive, which indicates that households in which any members of the family migrate outside the district tend to be less efficient (4%) in rice production. This finding is consistent with Anang and Asante's (2020) study of farm household access to agricultural services in northern Ghana. Nguyen et al. (2019) in their paper on the impact of migration on crop productivity find that migration without remittances decrease farm labour productivity growth and crop diversification of rural households. Our finding also confirms the results of a Burkina Faso study by Wouterse (2010) and a Nepalese study by Khanal (2013) which showed that even though migration provides households with needed liquidity support, TE does not improve. This negative association between outmigration of family members and efficiency in crop production can be explained by the fact that outmigration leads to a shortage of family labour to work on the farm, leading to poor management of farmlands. Our finding that labour is the most important input among all the inputs in rice production further supports this result. There may, therefore, be a need to create a policy environment that motivates people to become involved in farming.

The coefficient of the variable 'income source' is negative and significant, suggesting that households which had only agriculture as a source of income are more efficient in rice production compared to those with multiple sources of income. Results revealed that households involved only in agricultural activities (12%) are more efficient than those which had off-farm sources of income as well. This result reinforces the findings of Anang and Asante (2020), Coelli et al. (2005) and Rahman and Rahman (2009). These researchers find that Bangladeshi farming households which have opportunities for off-farm work and access to non-agricultural income have reduced TE. However, the current finding is not in line with a Taiwanese study by Chang and Wen (2011) and with the Central American study of Solis et al. (2009), both of which found that involvement in off-farm work is not necessarily associated with lower TE. Moreover, Kibaara (2005) in Kenya and Zhang et al. (2016) find a positive impact of off-farm employment on the level of farm technical efficiency.

Similarly, the variable 'training' has a negative and significant association with inefficiency. This indicates that households receiving training related to agriculture in the last five years are more efficient compared to those which did not receive such training. This finding is consistent with the study of Lampach et al. (2021) in Vietnam, which found that farmers participating in training on the integrated approach of plant protection measures achieved significantly higher efficiencies than those that did not. The positive association of human capital such as training and agricultural knowledge with farmers' efficiency in crop production is consistent with the Central American study of Solis et al. (2009).

The variable 'seed source' is positively and significantly associated with TE. This suggests that households which only relied on their own saved seed are less efficient compared to households that used seed bought from the market. This indicates that farmers' saved seed does not perform as well as seed bought from the market. This in turn suggests a

Table 4. Summary of results of technical efficiency scores by household characteristics.

Characteristics	Mean	Standard deviation	Significance[+]
Migration status			P = 0.098*
Yes		0.220	
No		0.221	
By income sources			P = 0.002**
Only agriculture		0.212	
Multiple sources		0.229	
By training			P = 0.042*
Yes		0.212	
No		0.275	
By number of varieties			P = 0.091*
Few (<2) (n = 175)		0.222	
More (>2) (n = 63)		0.219	
By seed sources			P = 0.000***
Only used own saved seed		0.274	
Also buy from market		0.198	
Types of varieties			P = 0.000***
Also grow hybrid varieties		0.186	
Only local		0.271	

[+] Level of significance was determined based on Kruskal-Wallis test.
***, ** and * denotes 1%, 5% and 10% statistically significant levels.

need for farmers' capacity building in quality seed production and storage. Another potential reason for the lower efficiency of farmers relying on their own saved seed could be that farmers give less attention to farm management practices when they use fewer inputs purchased from the market and vice versa. The finding that seed sources and training both have positive effects on TE indicates the importance of quality seed production for farmers in the study area.

The positive and significant coefficient of the variable 'varieties' implies that households that grow a greater number of rice varieties are less efficient compared to households cultivating fewer rice varieties. Our results support the findings of Llewelyn and Williams (1996) and Haji (2007) who conclude that crop diversification significantly reduces TE in Indonesian farms and economic efficiency in Ethiopian farms. However, our results are at odds with the findings of Lampach et al. (2021) who found that seed varieties significantly improve land productivity. Similarly, Coelli & Fleming (2004), Manjunatha et al. (2013), Rahman and Rahman (2009) found that crop diversification significantly improves the TE of farms in India and Bangladesh, respectively. Such a positive linkage may be due to unprecedented adverse weather conditions and plant diseases in these countries making farmers more likely to switch their crops. The finding is consistent with the study of Senapati (2020) which found that diverse crop varieties and short-term crops contribute to higher productivity and are less susceptible to climate shock.

Our results also show that households that grow hybrid or improved as well as traditional varieties of rice are significantly more efficient than those who cultivate traditional varieties only. This could be due to that improved seed varieties result in larger grains and a greater number of grains per plant leading to more output. This finding is consistent with the study of Lampach et al. (2021), who found that in the long term, technical efficiency can be improved through application of a high level of inputs, such as chemical fertilizers and the purchase of hybrid seeds. Our evidence also supports the findings of Rahman and Rahman (2009) which reveal that the adoption of modern rice varieties significantly improves technical efficiency in rice production in Bangladesh. However, in our sample, only 46% of households had cultivated modern or improved varieties of rice. Thus, in line with Ayoda and Mark (2020), we suggest for further development and wider dissemination of improved and hybrid varieties of rice to Sri Lankan farmers.

4. Conclusions and policy implications

This study employed the Cobb-Douglas stochastic frontier production function in measuring the level of TE among rice farmers in the Batticaloa district in Sri Lanka. The parameters of the stochastic frontier production function were estimated following the maximum likelihood method. The study shows that inputs - land, labour, fertilizer, seed and tractor use - are associated with changes in rice output. The effect of all the inputs is positive and the coefficients highly significant. The model for TE based on the frontier function includes the variables related to resource accessibility such as education, migration, income source, distance to the market, access to credit, agricultural training and seed sources. The study also includes the variables representing varietal diversification such as the number of rice varieties grown and whether households used hybrid or improved varieties. The results indicate that the variables included in the inefficiency model significantly explain the efficiency variations among farming households.

The average TE is found to be 0.71 and given the current state of technology, rice production in the study area could be increased by about 29%, on average, through better use of available resources that include land, labour, seed, fertilizer and tractors. Hence, a need is demonstrated for the government and farmer organizations to work collectively to ensure proper planning of land use, cultivation of high-quality seeds and optimal usage of fertilizers. Since labour is found to be the most important input contributing to rice output, we recommend policies that focus on convincing farmers to invest in more labour on their farms. This study also finds that the most important factors affecting TE levels are age, migration status, income sources, farmers' training, seed sources, varietal diversification and access to hybrid/improved varieties. Efficiency improvements can thus be achieved firstly by motivating more experienced farmers to be involved in rice farming. Secondly enhancing the capacity building of farmers in agricultural production can be achieved through training and thirdly by improving farmers' access to resources and hybrid rice varieties. In addition, this study suggests that efficiency can be further improved by encouraging and supporting farmers to be more intensively involved in agricultural production rather than migrating out of a district in search of alternative sources of income. It is thus evident that government regulations and mechanisms are necessary to enhance productivity via capacity building.

Declarations

Author contribution statement

Kanesh Suresh: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Clevo Wilson; Uttam Khanal: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Shunsuke Managi: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Samithamby Santhirakumar: Conceived and designed the experiments; Performed the experiments.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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