Sources of total factor productivity and its determinants of paddy farming in Mullaitivu: A Färe-Primont index approach

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Abstract

This study estimates the decompositions of farm-level total factor productivity indices and identifies the impact of household characters, farming characteristics, and economic characters on the indices of paddy farming in Mullaitivu district, Sri Lanka. Six villages where the paddy is mostly cultivated in the district were selected as the study area and from each village, 20 farmers were selected randomly. The relevant data related to paddy yield, its inputs, demographic and farming characteristics were gathered through the questionnaire in 2020. The Färe–Primont index and its various productivity components were used to analyze the data in the study. The frequency of efficiency components revealed that nearly 38% of the farmers attained less than 50% in total factor productive efficiency, while only 11% of them attained between 50% - 70% in the sample. Overall, the mean of total factor productivity was found to be 0.629 while the mean of total factor productive efficiency was 0.458showed that 62% and 45% of productivity and efficiency exist among the paddy farmers, respectively. The mean value of output-oriented efficiency was found to be 0.861, revealing that, 86% of total factor productivity can be increased by increasing the technical efficiency of paddy yield in the study. Determinants of total factor productivity and its sources were analyzed using the Tobit model and its results revealed that, total factor productivity, total factor productive efficiency, and input-oriented scale mix efficiency mainly determined by the quality of land, farm income, amount of saving, amount of loan and land ownership. Further, availability of training and farm income were the major drivers of output scale efficiency of paddy farms in the study.

Keywords: Fare - Primont index, input-oriented scale mix efficiency, output-oriented efficiency, total factor productivity, total factor productive efficiency.

INTRODUCTION

The agriculture sector of a country functions as a source of food and vast employment, which induces rural development. It has become the main source of economic livelihood for rural households in Sri Lanka not only by providing them with basic food requirements but also by generating income and increasing the number of jobs for rural communities and development. The study of productivity and efficiency has received significant attention in the economic literature and among policymakers in both rich and developing nations during the last several decades. (Donnell, 2012).

Increasing productivity fosters the growth of an economy, which motivates the competitiveness of producers within the economy. The components of farm-level total factor productivity (TFP) and the role of mix efficiency are examined in integrated paddy farming systems in Sri Lanka. In addition, increased agricultural productivity can support non-agricultural industries by shifting scarce resources (such as labor and capital) away from agriculture. (Donnell, 2010). Furthermore, the link to reduce at the farm level depends on the individual farmers' access to resources, inputs, and capacity to accept technology. (Irzet al**.** 2003). Higher TFP not only means more production from a given technological and resource base, but it also helps to alleviate rural poverty. (Fan, Hazell, and Thorat, 2000). The approach has also been used to assess the sustainability of a specific agricultural production system (Ali and Byerlee, 2003) or crop (Sidhu and Byerlee, 1992).

About 70% of the population, live in rural areas and the demand for paddy in Sri Lanka increases at a rate of 1.1% per year. To meet this demand, rice production should grow at the rate of 2.9% per year (Department of Agriculture, 2019). Further, majority of the rural people depend on agriculture as their main source of income in the Mullaitivu district. More than 61% percent of families are engaged in farming as their main occupation. At present, about 23737 farm families are directly involved in paddy farming and the district

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has 17320Ha of suitable land to undertake the paddy cultivation. (Department of Agriculture in Mullaitivu, 2019). Unfortunately, most of the farmers are smallholders with less than one acre of land, which may affect the productivity of paddy yield in farming. Thus, maintaining high productivity and high performance through efficient operations in output and input usage is vital for the self–sustainability of farmers in paddy production.

There are several productivity indices in the literature for computing the TFP, such as the Tornqvist index, the Fisher index, the Malmquist index, etc., which have been comprehensively used in empirical research. Recently, two more indexes, notably Hicks-Moorsteen TFP index proposed by Bjurek (1996) and Fare-Primont index introduced by O'Donnell (2011) are applied in generating productivity indices. They are more reliable and may be broken down into multiple components with no pricing data or any restricted assumptions about statistical noise. Therefore, the present study utilized the Fare-Primont index for computing the TFP and its decompositions and these modifications have been incorporated into technical change measures, technical efficiency changes, and scale efficiency changes for paddy farming in selected six villages in Mullaitivu district in 2020.

From the point of view of farmers and policymakers, it is extremely important to evaluate the performance of paddy farming in terms of efficiency and productivity in the study area. The policy implications help them understand how paddy farming has been reacting to the emerging issues and challenges and guide them to make the necessary strategies accordingly.

The objective of the study is to estimate the major components of total factor productivity and identify its determinant factors in terms of household characters, farming characteristics, and economic characters in paddy farming.

LITERATURE REVIEW

There are several studies on total factor productivity and efficiency measurements of the agriculture sector that emerged in the last two decades and recent years using different techniques, such as non-parametric data envelopment analysis and parametric stochastic frontier analysis. Many approaches were used by different researchers to analyze the technical efficiency and its determinants of various sectors. Mainly, most of the studies are based on non-parametric analysis like Malmquist index method, including data envelopment analysis (DEA) Malmquist index method, and Malmquist - Luenberger index method. But the researchers are rarely used the recent non–parametric analysis specially, Fare-Primont index method in the analysis of TFP in the agricultural field, especially in Sri Lanka. Besides that, most of the researchers use parametric analysis such as stochastic frontier and Translog production frontier to estimate the efficiency of any crops or any organizations in their study.

Efficiency studies based on the non-parametric data envelopment analysis

A study on Total Factor Productivity Change during Conflict and Post-Conflict Periods in Sri Lanka (2019) was done by Tharindi Gunaratna Nugawela using Solow's residual method and Hicks-Moorsteentotal factor productivity index approach. Findings of both approaches reveal that the growth of total factor productivity during the conflict period was higher than that of the post-conflict period and the decomposition of the Hicks-Moorsteen Index revealed that the main source of total factor productivity change throughout the sample period is technical change and efficiency change.

Based on big data in the Bank changes in total factor productivity in China's commercial banks from 2010 to 2014. The research explores the intricacies of the dynamic changes in TFP by evaluating sample data and total factor productivity. Domestic commercial banks are now undergoing more changes.

Sawaneh et al. (2013) used a non-parametric technique to analyze Malmquist productivity indicators and their segmentation into efficiency and technological change. Based on the findings, all nations, except for Malaysia, had growth in rice productivity from 1980 to 2010. Though, on average, technological advancements have maintained productivity increase throughout all times. The findings of this study suggest that inefficiencies and productivity improvements exist across rice-producing countries in Southeast Asia. Differences in inefficiency and the level of productivity increase vary from period to period and country to country. Of the two components of total factor productivity, technical change (TC) and efficiency change (EC), the former has proven to be the more powerful source of growth.

Khan, Salim, and Bloch (2014) examined nonparametric estimates of productivity and efficiency change in Australian broad-acre agriculture. Using state-level data from 1990 to 2011, they estimate distance functions to generate and deconstruct Färe-Primont indices of total factor productivity in Australian broad-acre agriculture. Their findings revealed TFP expanded at an annual rate of 1.36 percent in broad-acre agriculture from 1990 to 2011.

Fantu Nisrane Bachewe, Bethlehem Koru, and Alemayehu SeyoumTaffesse (2015) used the Färe-Primont index to examine the productivity and efficiency of smallholder teff farmers in Ethiopia. The findings of an econometric analysis of factors explaining efficiency and productivity among teff-producing families show that productivity and efficiency improve with education, availability to financing, and access to production information.

Tomas Baleentis (2015) investigated the drivers of total factor productivity increase on Lithuanian family farms. The Färe-Primont Indices were used to estimate and deconstruct total factor productivity, and the results demonstrated that technical efficiency was a significant factor contributing to a drop in TFP efficiency for crop and mixed farms. Meanwhile, throughout the research, scale efficiency created a big challenge for mixed farms. Lajos Baráth and Imre Fert (2016) investigated productivity and convergence in European agriculture and discovered that Färe - Primont TFP index has marginally declined across the EU throughout the studied period, although there are considerable disparities between 'new' and 'old' member states, as well as among member states in the research.

Asante and Villano (2019) analyze the components of farm-level total factor productivity (TFP) and the influence of mix efficiency in Ghanaian integrated crop-livestock systems. A Färe-Primont productivity index is calculated and broken down into many efficiency components. According to the findings, mix inefficiency is consistently bigger than technical and scale inefficiency. However, input-mix inefficiency was greater than output-mix inefficiency, implying that crop-livestock producers can achieve more productivity by changing their output mixes than by changing their input mixes.

Akamin and Ernest Molua (2019) conducted research in Central Africa on agricultural productivity growth, technical advances, and efficiency deterioration. Decomposing the Färe-Primont productivity index into technical changes, efficiency changes, and numerous additional efficiency measurements. Their findings revealed that efficiency declined in all four nations studied between 1980 and 2007 and that agricultural production and productivity growth were highest in Cameroon, with Chad substantially converging to Cameroon's level.

Another research was conducted by Asif Reza Anik, Sanzidur Rahman, and Jab Rani Sarker (2020) on five decades of productivity and efficiency increases in world agriculture from 1969 to 2013using Färe–Primont index approach. They revealed that global agricultural TFP rose at a 0.44 percent annual pace, with technology advancements and changes in mix efficiency being the primary contributors, while technical efficiency and scale efficiency improvements were minimal.

Mushoni Bulagi and Irrshad Kaseeram (2020) conducted research titled on productivity and efficiency change of small-scale sugarcane producers in Amatikulu and its policy-related sources, South Africa. The Färe-Primont Index results show that technological progress–driven TFP and mix efficiency, technical and scale-efficiency have slowed the annual increase in small-scale sugarcane production, while other components exhibited mixed outcomes in the research.

Efficiency studies based on the parametric analysis

A study by Kanesh Suresh et al. (2021) reveals 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 in the study. Using a sample of 120, Jeewanthi and Shantha(2021) investigated the technical efficiency of small-scale tea plantations in Sri Lanka using a stochastic production frontier. Their findings show that output can be boosted by 21.5 percent without increasing input, and that access to high-quality extension services has the greatest influence on tea production's technical efficiency. Wasantha Athukorala(2017) studied the role of agricultural extension services in improving technical efficiency in the paddy farming sector in Sri Lanka and discovered that the mean technical efficiency of rice farming in the study area is 0.61, indicating that there is room to increase output by 39% without increasing input.

Muditha Karunarathna (2014) looked at commercial vegetable producers who only grow a few distinct types of vegetables on their farms. According to the empirical findings, over 80% of the farmers polled were less than 55% technically efficient. Technical inefficiency is reduced by farming experience, family size, agricultural extension services, and educational attainment, but technical inefficiency is increased by farmers' age. Basnayake and Gunaratne (2012) investigated the estimation of technical efficiency and its drivers in the tea smallholder sector in Sri Lanka's mid-country Wet Zone from September to January 2001, using sixty smallholder tea producers from the Mid-country Wet Zone. They used Cobb - Douglas and Translog models to examine the data using maximum likelihood estimates of the stochastic frontier model for green leaf yield as a function of land extent, family labor, hired labor, fertilizer, chemicals, and dolomite. The Cobb-Douglas results suggested that the size of the farm, family labor, hired labor, fertilizer, and dolomite had significant effects on yield, whereas the Translog model estimated that the age of the farmer, education, occupation, crop type, and clone type all had significant effects on efficiency.

Geta et al. (2016) conducted a study in Southern Ethiopia to determine the productivity and efficiency of smallholder maize growers. Using human labor, application of chemical fertilizer, planting methods, use of hybrid maize seed, and application of integrated soil fertility management practices were important factors that positively influenced maize productivity, according to the results of the normalized Translog production function. Furthermore, the data envelopment analysis revealed that smallholder maize growers in the nation have an average technical efficiency of 0.4.

Thus, efficiency and productivity for any crops or organizations are measured by using either a parametric, such as stochastic frontier analysis, or a non-parametric approach like data envelopment analysis. The stochastic frontier analysis measures the relative efficiency of entities allowing multiple-input and multiple-output settings and, to apply this method, there is a need to specify the functional form of the production structure, which is often difficult to determine. In contrast, data envelopment analysis measures relative efficiency, allowing for multiple outputs requiring no functional form of the production structure. Among data envelopment analysis measures, the Malmquist productivity index is widely used by many researchers, even though they do not measure total factor productivity change when variable returns to scale are assumed.

To overcome this limitation, O'Donnell (2014) first proposed the Färe-Primont productivity index (Färe et al., 1994) within the DEA framework, and this total factor productivity index satisfies all regularity conditions of index numbers such as multiplicative completeness and transitivity. Also, this index is free from restrictive assumptions on farmers' production technology and optimizing behavior, the structure of markets returns to scale, and or price information (O'Donnell, 2014; Rahman and Salim, 2013). Further, the Färe-Primont TFP index also captures the effect of improvements in technology, and it does not require any restrictive assumptions about the nature of production technology, price information, behavior of the firms, or the level of competition in the input or output markets (O' Donnell, 2012).

There are several technical efficiency measurements for paddy farming and various crops in Sri Lanka that exist in recent literature and those studies have been investigated using different analyses, such as the stochastic frontier production approach and some of them analyzed the data using the Malmquist index. However, so far, no study has used the Färe-Primont TFP model to estimate the TFP and its various components. Therefore, this study aims to fill this research gap by applying the Färe–Primont index to measure the total factor productivity and its efficiency components of paddy farms. In this context, estimating total factor productivity and identifying the primary elements that affect the productivity and efficiency components of paddy farming in Sri Lanka are addressed.

MATERIALS AND METHODS

This paper uses the DEA linear programming to estimate the production technology and related levels of total factor productivity indices and its components in both input and output orientations using the Färe-Primont TFP index (O'Donnell, 2011). This index is used because it satisfies all desirable regularity conditions of index numbers, and it does not require price data for its computations. In addition to this, to identify the factors influencing the various components of total factor productivity, the Tobit model was also applied in the study.

Measuring Färe–Primont index and its different components

The Decomposition of Productivity Index Numbers (DPIN 3.0) program is used to estimate the production technology and associated efficiency measures of Färe–Primont index using Data Envelopment Analysis (DEA) linear programming (O'Donnell, 2010). Färe–Primont index was designed with the distance function as the aggregator function, and it is feasible to deconstruct the index into the output of technical advancement based on the economic connotations of linked technical efficiency.

O'Donnell (2010) defines the TFP index for a multi-input, a multi-output farm in a brief time, as well as the Färe–Primont index, which is based on two indices from Färe and Primont(Färe, R.; Primont, 1995), and itis defined as the ratio of aggregate output (Y_{it}) to an aggregate input (X_{it}):

$$TFP_{it} \equiv \frac{Y_{it}}{X_{it}} \ldots\ldots (1)$$

Where $Y_{it}$is is the aggregate level of output from firm i and $X_{it}$is the aggregated inputs of firm i in time t. The aggregate input and output quantities are obtained using aggregator functions with properties that are non-negative, non - decreasing, and linearly homogenous (O'Donnell, 2012).The corresponding index number, which compares the total factor productivity of paddy farmer I to the paddy farmer h during the same time, is as follows:

$$Y_{h,i} = \frac{Y_i}{X_i} = \frac{Y_i/X_i}{Y_h/X_h} = \frac{Y_{h,i}}{X_{h,i}} \ldots\ldots (2)$$

Where, $Y_{h,i} = \frac{Y_i}{Y_h}$ is an output quantity index, and $X_{h,i} = \frac{X_i}{X_h}$ is an input quantity index.

O'Donnell (2011) shows that the estimated aggregate outputs and inputs can be represented by the following nonnegative, non-decreasing, and linearly homogenous Färe-Primont aggregator functions as:

$$X_x = D_1(x_0, y, t_0) \ldots\ldots (3)$$

$$Y_y = D_0(x_0, y, t_0) \ldots\ldots (4)$$

Where x and y are vectors of input and output quantities respectively and D_I and D_0 are the Shepherd input and output distance functions (Shephard, 1970), respectively representing the production technology available in each period.

According to O'Donnell (2010), the homogeneity and monotonicity properties of these functions make them natural candidates of an input and output aggregator function. Then, following O'Donnell (2011), the associated Färe-Primont TFP index number is given as follows:

$$TFP_{h,i} = \frac{D_o(x_o, y_i, t_0)}{D_o(x_o, y_h, t_0)} \frac{D_1(x_h, y_o, t_0)}{D_1(x_i, y_o, t_0)} \ldots\ldots (5)$$

Measures of efficiency

Measures of efficiency can be calculated based on the orientation of production technology. An output orientation considers a maximal proportional expansion of the output vector given sets of inputs. An input orientation characterizes the production technology by looking at a minimal proportional contraction of the input vector given an output vector.

The computed TFP index in equation 6 is further decomposed into better measures of efficiency and based on the index, O'Donnell (2011) suggests that most economic measures of efficiency can be defined as the ratios of TFP measures. Thus, within the aggregate quantity framework, the estimated TFP index is decomposed into alternative measures of efficiency in terms of input and output orientations where the input- and output-oriented technical efficiencies measures, the minimum or minimum possible aggregate input or outputs to produce a level of aggregate output or inputs.

Input orientation TFP index

Under input orientation, total factor productive efficiency ($TFPE_n$), it can be shown as,

$$TFPE_n = ITE \times IME \times RISE = ITE \times ISE \times RME \ldots\ldots (6)$$

Under input orientation, the measure of productive efficiency can be expressed as:

Where,

$$ITE_{it} = \frac{Y_{it}/X_{it}}{Y_{it}/\bar{X}_{it}} = \frac{\overline{X_{it}}}{X_{it}}$$

$$IME_{it} = \frac{Y_{it}/\bar{X}_{it}}{Y_{it}/X_{it}}$$

$$RISE_{it} = \frac{Y_{it}/X_{it}}{TFP_t^*}$$

$$ISE_{it} = \frac{Y_{it}/\bar{X}_{it}}{Y_{it}/\bar{X}_{it}}$$

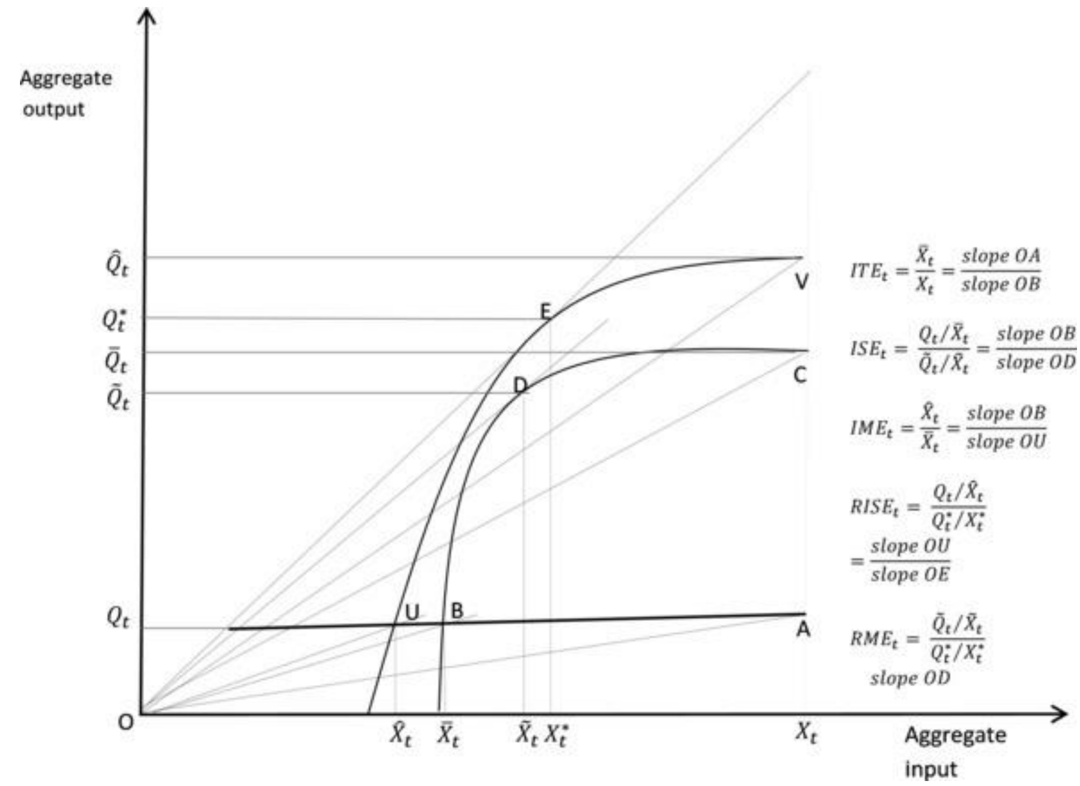
$$RME_{it} = \frac{\overline{Y_{it}}/\bar{X}_{it}}{TFP_t^*}$$

Besides the above indices, input scale mix efficiency (ISME) is also used in the study, which can be expressed as,

$$ISME_{it} = \frac{Y_{it}/\bar{X}_{it}}{TFP_t^*}$$

All the above indices, except input-oriented scale mix efficiency, can be shown graphically in Figure 1.

Figure 1: Input-oriented measures of efficiency for multiple–output farm



Source: O'Donnell (2011)

Output orientation TFP index

The highest potential aggregate output generated while maintaining the input vector and output mix constant is known as output-oriented technical efficiency and, under output orientation, TFP index, it can be shown as:

$TFPE_n = OTE \times OME \times ROSE = OTE \times OSE \times RME$.(7)

Under Output-technical efficiency (OTE) is given as:

$$OTE_{it} = \frac{Y_{it}/X_{it}}{\bar{Y}_{it}/X_{it}} = \frac{Y_{it}}{\bar{Y}_{it}}$$

$$OME_t = \frac{\bar{Q}}{\hat{Q}} = \frac{Slope of OC}{Slope of OV}$$

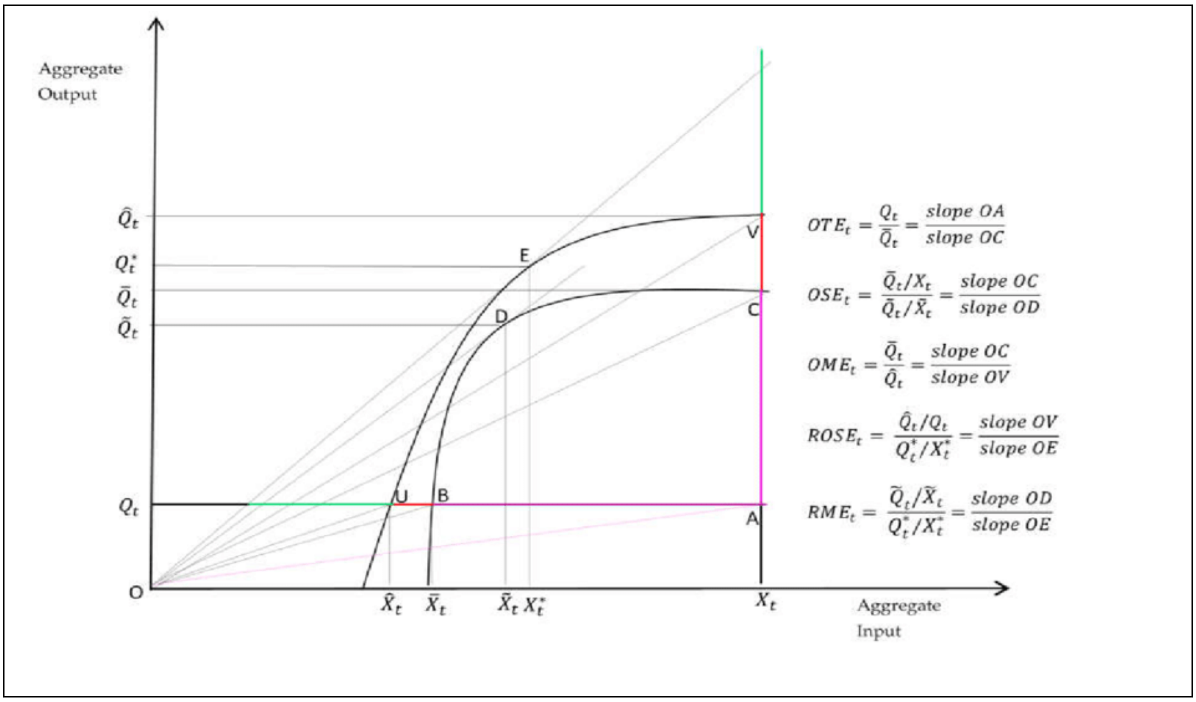
$$ROSE_{it} = \frac{\widehat{Y_{it}}/X_{it}}{Y^*{}_{it}/X^*{}_{it}}$$

$$OSE_{it} = \frac{\overline{Y_{it}}/\overline{X_{it}}}{Y_{it}/X_{it}}$$

$$RME_{it} = \frac{\overline{Y_{it}}/\bar{X}_{it}}{TFP_t^*}$$

All these indices can be shown graphically in Figure 2.

Figure 2: Output-oriented measures of efficiency for multiple–output farm



Source: O'Donnell (2011)

Table 1 summarizes the meanings and abbreviations of the various components of input and output-oriented total factor productivity indices used in the study.

Table 1: Definitions and abbreviations of the components of total factor productivity indices

Definitions	Abbreviations
Total factor productivity in economics measures the total factor productivity as the ratio of aggregate output to an aggregate input. Thus, it is a measure of productive efficiency which shows that much output can be produced from a certain number of inputs.	TFP
Total factor productive efficiency measures the difference between observed TFP and the maximum TFP possible using the available technology. Thus, the total factor of productive efficiency is the ratio of observed TFP and the maximum TFP.	TFPE
Input-oriented technical efficiency defined the difference between observed TFP and the maximum TFP holding the input mix, output mix, and output level fixed.	ITE
Input-oriented Scale efficiency defined the difference between observed TFP at a technically efficient point and the maximum TFP holding the input and output mixes fixed but levels vary.	ISE
Residual mix efficiency is defined by the difference between TFP at a technically and scale-efficient point and the maximum TFP possible when input and output mixes (and levels) can vary.	RME
Input-oriented scale-mix efficiency encompasses input-oriented scale efficiency and residual mix efficiency and thus compares the maximal total factor productivity at a point to that at the scale-efficient point.	ISME
Input Oriented Mix Efficiency defined the difference between observed TFP at a technically efficient point and the maximum TFP holding the output level fixed.	IME
Residual Input oriented scale efficiency defined the Difference between observed TFP at a technically efficient point and TFP at the point of maximum productivity.	RISE
Output-oriented technical efficiency is defined as the maximum aggregate output which is possible to produce from a level of aggregate input. Thus, it is the difference between observed TFP and the maximum TFP possible using the existing technology while holding the output mix, input mix fixed and the input level fixed.	OTE
Output-oriented scale efficiency is defined as the efficiency derived by varying the scale of firm operation size and therefore indicates economies or diseconomies of scale.	OSE
Residual output-oriented scale efficiency is defined by the difference between TFP at a technically and mix efficient point and the maximum TFP that is possible through altering both input and output with existing technology.	ROSE
The output-oriented scale-mix efficiency measures the increase in TFP between a technically efficient point with the observed scale and input mix to the point of maximum productivity.	OSME
Output-oriented mix efficiency accounts for productivity shortfalls associated with diseconomies of scope, which arise when a multiple output producing firm is less efficient than the specialized firms producing a single product.	OME

Source: From literature reviews.

Determinants of TFP growth and its components

Econometric analysis is conducted to identify the determinants of various components of efficiency and productivity using the Tobit model. The impact of household, farming, and economic characteristics on TFP, TFPE, OSE, and ISME was examined using the Tobit model. Since these efficiency scores lie between 0 and 1 and are considered as the limited dependent variable, the Tobit regression model is specified to find out the major determinants among the above three characteristics in the study.

The Tobit model can be written as below:

$$Totalfactorproductivity_J = \delta_0 + \delta_1 Gender + \delta_1 Education + \delta_2 Householdsize + \delta_3 Experience + \delta_4 Landowernership + \delta_5 Farmtraining + \delta_6 Extensionservice + \delta_7 Farmincome + \delta_8 Savings + \delta_9 Loan + e_j \quad (8)$$

Where, $Total\,factor\,productivity$ includes TFP, TFPE, OSE, and ISME was taken as four dependent variables which were estimated with the above explanatory variables in the study. The variables included in the regression model can have important implications for the operations and efficiency of paddy farms in the study.

Study area and data collection

The data used for this study were collected from a survey using a structured questionnaire in Mullaitivu district of Sri Lanka. This district is one of the newly created districts in Sri Lanka in 1979, which is in the Northern province of the country and surrounded by Mannar, Trincomalee, Vavuniya, and Kilinochchi Districts. Mullaitivu district has 17320Ha of suitable land to undertake the paddy cultivation with major tanks and medium tanks for paddy cultivation. Agriculture is the most important source of livelihood for most of the people in this district and, among agriculture, paddy is the major crop that is mainly carried out under rain-fed conditions in the district. Out of the 6 DS divisions in the district, the Maritimepattu DS division was selected as the study area and from this division, six villages were selected using a multi-stage sampling technique. Finally, 20 farmers from each village were selected randomly in 2020 and a total sample of 120 paddy farmers was used in the study.

Compared to other DS divisions, most paddy farmers are in the Maritimepattu DS division and thus, this division was selected as the study area. Through the survey, necessary inputs and output quantity data related to paddy farming were collected for estimating total factor productivity and its various components. Besides that, to examine the impact of demographic and farming characteristics on total factor productivity and its decompositions of paddy farms, the relevant information on these aspects was also collected in the study. The description of the variables used in the study is summarized in Table 2.

Table 2: Descriptions of the variables

Variables	Estimation Procedure
Yield of paddy	Kg (Acre)
Inputs of paddy farm	
Capital	(Rs/Acre)
Extent of land	(Acre)
Labour	(Man days)
Machinery	(Rs/Acre)
Quantity of Fertilizer	kg/Acre
Quantity of Seeds	Kg/Acre
quantity of pesticide	Liter/Acre
Demographic and farming characteristics	
Gender	Male=1, Female=0
Education level	Years
Household size	Number of family members
Experience in farming	Years
Ownership of Land	Dummy variables if yes=1, otherwise 0.
Availability of training	Dummy variables if yes=1, otherwise 0.
Extension services	Dummy variables if yes=1, otherwise 0.
Farm income	Per month in Rs
Amount of savings	Per month in Rs
Amount of loan	Per month in Rs

Source: Authors ‘survey, 2020.

RESULTS AND DISCUSSION

First part of this section, total factor productivity and efficiency performance of paddy farms obtained from Decomposing Productivity Index Numbers, version 3.0 (DPIN 3.0) program, which decomposed the productivity and index numbers (O'Donnell 2011). The second part of the section applied the econometric analysis to examine the factors influencing the total factor productivity and its components in the study.

The estimated efficiency scores in terms of TFP and its components were estimated for 120 farmers and their efficiency scores were measured in frequency. The estimated efficiency scores were ranged based on three categories and they coded as 1 for less than 50%, 2 for between 50% to 70%, and 3 for 71% and above. The efficiency ranges are presented in Table 2 and according to that, nearly 38% of the farmers belong to less than 50% in TFP while only 11% of them belong to between 50 and 70 percent of TFPE in the sample.

Table 3: Distribution of total factor productivity and efficiency scores

Ranges of the index (%)	Frequency	Percentage
TFP		
Less than 50	45	37.5
Between 50 and 70	44	36.7
71 and above	31	25.8
TFPE		
Less than 50	76	63.3
Between 50 and 70	13	10.8
71 and above	31	25.8
OTE		
Less than 50	2	1.7
Between 50 and 70	101	84.2
71 and above	17	14.2
OSME		
Less than 50	57	47.5
Between 50 and 70	26	21.7
71 and above	37	30.8
ROSE		
Less than 50	57	47.5
Between 50 and 70	26	21.7
71 and above	37	30.8

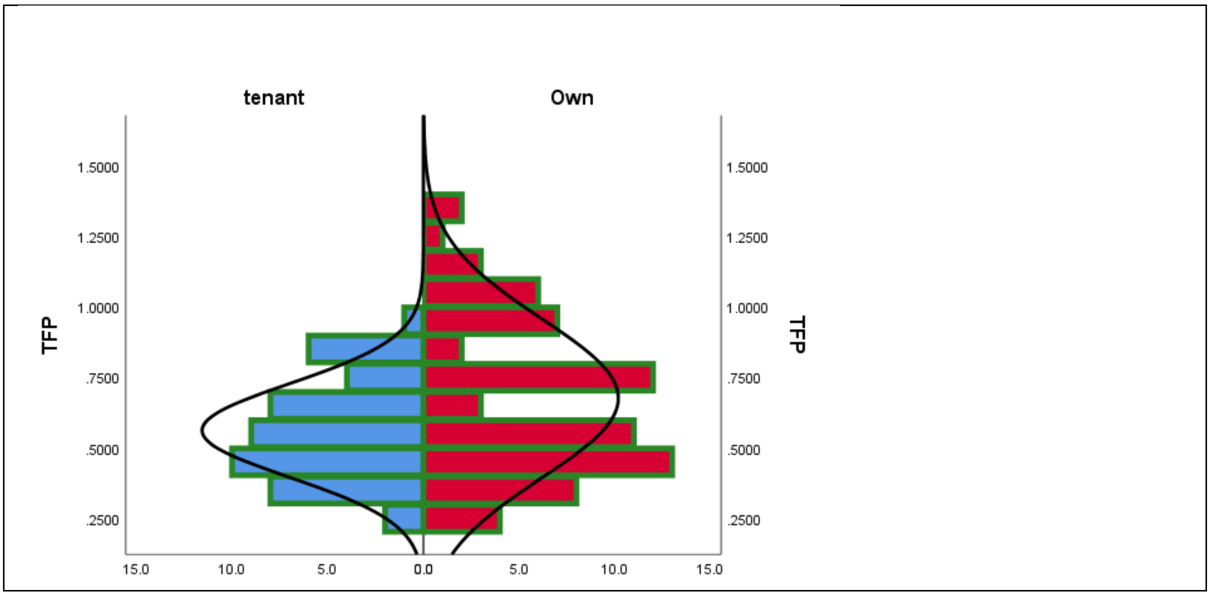
OSE		
Less than 50	……	…..
Between 50 and 70	118	98.3
71 and above	2	1.7
RME		
Less than 50	45	37.5
Between 50 and 70	44	36.7
71 and above	31	25.8

Source: Authors' calculation using Decomposing Productivity Index Numbers, version 3.0

Out of 120 farmers, 101 of them attained the performance in OTE between 50 and 70 percent, and in the case of OSME majority of them belong to less than 50% efficiency. Relatively, the efficiency in terms of OSE between 50% and 70% was attained by 98.3% of the farmers, which is higher than other efficiency components in the study.

The dispersion of TFP index across own and tenant land cultivators is illustrated using a histogram in Figure 3.

Figure 3: Dispersion of TFP index across owner and tenant farmers



The above graph suggests that relatively the distribution of TFP index is more spread among own land farmers than tenants.

Results of total factor productivity and efficiency scores obtained from decomposition of Fare–Primont index are presented in terms of mean and standard deviation. Overall, the mean TFP was found to be 62 while the mean TFPE was 45, as showed that 62% and 45% of productivity and efficiency exist among the smallholder paddy farmers in the study area. OTE measures how much TFP can be increased by increasing the technical efficiency of outputs. Overall, the average OTE was found to be 0.86, which reveals that 86% of TFP can be increased by increasing the technical efficiency of paddy yield in the study. The estimated mean levels of other indices, such as OSME, ROSE, OSE, and RME also illustrated in Table 4. According to that, the average OSME and ROSE levels were estimated at 53% for both, while OSE and RME were at 93% and 57% respectively.

Table 4: Descriptive statistics of TFP and efficiency levels

Variables	Minimum	Maximum	Mean	Std. Deviation
TFP	0.21	1.37	.6297	.247
TFPE	0.16	1.00	.4580	.180
OTE	0.48	1.00	.8610	.141
OSME	0.16	1.00	.5361	.191
ROSE	0.16	1.00	.5361	.191
OSE	0.62	1.00	.9321	.066
RME	0.20	1.00	.5733	.194
ITE	0.76	1.00	.9467	.055
ISE	0.48	1.00	.8450	.129
IME	0.80	1.00	.9343	.045
RISE	0.176	1.000	5143	.185

Source: Authors' calculation using Decomposing Productivity Index Numbers, version 3.0

The mean value of residual output scale efficiency (ROSE) measures the increases in TFP resulting from increasing the scale of input used at an output, which is estimated on average at 53% across farmers in the study. It implies that farmers who are cultivating paddy could enhance their productivity of paddy by improving the scale of production by 47% with the input and output mixes. Comparing the results for the measures of efficiency from output orientation indicates that, on average, OSE and OTE contributed significantly to TFPE, whereas ROSE contributes marginally. This suggests that relatively low contribution given by the scale improvements towards productivity in paddy farming rather than productivity improvements mostly through scale and technical efficiencies from output orientations. However, from the input side, TFPE is constituted of input-oriented technical efficiency (ITE), input-oriented mix efficiency (IME), and input-oriented scale efficiency (ISE). But residual input scale efficiency (RISE) contributes marginally to the study. In addition to estimating the sources of total factor productivity, the impact of household characteristics, farming characters, and economic characters on TFP and its major components, such as TFPE, OSE, and ISME, the Tobit model were employed in the study. Since the above four indices lie between 0and 1 considered as limited dependent variables, the Tobit model is considered as an appropriate model and thus it is employed in the study. The estimated results derived from the Tobit regression model were given in Table 5and according to the log-likelihood and significant values of each model, they were significant at a 1% level. Thus, the estimated Tobit model was adequate for explaining the impact of the three characteristics on different components of TFP in the study. Among household characteristics, only the education of farmers has significantly affected TFP, TFPE, OSE, and ISME, which indicates that farmers with better educational qualifications perform well in TFP, TFPE, OSE, and ISME in the study. Education is a vital technical efficiency that enhances their ability to comprehend the production-related technical aspects and it will ultimately contribute towards higher TFP and other indices, TFPE, OSE, and ISME among the selected sample. The coefficient of education has a positive and significant impact on all indices and compared to OSE and ISME, and as the farmers' education increases, it would enhance the improvements on TFP and TFPE in the study.

Table 5: Determinants of total factor productivity and its components

Variables	Dependent variables			
	TFP	TFPE	OSE	ISME
Household characteristics				
Gender	-0.050	-0.0366	-0.0046	-0.0314
	(0.037)	(0.027)	(0.002)	(0.027)
Education	0.013*	0.0097*	0.0046**	0.010**
	(0.007)	(0.005)	(0.0022)	(0.005)
Household size	0.011	0.0080	-0.0021	0.0068
	(0.014)	(0.0102)	(0.0045)	(0.0103)
Farming characteristics				
Experience in farming	-0.0022	-0.0016	-0.000126	-0.0012
	(0.0020)	(0.0014)	(0.0006)	(0.0014)
Ownership of land	0.092**	0.0670**	-0.0152	0.073***
	(0.037)	(0.032)	(0.118)	(0.027)
Availability of training	-0.0452	-0.0329	-0.0377***	-0.0317
	(0.044)	(0.0321)	(0.014)	(0.0323)
Extension services	0.00091	0.00066	-0.019*	-0.00022
	(0.036)	(0.0264)	(0.0116)	(0.0265)
Land quality	0.1946***	0.1415***	-0.025	0.1229***
	(0.0584)	(0.0425)	(0.018)	(0.0427)
Economic characteristics				
Farm income	0.000021***	0.00001***	7.00e-06***	0.000018***
	(7.22e-06)	(5.25e -08)	(2.30e-06)	(5.28e-06)
Amount of saving	0.000040***	0.000029***	9.59e-06**	0.000032***
	(0.0000143)	(0.00001)	(4.56e-06)	(0.000010)
Amount of loan	2.23e - 07***	1.62e-07***	5.39e-08**	1.85e-07***
	(6.82e - 08)	(4.96e-08)	(2.18e-06)	(4.99e-08)
Constant	0.1983	0.1442	0.8737	0.1259
	(0.1110)	(0.080)	(0.035)	(0.0812)
Log-likelihood	30.10	67.99	165.11	67.34

LR Chi ^{2}	69.27***	69.27***	28.10***	74.65***

Note: ***, ** and * represents the significant levels at 1%, 5% and 10% respectively. Standard errors are in the parentheses.
Source: Calculated by the author using DPIN 3.0 Decomposing Productivity Index Numbers, version 3.0.

Ownership of land has positively affected TFP, TFPE, and ISME at significant levels at 5% and 1% while it has a negative impact on OSE. However, it is insignificant in the model. For the farmers who have their land, the probability of improving TFP, TFPE, and ISME will be more than tenant cultivators. In other words, the farmers operated by own land significantly improve TFP, TFPE, and ISME, which implies that own land farmers are adopting improved technologies in paddy farming and can improve these indices in the study.

Framers' training and extension services have negative signs in all indices, even though they have a significant impact only on OSE, revealing that the farmers who have training on-farm practices are less likely to attain the efficiency in the output scale. Similarly, extension services significantly reduce the OSE, indicating that it not much contributed to increase the performance through output-oriented scale efficiency in the study. The quality of land significantly improves all indices except OSE, which implies that as the quality of land increases, it will significantly improve the total factor productivity, total factor productive efficiency, and input-oriented scale and mix efficiency, but reduces output-oriented scale efficiency. The implication is that the use of quality land enables farmers to adopt improved technologies, which ultimately helps them in deriving economies of scope by optimizing input-output mix but is unable to improve scale efficiency. The above table suggests that all three farming characters were significantly affecting all the above indices with positive at 1% and 5% levels. The farmers who have more income and savings as the major economic assets have more probability of improving the components of TFP, as mentioned in the table. When they have more assets to invest in paddy farming to adopt new farming techniques, will enhance the efficiency of farming in paddy in the district. Similarly, the farmers who have credit accessibility also motivate them to adopt new farm management practices to increase the efficiency and its components, and thus the probability of attaining the TFP and its decompositions also increases further in the study.

CONCLUSION

This study estimates the various decompositions of total factor productivity and examines the impact of household characters, farming, and economic characters on these indices among the paddy farmers in Mullaitivu district of Sri Lanka. Frequency distribution of different efficiency indices showed that 37.5% of farmers belong to less than 50% in total factor productivity while 63.3% of them belong to the same range in total factor productive efficiency. Compared to other components of total factor productivity, output-oriented scale efficiency and output-oriented technical efficiency attained more performance in the study. Results of the Tobit model revealed that education, ownership of land, training opportunity, extension services, and land quality were significantly influencing the total factor productivity and its components in the model. All three farming characteristics, such as farm income, savings, and amount of loan, are strongly influencing the components of total factor productivity in the study.

Thus, total factor productivity, total factor productive efficiency, and input-oriented scale mix efficiency are mainly determined by the quality of land, farm income, amount of saving, amount of loan, and land ownership. Tobit regression analyses were conducted to explain the determinants of total factor productivity, total factor productive efficiency, and input-oriented scale mix efficiency among paddy farms. Its results showed that performance of these indices improves with the quality of land, farm income, amount of saving, amount of loan, and land ownership and they are the major factors influencing these indices in the study. Further, the availability of training and farm income generation activities helps to improve the output scale efficiency of paddy farms in the study. This study was done by the researchers by considering 120 selected farmers who are cultivating paddy in Mullaitivu district and, therefore, the findings of the study cannot be generalized throughout the country. Also, the components of total factor productivity may determine by other factors like environmental characteristics and climate changes. These aspects also can be considered as other factors to determine the total factor productivity and its various components of the paddy sector in future research.

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