Technical Efficiency of Small-Scale Marine Fishing Households: Evidence from a Stochastic Frontier Analysis

by
Ann Fernando, Udith Jayasinghe-Mudalige, Jagath Edirisinghe, Menuka Udugama, Keminda Herath and Sashika Guruge
Dept. of Agribusiness Management, Faculty of Agriculture & Plantation Management
Wayamba University of Sri Lanka, Makandura, Gonawila (NWP), 60170, Sri Lanka
annsweetydo@gmail.com, udith@hotmail.com, jagathed@yahoo.com,
menukaudugama@gmail.com, lakminikem@yahoo.com, guruge84@yahoo.com

Abstract. Stochastic Frontier analysis was used to estimate the technical efficiency and to explore the determinants of inefficiency of small-scale marine fishing households in Sri Lanka. Data were collected from a randomly selected sample of 124 fishing households from four coastal villages (Kadawatha, Ulhitiyawa, Kolindadiya, Katuneriya) located in the Chilaw Fishing District from March to April 2014 by means of in-depth personal interviews carried out with the help of a pre-tested structured questionnaire, followed by on-site inspection of resources utilized by each household for marine fishing. Six Stochastic Frontiers were estimated, assuming three specifications for distribution of the inefficiency term (i.e. Half normal, Truncated normal, Exponential), for the Cobb-Douglas and Translogarithmic Frontiers. The Likelihood Ratio tests carried out in this context confirmed that the Translogarithmic form to be the best fit. The results reveal that Mean Technical Efficiency of the households was 59.8% in relation to the most efficient household in the sample, or stated differently, an efficiency gain of 40.2% can further be achieved with the existing resource-base. The inefficiency model indicates that increase in household size increases the efficiency due to increase in availability of labor. It highlights the necessity of capacity development of small-scale fishing communities, alongside provision of a schema of appropriate economic incentives to promote adoption of appropriate technology and coordinated action towards effective utilization of existing resource-base, which largely possess the characteristics of a ‘public good’.

Key words: Fisheries sector, Stochastic Frontier Analysis, Technical efficiency
JEL classification: C13, O12, Q12, Q22

1 Introduction

The fisheries sector of Sri Lanka contributes to nearly 1.8 percent to the Gross Domestic Product (GDP) and provides both direct and indirect employment, to around 650,000 people. Contribution of the marine fisheries (i.e. coastal and deep sea) segment to the fisheries sector is around 86 percent. The coastal fish production contributes to about 53 percent of the total fish production, while the off shore/deep sea and fresh water fishery, respectively contribute nearly 33 and 14 percent to the national production. More importantly, the fisheries sector is directly linked with the livelihood of approximately half of the population of Sri Lanka who resides along the coastal belt of the island (Ministry of Fisheries and Aquatic Resources of Sri Lanka, 2013).

By value, fish imports account for about 1.2 percent of the total imports to the country to which dried fish, canned fish, and Maldives fish account for about 55, 20 and 25 percent, respectively. Fishery products exported from Sri Lanka include fresh, chilled and frozen tuna fish, shrimp, lobsters, shark fins, and sea cucumbers etc. However, during the last decade, the income generated through exporting fish has remained at less than 3 percent of the total value of exports of the country. At present, contribution of fisheries sector in relation to export earnings is relatively insignificant, i.e. only about 7 percent of the local fish catch is exported (Department of Census and Statistics, 2012).

These statistics suggest that fisheries sector plays a very important role in shaping the socio-economic status of Sri Lanka, and possess far more potential to contribute by way of enhancing food and nutrition status of households, generating direct and indirect employment, not only with respect to
‘production/harvesting’, but also ‘throughout the food-value chain’ (i.e. processing, storage, handling etc.), and emerging as a key source of foreign exchange.

According to the Food and Agriculture Organization (FAO) of the United Nations, ‘small-scale fishing’ include those households engaging in fisheries using relatively small-scale of capital and energy, relatively small fishing vessels, mainly short fishing trips, close to shore and mainly for local consumption. Though the “size” may be considered “small” in relation to ‘scale of operation’, the “relative contribution” of sector, as a whole, is “large”, from both ‘socio-economic’ (e.g. food security, employment, revenue generate) and ‘political’ point of view (e.g. large vote base, population is geographically concentrated along the coastal belt, and representation of major nationalities, including Sinhalese, Tamil and Muslims. Thus, it is of paramount importance that the fisheries sector works at its best in terms of all these performance indicators, including the most important of which – ‘efficiency criterion’.

In fact, the role that food and agriculture sector of a country should play in the process of its socioeconomic development has been the purview of both policy planners and economist for long time. In this process, a greater emphasis must be placed on the innovation and adoption of new technologies developed to augment both output and income of agribusinesses, including agricultural and livestock farms and operations and various sectors involve with fisheries (Hayami & Ruttan, 1985; Kuznets, 1966; Schultz, 1964). Nevertheless, growth measured in terms of “output” is not only an outcome of technological innovations, but also by the extent to which they are in practice, or ‘efficiency’ they are at work.

Bravo-Ureta and Pinheiro (1993) provide an excellent review and critique on the use of frontier models to examine ‘efficiency’ of agricultural operations in developing countries. It highlights that average technical efficiency index from 30 studies reviewed from 14 countries is 72 percent, and suggests that there is considerable room to increase agricultural output without additional inputs and given existing technology. The variables most frequently used for this purpose have been farmer education and experience, contacts with extension, access to credit, and farm size. With the exception of farm size, the results reveal that these variables tend to have a positive and statistically significant impact on TE. It concludes that a considerable effort has been devoted to measuring efficiency in developing country agriculture using a wide range of frontier models. Despite all this work the extent to which efficiency measures are sensitive to the choice of methodology remains uncertain.

In the context of Sri Lanka, a number of empirical studies were carried out to examine TE of different agricultural systems. Ekanayake (1987), for example, studied TE of rice farmers with special attention to farmers’ access to water using Stochastic Cobb-Douglas Production Frontiers through Maximum Likelihood, and found that there was no significant technical inefficiency for the farmers with better access to water. It was revealed that farmer’s literacy and experience as well as credit availability had a significant positive impact on the level of TE of those who have poor access to water.

Kularatne et al. (2012) examined the factors affecting TE of irrigated rice farmers in village irrigation systems in Sri Lanka. The primary data collected from 460 rice farmers in the Kurunagala District were estimated through a Stochastic Translog Production Frontier for rice production. The mean TE of rice farming was found to be 0.72, although 63 percent of farmers exceeded this average. Membership of, and the participation rate in collective actions organized by, farmer organizations were considered to be the major factors affecting this behavior.

Amarasuriya et al. (2010) estimate the current level of, and factors affecting TE of intercropped pineapple production in Kurunegala district. Based on the Stochastic Production Frontier Function approach, the study found that the extent of land, labour, fertilizer and plant density had significant impact on pineapple production. Technical inefficiency was regressed as a multivariate function, and revealed that it was significantly
affected by season, ownership, experience, off-farm income, and constraint index. Further, the mean TE of pineapple production was eighty-five percent. In a similar analysis, Basnayake and Gunaratne (2002) estimating TE and its determinants in the tea smallholding sector in the Mid Country Wet Zone of Sri Lanka, found the mean TE to be 64.6 percent. Lindara et al (2004) estimates the TE of spice-based Agroforestry systems to identify the potential increase in production without incurring additional costs for farm inputs, where data were collected by means of a field survey covering 120 Agroforestry farmers in six Divisional Secretariats in Matale district. The results from Stochastic Frontier Production Function using a Cobb-Douglas model show that mean TE of the systems was 84.3 percent, and hired labour, organic and inorganic fertilizers, land size, and soil fertility maintenance cost showed significant positive effects on the agroforestry production. Illukpitiya (2005) estimates the TE in agriculture and dependency on forest resources of rural households in Sri Lanka. Findings of the study showed that the mean TE in agricultural farming in forest peripheries ranges between 67 – 73 percent. Factors such as age, education, experience, extension, and the nutrition status of the household head are mainly responsible for determining the level of inefficiency. However, there is a paucity of in literature with regard to TE of fish production systems, and to the best knowledge of authors, there is no systematic study on the performance of small-scale coastal fishing households in Sri Lanka. In this shed of light, this study was aimed to assess TE as well as the determinants of the inefficiency of this particular sector using the Stochastic Production Frontier approach. The availability of such knowledge can be a valuable asset that aid policymakers in designing appropriate policies to improve the overall efficiency of the sector, and hence, improve the general welfare of fishing households.

2 Methodology

2.1 Theoretical Framework

Farrell (1957) in his original paper evaluates the term ‘economic efficiency’ using an efficient unit isoquant and decomposed which into two distinct measures, namely ‘technical’ and ‘allocative’ efficiency. Technical efficiency (TE) can be defined as the ‘firm’s ability to produce maximum output given a set of inputs and technology’, or stated differently, ‘technical inefficiency’ means the failure of firm to attain the highest possible level of output given inputs and technology. Allocative efficiency, also referred to as ‘price efficiency’, measures the ‘success of the firm in choosing the optimal proportions of inputs’, or in economic terms, the state at which the ratio of Marginal Products for each pair of inputs is equal to the ratio of their Market Prices.

Over time, a large number of frontier models that have been developed based on Farrell’s work were classified into two basic types: ‘parametric’ and ‘non-parametric’, where the former relies on a specific functional form and the latter does not. Further, they were classified as ‘deterministic’ and ‘stochastic’ frontiers, where the former model assumes that any deviation from the frontier is due to inefficiency, and the latter approach allows for statistical noise (Bravo-Ureta and Pinheiro, 1993; Green, 1980). As a result of progressive developments in the methodologies of estimating efficiency frontiers, an array of techniques are available for an analyst, depending on the problem to be studied, nature of data, and interpretations needed, including: Classical Stochastic Frontiers Analysis (CSFA), Bayesian Stochastic Frontier Analysis, and Data Envelopment Analysis (Balcombe et al., 2006). For the purpose of this particular analysis, we employ CSFA, and is briefed, in turn.

It is assumed that a stochastic frontier contains an error term that is composed of two elements: a random error capturing statistical noise, and a one-sided non-negative error capturing the inefficiency. By incorporating this decomposed error term, the frontier production function can be expressed as follows (Aigner et al., 1977;

\[
\ln(Y_i) = f(X_i \beta) + \varepsilon_i \quad (1)
\]

\[
\varepsilon_i = V_i - U_i \quad (i = 1, 2...N)
\]

where: \( \ln \) = natural logarithm of base e; \( Y_i \) = production level; \( X_i \) = input level; \( \beta \) = vector of unknown parameter to be estimated; \( \varepsilon_i \) = composed error term; \( V_i \) = independent and identically distributed random errors \( N(0, \sigma^2) \); \( U_i \) = non-negative or one sided (inefficiency) error term assumed to be independently and identically distributed.

Based on Battese and Coelli (1995), the technically efficiency effects can, thus, be defined by:

\[
U_i = Z_i \delta + W_i \quad (i = 1, 2...N) \quad (2)
\]

Where, \( Z_i \) = a vector of explanatory variables associated with the technical inefficiency effects; \( \delta \) = a vector of unknown parameters to be estimated; \( W_i \) = unobservable random variables that are assumed to be identically distributed, obtained by truncation of the normal distribution with mean zero and unknown variance \( \sigma^2 \).

The evidence in the literature with regard to the importance of choice of the functional form on estimates of TE is, however, mixed. Some authors argue that the choice of functional form makes a little difference to the estimates of TE. Ahmad and Bravo-Ureta (1996) and Battese and Broca (1997), for example, state that switching from a Cobb–Douglas to Translog functional form gives out almost identical average, minimum and maximum estimates. Conversely, Koop et al. (1994), for the case of Cobb–Douglas and Almost Ideal Model set for a cost function, found that the choice of functional form have an impact on corresponding estimates. To be fair, we have decided to go along with both Cobb-Douglas and Translogarithmic functional forms for the purpose of this analysis in order to specify the stochastic production frontier. Further, the ‘Half-normal’, ‘Truncated-normal’ and ‘Exponential’ distributions were assumed for the case of inefficiency error term (Amarasuriya et al., 2010; Basnayake and Gunaratne, 2002).

The Cobb-Douglas model specified is as follows:

\[
\ln(Y_i) = \beta_0 + \beta_1 \cdot \ln(Gear) + \beta_2 \cdot \ln(Capital) + (V_i - U_i) \quad (3)
\]

where; \( Y_i \) = fishing output (kg/visit); \( Gear \) = value of the fishing gears used per visit (Rs. million); \( Capital \) = value of the fishing boat and the engine (Rs. million); \( V_i \) = random factors; \( U_i \) = technical inefficiency effects; \( \beta_0 \) = constant; \( \beta_1 \) and \( \beta_2 \) = coefficients of input variables Gear and Capital.

The Inefficiency Model is then specified, based on Battese and Coelli (1995) as:

\[
U_i = \delta_0 + \delta_1 \cdot HZ + \delta_2 \cdot OI + \delta_3 \cdot EX + \delta_4 \cdot DI + \delta_5 \cdot GP + W_i \quad (4)
\]

Where, \( U_i \) = technical inefficiency effect of the \( i \)-th household; \( HZ \) = household size; \( OI \) = other income (Rs.); \( EX \) = experience of the household head (years); \( DI \) = distance travelled to the fishing ground (km); \( GP \) = participation in another group (1 = participate; 0 = otherwise); \( \delta_0 \) = constant; \( \delta_1 \) to \( \delta_5 \) = coefficients of inefficiency variables.

The Translogarithmic model is specified as follows:

\[
\ln(Y_i) = \beta_0 + \beta_1 \cdot \ln(Gear) + \beta_2 \cdot \ln(Capital) + 0.5\beta_{11} \cdot (\ln(Gear))^2 + 0.5\beta_{22} \cdot (\ln(Capital))^2 + \beta_{12} \cdot [\ln(Gear) \cdot \ln(Capital)] + (V_i - U_i) \quad (5)
\]

The inefficiency model and its variables are as same as the Cobb–Douglas model. In all the cases, the frontier function itself and the inefficiency part were estimated in one step using Maximum Likelihood Estimation (MLE) to achieve both efficiency and consistency in estimation.

As the Cobb-Douglas functional form is nested within the Translogarithmic functional form, Likelihood Ratio (LR) test, as shown in equation 6, indicates the adequate representation of either form of Frontier
Production Function (Basnayake and Gunaratne, 2002).

\[ LR = -2 [\ln L(H_0) - \ln L(H_1)] \]  

(6)

where, LR = likelihood ratio; \(H_0\) = restricted model (log likelihood value of the Cobb-Douglas model), and \(H_1\) = unrestricted model (log likelihood value of the Translogarithmic model).

2.2 Study Area and Data

A number of fishing villages, which were located within the 60 Landing Sites demarcated by the Chilaw Fishing District to cover corresponding Grama Niladhari divisions (Dept. of Coastal Conservation, 2007), were earmarked initially, and in turn, carried out personal and telephone-based discussions with various personnel, including Grama Niladhari and other government officials who possess administrative powers and relationships with fishers, community leaders etc. to select the best sites to collect data.

At the end of this ‘site identification’ process, four coastal villages, namely Kadawatha, Ulhitiyawa, Kolinjadiya and Katuneriya, located in the Chilaaw Fishing District were selected, on the justification that almost all households in these villages are involved with fishing related activities at small to medium-scale, easy access, interest shown to provide information with minimum restrictions to insect their fishing equipment/gear etc. A randomly selected sample of 124 small–scale fishing households in those villages were contacted by means of a personal interview carried out with a help of a structured questionnaire from March to April 2014. During the interview, in addition to the recorded data on their socio-economic and demographic conditions, the ‘physical infrastructure’ belonging to the household that aid in fishing such as fishing gears, fishing boats and engines were observed. The estimates of variables of the models were obtained through the statistical package STATA (version11.2).

3 Results and Discussion

3.1 Descriptive Statistics of the Variables

The summary statistics of the variables used in the study sample are given in Table 1. It shows that fishing output varied substantially amongst the households in the sample ranging from a minimum value of 2.0 kg/visit to a maximum of 452.5 kg/visit with Mean 39.5 kg/visit.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Average</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fish output</td>
<td>39.5</td>
<td>2.0</td>
<td>452.5</td>
</tr>
<tr>
<td>Gear</td>
<td>0.3</td>
<td>0.1</td>
<td>0.9</td>
</tr>
<tr>
<td>Capital</td>
<td>0.5</td>
<td>0.1</td>
<td>1.5</td>
</tr>
<tr>
<td>OI</td>
<td>1481.0</td>
<td>0.0</td>
<td>20000.0</td>
</tr>
<tr>
<td>EX</td>
<td>22.3</td>
<td>1.0</td>
<td>50.0</td>
</tr>
<tr>
<td>HZ</td>
<td>3.3</td>
<td>1.0</td>
<td>9.0</td>
</tr>
<tr>
<td>DI</td>
<td>26.5</td>
<td>12.0</td>
<td>40.0</td>
</tr>
</tbody>
</table>

(Variables are same as defined as earlier)

3.2 Effect of Different Variables on Technical Efficiency

The estimates of different variables included in the Cobb-Douglas and Translogarithmic models for all three specifications to express the distribution of the inefficiency term (i.e. Half normal, Truncated normal, and Exponential) are reported in Table 2. Based on the outcome of LR test, the Translogarithmic model was selected as the best-fitted Stochastic Production Frontier model; thus, the results of which is of interest for this discussion.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Half normal</th>
<th>Exponential</th>
<th>Truncated normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gear</td>
<td>-0.11</td>
<td>0.41</td>
<td>-0.14</td>
</tr>
<tr>
<td>Capital</td>
<td>0.58</td>
<td>0.01*</td>
<td>0.59</td>
</tr>
<tr>
<td>Lambda</td>
<td>2.28</td>
<td>1.25</td>
<td></td>
</tr>
</tbody>
</table>

| Gear           | 0.70        | 0.30        | 0.68             | 0.31              | 0.67              | 0.32             |
| Capital        | 0.64        | 0.17        | 0.66             | 0.16              | 0.68              | 0.15             |
| (Gear)^2       | -0.15       | 0.72        | -0.14            | 0.73              | -0.14             | 0.73             |
| (Capital)^2    | -1.67       | 0.02*       | -1.63            | 0.02*             | -1.57             | 0.03*            |
| Gearcapital    | 1.34        | 0.05*       | 1.33             | 0.05*             | 1.30              | 0.06*            |
| Lambda         | 2.10        | 1.17        |                  |                   | 4.46              |                 |
| LR stat.       | 4.07        | 4.16        | 3.36             |                   |                   |                 |

Table 1. Summary statistics of the variables

Table 2. Maximum Likelihood Estimates of Variables
Based on the estimated Lambda value, we can infer that the vast majority of fisheries households in the sample perform poorly as a result of their inefficiency, but not due to the random errors. The positive (negative) coefficient of each variable implies that any increase (decrease) in the value of the variable would lead to an increase (decrease) in the level of production. Even though the estimates of variables “Gear” and “(Gear)²” were statistically not significant, the signs of which – positive and negative, respectively – provide some insight into the analysis. It reveals that the increase in fishing gears would increase the production up to a certain optimum level; however, further increase of which would result decreasing of the fish output, i.e. it falls into a region of diseconomies of scale. Similarly, the variables “Capital” and “(Capital)²” can be considered together. The variable “(Capital)²” was statistically significant at 5% interval. The Maximum Likelihood estimates of the coefficients of these variables show a positive and negative sign, respectively. This implies that an initial increase in fishing capital would increase the fish production up to a certain level, and beyond that, like in the case of fishing gear, further increase to which would result decreasing in production. The variable ‘Gearcapital’ denotes the possible interaction effect of these two major inputs used in the fish production (i.e. fishing gear and fishing capital). The positive coefficient for this particular variable tells us that a one percent increase of possible combination of these two inputs would significantly increase the fish production by 1.3 percent. The estimates of coefficients of Inefficiency Model are reported in Table 3.

Table 3. Estimates of variables in the inefficiency model

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>HZ</td>
<td>-0.24</td>
<td>0.02*</td>
<td>-0.33</td>
<td>0.05*</td>
<td>-1.74</td>
<td>0.61</td>
</tr>
</tbody>
</table>

For this case also, the Translogarithmic Production Frontier, as confirmed by the Likelihood Ratio test, is selected for the discussion. The estimate of coefficient of the variable “Household Size” is negative and statistically significant in all the models. This signifies that a fisherman whose household size is “large”, in general, is more efficient than his counterpart, i.e. fisherman whose household size is comparatively “small”. This can be due to the fact that the ability for particular household to provide continuous, dedicated and non-priced labor into the process of fish production for a household with less members is relatively scarce; thus, has to depend on other external sources. Although it was not statistically significant, sign of coefficient of many other variables, including “Other income”, “Distance to the fishing ground”, “Group participation”, and “Experience of the household head”, provides an intuition on the potential contribution of corresponding variable to increase efficiency of fish production. The results indicate that the fishermen who earn through other part-time engagements on top of their regular earnings from fishing (“Other income”) was not significantly affected in this respect, or in other words, it was observed that it is the amount of income that matters and not from where it comes from for these households since other income earned did not have any impact to adjust their level of efficiency.
Surprisingly, number of years a fisherman was involved with fishing activity, denoted as “Experience of the household head”, did not increase the efficiency in fish catching significantly. From one hand, this may be due to the fact that small-scale operations that they undergo at present, or availability of certain technologies such as Geographic Positioning Systems (GPS) and advanced boat engines etc., on the other hand, may diminish the role that fisher’s experience has to play to be in this profession continuously. Further, the distance traveled by a fisherman from his home to the fishing ground (“Distance”) also did not increase the efficiency of fish production significantly relative to their counterparts. In fact, in the case of fishing, the home and fish landing site is relatively close and most of the fisherman tend to use certain own transportation facilities like three-wheelers, motor-cycles etc. for this purpose, which may be different for other businesses like agricultural and livestock operations. Moreover, there is no difference in TE between a fisherman who participates in fishing related activities in another group/s and is involved with his peer group only.

The distribution of TE computed through the Translogarithmic Production Frontier for the three types of distributions of the inefficiency error term (i.e. Half normal, Truncated normal and Exponential) is depicted in Figure 1.

We may notice that all three distributions were ‘skewed to the left’ indicating that, pertaining to this sample, a higher proportion of households were relatively efficient. As shown in Half-normal distribution, the highest percentage of households was included in 60 to 70 percent category of TE which for the Exponential and Truncated distributions were 70 to 80 percent. Overall, we may imply that the highest percentage of households was efficient in the range of 60 to 80 percent, and more importantly, there is a scope of increasing their efficiency by another 40 percent. It also highlights that none of the households was ‘fully efficient’ in either distribution. The average TE estimated using the Translogarithmic model was 59.8 percent relative to the most efficient household suggesting that an efficiency gain of 40.2 percent can be achieved with the prevailing resource base.

4 Conclusions

The marine fisheries sector plays an indispensable role in the economy of Sri Lanka; thus, any effort to increase the efficiency of resource utilization towards fish harvesting would have a sizeable impact on general welfare of fishing households by way of income generation, employment, and food & nutritional security, and at the macroeconomic level, by reducing the burden of costs of importing fish products. The purpose of this study was, therefore, to assess the performance of small-scale fishing households in Sri Lanka in terms of TE and to explore the determinants of inefficiency. The fishing households located along the coastal belt in the Chilaw Fishing District were used as the case.

On the justification that estimation of TE vary according to the distribution pattern of the error term, study utilized Stochastic Production Frontier methodology with three important distributions, including Half normal, Truncated normal, Exponential. The outcome of analysis suggests that Translogarithmic model was the best-fitted model to make inferences. The results reveal that an increase in the value of ‘Fishing gear’ and ‘Capital’ increases the efficiency by 1.3%
and decreases with overuse of gear and capitalization. The inefficiency model indicates that increase in household size increases the efficiency due to increase in availability of labour. Mean TE of the households was 59.8% in relation to the most efficient household in the sample, i.e. an efficiency gain of 40.2% can further be achieved with the existing resource-base. From a policy point of view, the outcome of analysis highlights the necessity of capacity development of small-scale fishing communities, alongside provision of a schema of an appropriate economic incentives embodied with both fiscal and legal instruments, to promote adoption of appropriate technology and coordinated action towards effective utilization of existing resource-base, which largely possess the characteristics of a ‘public good’. Last but not least, further work is much warranted to get a better understanding of the key determinants of growth of output and productivity. In fact, any changes to the level of efficiency can be evaluated through a panel data analysis that uses information gathered from the same sample after a certain time period, and can, in turn, use recent advances in panel data methodologies in production frontier models that permit joint estimation of efficiency and its determinants, where one can examine critically in which areas output and inputs has shown a growth along with technological change.

References


### Authors’ description

Ann Fernando is a Final Year Research Student specialized in agribusiness management of the Wayamba University of Sri Lanka.

Udith K. Jayasinghe-Mudalige is a Professor (Chair) of the Wayamba University of Sri Lanka and Fulbright Visiting Professor at the University of Massachusetts, USA. His research interests include food & agricultural economics and business management.

Jagath Edirisinghe is a Senior Lecturer in the Wayamba University of Sri Lanka. His research interests include food and agricultural economics and marketing.

Menuka Udugama is a Lecturer in the Wayamba University of Sri Lanka and PhD candidate at the University of Reading, UK. Her research interests include agricultural, resource and environmental economics.

Keminda Herath is a Lecturer in the Wayamba University of Sri Lanka and PhD candidate at the University of Peradeniya, Sri Lanka. His research interests include statistical modelling.

Sashika Guruge is a Lecturer in the Wayamba University of Sri Lanka and M.Phil. candidate at the Wayamba University of Sri Lanka. Her research interests include agricultural business, finance and accounting.