Technical Efficiency of Turmeric Production in Sri Lanka: A Stochastic Frontier Approach

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Abstract

While acknowledging the substantial contribution of Sri Lanka's agricultural sector to the economy's total agricultural output, experts have found that spices are not produced at total capacity. Among agricultural export items, turmeric is still not fully exploiting the country's agricultural resources. Due to input-related issues, this sector is affected by several deficiencies. Accordingly, this study has been designed to estimate the technical efficiency of turmeric production and determinants of technical inefficiency in Sri Lanka using cross-sectional survey data collected from turmeric producers from six districts in Sri Lanka. The sample was decided using a multistage random sampling approach. The data was analyzed using maximum likelihood estimates of the stochastic frontier production function and technical inefficiency model. The results revealed that the average technical efficiency of the turmeric sector was 74%, with a 26% margin for improvement through better use of available resources and technology. The results of the Cobb-Douglas production function and stochastic frontier production function showed that the size of the land and the number of seeds were the major inputs that determine the production. The results of the inefficiency model revealed that family size and farmer's experience have significant effect on technical inefficiency.

Keywords*: Inefficiency, Resource Optimization, Sri Lanka, Stochastic Frontier Approach, Technical Efficiency, Turmeric Production*

Introduction

Annual turmeric requirement of Sri Lanka is around 6,800 MT. Sri Lanka imported 4,958 MT of turmeric in 2017 and domestic turmeric production is 1866 MT in the same year. Sri Lanka is one of the major turmeric importing countries in Asia and mainly imported from India, which range from 5000 to 6000 MT and at a cost of around Rs. 1142 million. Since 1986, the cultivation has been kept up-to-date with unsolved technological and behavioral issues. Low productivity, rising production costs, dropping local pricing, illogical fertilizer use, financial capacities, unanticipated adverse climate changes, and ignorance of local turmeric quality are only a few of them (Department of Export Agriculture [DEA], 2019).

Sri Lanka has a total land area of around 6,561,000 hectares, with a total agricultural land area of 4,369 hectares (World Bank, 2020). There are 923 hectares of turmeric growing area in the country. It accounts for 0.04% of Sri Lanka's overall land area and 21% of the country's total agricultural land area. According to DEA (2019) and Abeynayaka *et al*., (2020), Kurunegala, Gampaha, Kalutara, Kandy, Matale, and Ampara are the main turmeric growing districts and profitable areas in Sri Lanka. Furthermore, due to its popularity among farmers as an income-generating product in paddy land and other cultivation areas in Sri Lanka, the turmeric sector is regarded as a vital agricultural crop. In 2020, as per the Department of Export Agriculture's figures, there are 12,900 turmeric farmers in the agricultural sector in Sri Lanka (Department of Export Agriculture [DEA], 2019).

Output maximization is generally attributed to inputs, technology, and the technical efficiency of production. However, it would be reasonably difficult to spend a large amount on technological changes and apply more input in the short term due to the nature of the producers. The term 'technical efficiency' refers to the maximization of output from a given level of inputs using the technology available. The technical efficiency of the turmeric production can be used to determine farmers' ability to raise current output from a given set of inputs. If farmers' technical efficiency is below the expected level, it appears that they can raise their yield from existing inputs by reducing inefficiencies in their production. This will most likely be significant in the long run because it improves economic efficiency by lowering the costs.

Turmeric, as a fast-increasing sub-sector of the Sri Lankan agricultural economy, must focus on maximizing efficiency in the use of its existing resources to achieve maximum possible output. Importantly, this would enable the country to be self-sufficient in this crop while avoiding any import requirement and enabling exportation to reduce the burden on the Balance of Payments (BoP). Thus, the farmers engaging in this crop production must be technically efficient. However, research suggests that it performs at a lower-than-potential level due to inefficiencies in the turmeric crop production process (Naik & Hosamani, 2017). As a result, Sri Lanka faces an inefficiency problem in utilizing its available turmeric resources. Therefore, this research examines if turmeric farmers can increase their output without additional input requirements and related costs.

With this explanatory study, turmeric farmers will most likely be able to increase their efficiency by eliminating inefficiencies in production. Accordingly, this study has focused on the turmeric industry to determine its level of technical efficiency and capacity to get the most out of a given set of inputs and technologies. The findings of this study would certainly enable the turmeric producers to maximize their yield by optimizing their existing resources without committing to newer inputs and technological investments. Furthermore, the results and findings of this study will have ramifications for the turmeric industry's responsible authorities in directing farmers to improve their efficiency to reach the national level goals.

Hence, the objective of this empirical research is to determine the level of technical efficiency of turmeric production in Sri Lanka. Furthermore, this study concludes with critical initiatives to enhance the technical efficiency of this industry, which will likely provide perspectives to the turmeric plantation sector. These initiatives would probably provide remedies to this industry that encounters difficulties in optimizing its resources in maximizing the output.

Literature review

Technical efficiency in production

Technical efficiency and allocative efficiency are two elements of resource efficiency or economic efficiency. Much of the efficiency literature is based, directly or indirectly, on pioneering work that claimed efficiency could only be properly measured in a relative sense. Allocative efficiency attempts to represent the ability of producers to utilize inputs in optimal proportions with respect to pricing (Khai & Yabe, 2011). The study of efficiency in economics is vital; despite its difficulty and states that technical progress is one of the main drivers of economic growth (Colman & Young, 1989). According to them, allocative efficiency occurs when variables are utilized in magnitude that maximize producer profitability, given the input prices. It occurs when farmers arrange all inputs to the point where the increased benefits, or marginal returns, equal the additional or marginal expenses, all other factors being equal. Only the changes in other constant factors, such as relative pricing of materials utilized, agricultural technology, or institutional structures, can disrupt this equilibrium (Stevens & Jabara, 1988).

Technical Efficiency is a metric that determines whether a particular technology's output meets its maximum potential. As interpreted by Forsund *et al*., (1980), technical efficiency is generated from the production function and is an important component of productive efficiency. Liverpool-Tasie *et al*., (2011) described technical efficiency in agriculture as the ratio of the total farm output to the total amount of farm inputs used in agricultural production. Accordingly, it is the ability to obtain the highest output level for a given level of input, based on the level of alternative technology currently available (Ellis, 1993). Technical efficiency can be improved by maximizing the output of the inputs used in production or minimizing the inputs used for output (Khai & Yabe, 2011). Thus, economic efficiency offers a theoretical framework for a measure of producer performance in response to economic incentives, which is frequently relevant for policy objectives. The concept of technical efficiency solely relates to the physical aspects of a manufacturing process.

The importance of measuring technical efficiency in production has been emphasized by many scholars such as Schultz and Schultz (1982), Kuznets and Murphy (1966), Kawagoe *et al*., (1985). They have claimed that economic growth depends entirely on advanced technologies and the ability to adapt to them. Accordingly, high output growth can be achieved by increasing the speed of technological innovations and technological applications used in production. Productivity growth of the production system could be divided into two categories known as technical development and efficiency, and such division makes it easier to investigate the origins of production improvement from a variety of angles (Kawagoe *et al.*, 1985).

More precisely, technical efficiency denotes an entrepreneur's capacity to run a firm and technological development denotes an advance in manufacturing procedures resulting in higher output levels. Increases in technical efficiency are derived from superior decision-making, which depends on the entrepreneur's know-how, experience, and education (Ahmad, & Bravo-Ureta, 1996). In output maximization, the efforts to increase the technical efficiency of the product should be coordinated with the development of new technologies. Technical efficiency can be used to quantify efficiency at the firm level. However, regarding a single product, apparently, the use of technical efficiency is more sensitive than any other form of efficiency (Bravo-Ureta & Pinheiro, 1997).

Determinants of technical efficiency

Different scholars have assessed various farmers' and farm characteristics as determinants of technical efficiency. Among these determinants, demographics such as age, gender, education, experience of the farmer and other income sources, credit availability, membership of farming associations and size of the household are fundamental. According to their empirical study, Goyal *et al*. (2006) claim that the farmer's age doesn't have a major impact on technical inefficiency. They have further claimed that male farmers work more efficiently and are more likely to be efficient than their female counterparts. However, Ajibefun and Abdulkadir (2004) and Novak *et al*. (2015) has confirmed that there is significant positive impact of farmer's age on efficiency. Jayakody and Dishanka (2019) claimed that increase in the age, education, experience of farmers has a positive productivity impact and reduces technical inefficiency. Further, they have found that membership in farmers' associations and credit accessibility are also significant in improving technical efficiency.

Addo and Salhofer (2022) has found that not only farmer's age and specialization based on experience, but also higher share of family labour is also significant in technical efficiency. Shantha (2019) has claimed that alternative sources of revenue will have an impact on inefficiency. As per his research, off-farm operation has a negative and significant effect on farmer's inefficiency in production. The rationale for this income from off-farm or non-farm activities that can be used as extra money to purchase agricultural inputs and eventually improve paddy farmer's risk management capacity. Tipi *et al*. (2009), have found that membership of a cooperative significantly influences efficiency. However, they have further identified that farmer's age and off-farm income affect efficiency. Alwarritzi *et al*. (2015) have revealed that one of the specific reasons for credit access being insignificant is the inappropriate utilization of credit by farmers.

Accordingly, the determinants of technical efficiency or inefficiency can vary as per contextual factors such as the nature of the product, natural and socio-cultural factors. Latruffe *et al.* (2004) based on their study on Polish crop and livestock farms have found that some of the determinants of technical efficiency in crop sector are different from livestock sector.

Measuring technical efficiency through stochastic frontier model

According to Farrell (1957), the stochastic frontier model was developed to provide a method for estimating the productive efficiency of observable units. Many economists, especially Charnes, Cooper, and Rhodes (1981) and Banker, Charnes, and Cooper (1984) have adopted the non-parametric approach to measure the technical efficiency in their studies. Importantly, there are deterministic and stochastic frontiers in these models. Deterministic models have indicated higher technical efficiency ratings since any deviation from the frontier is considered inefficient. On the other hand, the stochastic frontier method has taken statistical noise into consideration. Aigner et. al. (1977) and Meeusen and van Den Broeck (1977) further developed the stochastic frontier model concurrently but separately. Accordingly, this section highlights various empirical studies in which stochastic frontier model has been adopted and the results/findings of those.

Cobb-Douglas stochastic frontier production function has also been utilized in a study on tea farmers in Vietnam's Northern Mountainous region to estimate tea output and production efficiency (Hong & Yabe, 2015). The researchers discovered that the average technical efficiency level of tea farmers in the study region was 89.6%, and that with the same level of inputs and technology, the farmers could have improved their production by another 10.4%. Rawlins (1985) has studied how the Jamaicans'

Second Integrated Rural Development Project (IRDP II) affected crop growers' technical efficiency. The data of 172 farmers were analyzed, 80 of them took part in the research while the rest 92 were non-participants. Cobb-Douglas stochastic production frontier has been adopted for both participating and non-participating farms independently. The results demonstrated that the non-participating farmers' mean technical efficiency was greater (74.5%) than that of the participating farmers (70.6%). Furthermore, there was a higher range of individual outputs below potential and a lesser propensity for the frontier to vary among farms for participating farmers compared to non-participating farmers. The mean technical efficiency score for the entire sample was lower (68.5%) than the mean of two other frontiers.

Technical efficiency levels of large landowners range from 84.5% to 97.8% (Banik, 1994). This has been confirmed by Khai and Yabe (2011) in their study to investigate the utilization of resources in rice cultivation in Colombia. A stochastic frontier function has been estimated with a Cobb-Douglas specification and found that rice producers' technical efficiency was 85.8% on average. The technical inefficiency in the form of input overutilization has averaged 14.2%. Bravo-Ureta and Pinheiro (1997) evaluated the technical efficiency of farmers cultivating cotton in Eastern Paraguay using the stochastic frontier method. The average technical efficiency score of 58% has indicated that a considerable improvement in input utilization will result in significant productivity improvement. Sharif and Dar (1996) have used stochastic frontiers to determine the efficiency distributions of farmers growing conventional and high-yielding rice cultivars in Bangladesh. Data have been analyzed using a stochastic frontier technique based on maximum likelihood and corrected ordinary least square techniques, as well as half normal and exponential assumptions about technical inefficiency. According to the results, inefficiency has accounted for much of the variability in the yield of high yielding varieties, whereas random variables accounted for much of the variability in conventional rice farming. Bravo-Ureta and Pinheiro (1997), have assessed the technical, economic, and allocative efficiency of peasant farming in the Dominican Republic's Dajabon region. Data for the study came from a random survey of 60 small agricultural farms conducted in the spring of 1988. The researchers employed a stochastic frontier production function with a Cobb-Douglas specification. According to the results, the farmers' technical efficiency score has averaged 70%. Given current technology, the results showed that significant increases in output may be achieved.

Seyoum *et al.* (1998) have analyzed maize farmers' production and technical efficiency in a project in Eastern Ethiopia using stochastic frontier production function with Cobb-Douglas specification. The project participants' mean frontier output was substantially higher than that of non-participating farmers. As the mean technical efficiency levels of project participants and non-participating farmers were reported to be 97% and 79%, respectively. This result confirmed that farmers within the project are technically more efficient than farmers outside the project based on their unique technologies. Based on the data from Ratnapura district in Sri Lanka, Jayakody and Dishanka (2019) has measured the technical efficiency of low-grown tea smallholders. The stochastic frontier model has been applied with Cobb-Douglas specification to analyze the data and concluded that tea smallholders' technical efficiency could be further improved as the average technical efficiency was 56%.

Chakraborty *et al*. (2002) have investigated cotton farmers' technical efficiency in Texas, the USA. Data from 74 farms in 1998 was used (51 irrigated and 23 non-irrigated). Based on the results, the mean technical efficiency scores obtained using the stochastic frontier approach with Cobb-Douglas specification and data envelopment analysis methodology were similar. However, individual farm scores have been different between irrigated fields (80%) and irrigated farms (70%). Reddy (2002) has investigated the impact of the farmers' tenancy status on the technical efficiency of sugarcane plantations in Fiji. According to the data acquired for the crop year 1996-97, a stochastic frontier production function with Cobb-Douglas specification has been applied to measure technical efficiency. The research has included a total sample size of 399 farms, with 199 tenant farms and 200 owner farms. In terms of input utilization, production, and technical efficiency, considerable discrepancies between two types of farms were found. Tenant-operated farms had an average technical efficiency of 82.3%, whereas owner-operated farms had an average technical efficiency of 90.3%.

Onyenweaku and Nwaru (2005) have assessed the technical efficiency of food crop producers in Nigeria's Imo state. Data of 187 farmers from the state's three agricultural zones were analyzed. A stochastic production frontier using the Cobb-Douglas specification has been calculated and found that the farmers' mean technical efficiency was 57.1% with a minimum of 31.1% and a maximum of 95.1%. According to the findings, wide range of technical efficiency ratings suggest that farmers have several opportunities to boost their food crop production and revenue by improving technical efficiency. Asadullah and Rehman (2006) have investigated agriculture production and efficiency in rural Bangladesh using data from 2678 rice-producing families in 141 villages in the Chandpur district. A stochastic production frontier technique was used with Cobb-Douglas specification to analyze the data and found that rice producers had a mean efficiency level of 73.0%. Adeshina, Ologbon and Idowu (2020) have discovered efficiency differences in rice production in Oyo state, Nigeria. The stochastic frontier production function has been applied on the data of 128 rice farmers. The mean technical efficiency, allocative efficiency, and economic efficiency of 88.5%, 66.9% and 58.3% respectively showed that there is room for improvement in technical efficiency by 11.5%, allocative efficiency by

33.1% and economic efficiency by 41.7% with the present technology. Zewdie *et al* (2021) have examined the agricultural technical efficiency of large-scale irrigation users, small-scale irrigation users and non-user farmers in Ethiopia, using 1026 household-level cross-section data and adopting a technology flexible stochastic frontier approach. The results indicate that, due to poor extension services and old-style agronomic practices, the mean technical efficiency of farmers is 44.33%, implying that there is a wider room for increasing crop production in the study areas through increasing the efficiency of smallholder farmers without additional investment in novel agricultural technologies. Results also show that large-scale irrigation user farmers are less technically efficient with a score of 21.05% than small-scale irrigation user farmers with a score of 60.29%. However, improving irrigation infrastructure shifts the frontier up and has a positive impact on smallholder farmers' output. Khan, Huda, and Alam (2010) have investigated rice farmers' technical efficiency in Bangladesh. Data from 150 farmers in Bangladesh's Jamalpur area has been analyzed. The data has been analyzed separately for farmers cultivating Aman (wet) and Boro (dry) rice crops using a stochastic frontier production function with Cobb-Douglas form. Wet rice crop farmers scored 95% efficiency, whereas dry rice crop farmers scored 91% efficiency. It was believed that because the farmers in the study region were efficient enough in rice production, new rice species could be developed to improve rice output in the area.

Research methodology

This study has been conceptualized on the positivistic research paradigm. Thus, the Cobb-Douglas production function was used as the theoretical foundation from which study hypotheses have been deduced. This production function is intermediate between a linear production function and a fixed proportions production function. In this function there are two major inputs; labour (L) and Capital (K) and the function takes the following form.

$$Q = AL^{\alpha}.K^{\beta}$$

Where, Q denotes output, L is labor quantity, K is quantity of capital and A, α, and β are positive constant. Cobb-Douglas production function was employed in the study to calculate the efficiency scores of turmeric farmers. Turmeric production was considered as an output, and three inputs namely as land size (acres), seed (kg/year), and labour (hours/year) were designated as production inputs. Thus, the Cobb-Douglas production function's empirical model is provided by:

$$Ln\, Y_i = \beta_0 + \beta_1 LnX_{1i} + \beta_2 LnX_{2i} + \beta_3 LnX_{3i} + (V_i \; - \; U_i)$$

βi is unknown parameters to be estimated (β_1, β_2, and β_3 are the coefficients of each independent variable), Vi is a two-sided random error that depicts elements beyond the farmer's control and Ui is a non-negative one-sided random error that indicates technical inefficiency.

The error term in the stochastic frontier model is decomposed into a two-sided random error component that reflects random factors outside the control of the firm (the decision-making unit) and a one-sided efficiency component. Meeusen et.al. (1977) and Aigner et. al.; (1977) were the first to develop the model. The formula for the stochastic production frontier is as below.

$$Yi = f(Xij) + \varepsilon j;\ \varepsilon j = Vj - Uj$$

where, *Yi* is the production, *Xij* is the input level, and εj is the composed error term. The elements outside the *i*th number of farmers are Vj and the random control variables of the *i*th number of farmer's output are denoted by Uj. Most of the empirical studies assume that Vj is identically and independently distributed as N(0, $\sigma^2{}_v$). A one-sided component | Uj | > 0 indicate technical inefficiency relative to the stochastic frontier. Thus, | Uj | = 0 for a farm whose production lies on the frontier, and | Uj | > 0 for one whose production is below the frontier. Assuming that Uj is identically and independently distributed as | N (0, $\sigma^2{}_u$); the distribution of Uj is half-normal. According to Battese and Corra (1977), the variance ratio parameter γ which relates the variability of Uj to the total variability (σ^2) can be calculated in the following manner.

$$\gamma = \sigma^2{}_{u}/\sigma^2 ,$$

$$\text{where } \sigma^2 = \sigma^2{}_u + \sigma^2{}_v ;$$

$$\text{So that } 0 \le \gamma \le 1$$

If $\gamma \to 0$, the difference between a farmer's yield and the efficient yield is mainly due to statistical error. On the other hand, if $\gamma \to 1$, the difference is attributed to the farmer's less than efficient use of the technology. The parameters of the stochastic frontier production function model can be estimated by the method of maximum likelihood, using the computer program, FRONTIER Version 4.1 (Coelli, 1996).

After adopting the stochastic frontier production for the estimation of the technical scores, the inefficiency effect model was applied to determine the effect of farmer (demographic) and farming characteristics on the technical inefficiency. Variables relevant to farmer and farming characteristics across turmeric farmers were collected from participants in the research area for this purpose. Accordingly, the following model was applied to determine the technical inefficiency in terms of the qualities of eight identified variables explained below.

$$ln\ Y\mathrm{i} = \beta_0 + \sum_{i=j}^{m} \beta_i \ \ \ln Xi + (Vj - Uj)$$

where i denotes as *i*th farmer, *j* is *i*th farmer's output, *ln* is natural logarithm, *Vj* is assumed to be independently and identically distributed random error, having N(0, $\sigma^2{}_v$) distribution, *Ui* is non-negative random variables, associated with the technical inefficiency of production of the farmers involved. It is assumed that the inefficiency effects are independently distributed and *Ui* arise by truncation (at zero) of the normal distribution with mean, μ_i and variance σ^2, where μ_i is defined by: $\mu_i = \delta_i z_i$

$$\mu_i = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + \delta_5 Z_5 + \delta_6 Z_6 + \delta_7 Z_7 + \delta_8 Z_8$$

where z_i, are variables which may influence the efficiency of a firm.

μ_i = Technical inefficiency
δ = regression coefficient
Z1 = Age of the farmers in years
Z2 = Gender is coded as 1 for male and 0 for female
Z3 = Family size (Number of family members)
Z4 = Years of education (number of years of schooling)
Z5 = Farming experience in years
Z6 = Other income; coded as 1 for farmer has other income and 0 for farmer has no other income
Z7 = Access to credit (a dummy variable which equals one if the farmer has access to credit and zero if the farmer has no access to credit)
Z8 = Membership (a dummy variable which equals one if the farmer is registered with DEA and zero if the farmer is not registered with DEA)

The turmeric farmers in Sri Lanka made up the study's population and the sampling frame. The study sample was chosen from the population using a multistage random selection process. Gampaha, Kandy, Kalutara, Kurunegala, Ampara, and Matale districts of Sri Lanka were chosen for the sampling frame. According to recent agricultural statistics there are approximately 12,900 farmers involved in turmeric production in those districts (DEA, 2019). The sample size was calculated with a 7% margin of error, and it was determined as follows.

$n = [\, z^2 * p * q \,/\, e^2 \,] \,/\, [\, 1 + (z^2 * p * q \,/\, (e^2 * \mathrm{N}))\,]$
Where,
z = 1.96 for a confidence level (α) of 95%
p = Proportion
N = Population size
e = margin of Error (sample size based on 7% margin of error)
z = 1.96, p = 0.5, N = 12,900, e = 0.07
n = [1.96^2 * 0.5 * 0.5 / 0.07^2] / [1 + (1.96^2 * 0.5 * 0.5 / (0.07^2 * 12900))]
n = 193 (required minimum sample size)

A sample size of 200 was decided from the above districts to meet the above requirement. An interview-based questionnaire survey was conducted to collect data. The maximum likelihood estimates among the models specified above and the expected technical efficiency are derived applying computer software SPSS version 28 and frontier version 4.1

Results and discussion

Results of Cobb–Douglas production function

The Cobb-Douglas production function determines the impact of land size and other inputs on turmeric output in the research locations. The ordinary least square method was used, with the log form of turmeric production as the dependent variable and the log form of other inputs as explanatory variables. The adjusted R^2 is 0.827, indicating that the input used in the study explained 82% of the variation in turmeric production. Furthermore, the F-value was 112.65, which is statistically significant at the 1% level, showing that the overall estimated linear regression model is sufficient to investigate the impact of the independent variables on turmeric output.

Table1: Results of Cobb-Douglas production function for input variables

Variables	**Coefficients**	**Standard error**	**t - value**	**Sig.**
Ln land	0.424	0.056	7.52	0.000***
Ln seed	0.482	0.039	12.25	0.000***
Ln labour	0.125	0.160	0.777	0.438
Constant	5.05	0.342	14.81	0.000***

Items	*Values*
R	0.796
R^2	0.633
Adjusted R^2	0.827
F – value	112.65***

Note: *** *represents 1% significant level*

The computed coefficients of parameters for logs of land size and seeds were significant when using the ordinary least square approach. The elasticity of turmeric output with respective inputs is reflected by the coefficients of each variable, which refers to the percentage change in output because of a 1% change in the input. The coefficient of land is 0.424, which denotes that if the cultivated land is increased by 1%, it will result in a 0.424% increase in turmeric output while all other inputs remain constant. Seed has a positive coefficient, which means that if farmers raise seed by 1%, turmeric production will improve by 0.482% on average.

Estimation of stochastic production frontier

The existence of inefficiency in the production of turmeric among farmers in the study area is also important in estimating technical efficiency and its causes. Accordingly, the variance parameters; sigma-squared and gamma were found to be significant. The coefficient of gamma (γ) was 0.579, indicating that technical inefficiency considered more than half of the inefficiencies in turmeric farms, while random error accounted for the remaining inefficiencies. As a result, the mode's explanatory factors contribute significantly to understanding the inefficiency effect linked with turmeric production in the study area.

In other words, the projected value of 0.579 implies that technological inefficiency accounts for 58% of the variation in turmeric output and 58% of the differences between observed and frontier output. With a statistically significant likelihood ratio test value of 38.92, the coefficients of the explanatory variables in the efficiency model are both zero and strongly rejected. This suggests that there had been farmer-specific and farm-specific factors influencing the technical inefficiencies among the turmeric farmers selected from the specified districts.

Table 2: Estimation of variance using stochastic production frontier

Variance parameters	**Parameters**	**Coefficients**	**Standard error**	**t–value**
Sigma squared	σ^2	0.737	0.043^{***}	3.03
Gamma	γ	0.579	0.020^{***}	3.60
Log likelihood hood		-190.83		
Chi – square value		38.92^{***}		

Note: *** represents 1% significant level

An empirical stochastic production frontier model was used to determine the level of technological efficiency of turmeric production in the study area. The total amount of turmeric output produced by farmers was used as the dependent variable. The inputs of turmeric production in log form along with their log squared forms were used as the independent variables. Table 3 displays the effects of the maximum likelihood estimates of the stochastic production function.

The p-values of land size and seeds were 0.000, as per the outcomes of this model in Table 3. This confirms that these two input variables are highly significant. Land size (0.369) and seeds (0.470) imply a significant positive impact, according to the assessed maximum likelihood (ML) coefficients. Each variable's output elasticity is explained by the model coefficients. Seeds have the highest output elasticity, with a coefficient of 0.470. This number indicates that increasing the quantity of seeds by 1% would result in a 0.47% increase in total turmeric yield.

This could have been justified by the fact that farmers can receive a higher part of yield per year if they employ more high-quality seeds. Farmers who employ low-quality seed varieties in different ratios may have an unsatisfactory turmeric yield. The output elasticity of land size and seeds is significantly higher than the output elasticity of labour. The rationale for the high output elasticity of land size and seeds is that farmers can acquire higher yield by increasing the area of their land and the number of seeds they apply. The use of unpaid family labour, of which the degree of productivity may be low due to informalities in application, could be the cause of the low output elasticity of labour.

Table 3: Maximum likelihood estimates of the stochastic frontier production function for turmeric production

Variables	**Parameters**	**Coefficients**	**Standard error**	**t–value**
Production frontier				
Ln land	β_1	0.369^{***}	0.053	6.88
Ln seed	β_2	0.470^{***}	0.035	13.19
Ln labour	β_3	0.161	0.163	0.986
Constant	β_0	5.354	0.380	14.07
Returns to scale		1.00		

Note: ***, ** and * represents 1%, 5% and 10% significant levels respectively

Distribution of technical efficiency

All six districts of the study had an average technical efficiency of 74 per cent with a standard deviation of 13.5%. This ranges from 24 per cent to 94 per cent, implying a greater degree of inefficiency. With the given technology and inputs, this score indicated that those farmers were only producing 74% of their maximum achievable output. This further implies that by using best practices to make significant changes, there is a possibility of expanding turmeric production by another 26%. Turmeric output could be boosted by operating crops at the frontier level without even using additional inputs. Most farmers would have to embrace improved technologies in their farming to eliminate inefficiencies and attain higher levels of efficiency. Farmers should learn about agricultural innovations both locally and from their neighbouring countries, such as India, which has a thriving agricultural sector.

Out of 200 turmeric producers, only 38% had 81% technical efficiency level. This indicates a substantial number of turmeric producers in the sample has a considerable margin to increase their production efficiency. Only 36.5% of them were operating at a level of efficiency between 71% and 80%. Only 10% of farmers were able to achieve an efficiency level between 60% and 70%. About 9% of them were running at a level of efficiency between 50% and 60%, while only 6.5% were operating at an efficiency level below 50%.

Table 4: Average technical efficiency

Technical efficiency scores			
Mean	0.73995	Kurtosis	2.840177
Standard Error	0.009604	Skewness	-1.66952
Median	0.78	Range	0.7
Mode	0.81	Minimum	0.24
Standard Deviation	0.135815	Maximum	0.94
Sample Variance	0.018446	Sum	147.99
Count	200		
Confidence Level (95%)	0.018938		

Determinants of technical inefficiency

A technical inefficiency effects model was constructed to determine the sources of technical efficiency differentials across the sample. The computed coefficients of the explanatory factors for the technical inefficiency effect have significant implications, which are addressed in this section. Using parameter estimates from the inefficiency model, the determinants of technical efficiency were investigated. A negative sign on an inefficiency parameter in this model indicates that the corresponding variable lowers technical inefficiency. A positive indication suggests that the connected variable is increasing or decreasing technical inefficiency. The inefficiency model results emphasize that family size is highly significant at 1% level of significance and farmer experience is significant at 5%. Moreover, farmer education and DEA registration (membership) are significant at 10% level of significance.

The family size is a significant positive determinant of technical inefficiency which significantly reduces productive efficiency. This indicates that larger family size reduces the efficiency level of the farmer. Although family size could be significant for a higher level of output through family labour, it may not improve technical efficiency. Technical efficiency is about reaching a higher level of output from the given amount of input. Besides, the maximum likelihood assessment confirmed (see, Table 3) that labour is insignificant and does not have a considerable impact on productivity. Therefore, large family sizes could further increase inefficiency due to informalities in employment of the resource.

Table 5: Maximum likelihood estimates of inefficiency effects model

Variables	Parameters	Coefficients	Stand. error	t-value
Age	δ1	0.018	0.016	1.11
Gender	δ2	-0.091	0.670	-0.13
Family size	δ3	0.654***	0.195	3.35
Education	δ4	-0.077*	0.056	-1.37
Experience	δ5	-0.102**	0.051	-2.00
Other income	δ6	-0.400	0.371	-1.07
Credit accessibility	δ7	-0.250	1.00	-0.24
Membership	δ8	-0.653*	0.407	-1.60
Constant	δ0	-2.809	1.19	-2.34

Note: ***, ** and * represents 1%, 5% and 10% significant levels, respectively

The results reveal that the famer's agricultural experience has a negative and significant impact on technical inefficiency. This confirms that more experienced and elderly farmers are more productive than younger and inexperienced farmers. Their efficiency is attributable to their excellent management abilities, which they have developed through time and enabled them to properly utilize available resources to achieve optimal output. Furthermore, seasoned farmers are well-versed in traditional farming techniques and more likely to adapt to changes in the environment.

The results confirm that educational attainment is adversely connected with technical inefficiency, significantly. It implies that educated farmers are more productive and technically efficient than those who are less educated. The reason for this could be the fact that education improves a farmer's capacity to make effective judgments about how to use available resources optimally. Besides, highly educated farmers have expertise to access relevant and reliable information, adapt to market changes, and learn innovative cultivation methods and technology. Importantly, unlike less educated farmers, highly educated farmers are inclined to gain new knowledge in new agricultural advancements.

The coefficient of the DEA registration has negatively and significantly affected the technical inefficiency. This indicates that farmers who are registered at DEA are more efficient than farmers who are not registered. Apparently, the reason for this disparity is that those who are registered at DEA will get more attention from DEA to improve their operational efficiency. Further, if the farmer is a member or registered at DEA, the member is exposed to new information and knowledge on problems, developments, price changes and techniques on turmeric cultivation activities such as fertilizing, land development, replanting, export opportunities, market for their product and financing.

Nonetheless, age, gender, other sources of income, and credit availability have had no significant impact on technical inefficiency. According to the results of previous empirical studies, it could be concluded that the determinants of technical inefficiency are subjective and context specific. These determinants could vary even within the same sector across regions. This emphasizes the non-generalizability of previous empirical findings to other contexts. Hence, it is required to conduct similar studies across sectors, industries, regions and identify context-specific factors that contribute efficiency.

Conclusion

The findings of the stochastic production frontier showed that technical inefficiency accounts for 58% of the overall variance in turmeric output as well as 58% of the differences between observed output and the frontier output. Furthermore, half of the inefficiencies in turmeric farms were linked to technical inefficiency with remaining inefficiency has been caused by random errors as compensated for by certain other characters. As a result, this suggests that the explanatory variables quantified in the model contribute significantly to the explanation of the inefficiency impact related to the production of turmeric in the research area.

These farmers were only producing 74% of their maximum feasible output level with scores ranging from 24% to 94%. This has indicated that there is a potential for further growth in output given the existing resources and technology. There is still potential for turmeric farmers to boost their technical efficiency because the output might be increased by 26% with the current inputs and technology. It was revealed that 38% of farmers were at an efficiency level of 81% or higher. Only 6.5% of farmers were at an efficiency level lower than 50%, while 9% of them were functioning between 60% and 50% efficiency level.

The results of the inefficiency model have indicated that farmers’ level of education and DEA membership/registration are instrumental in eliminating inefficiency. Therefore, it is essential to improve the agricultural and farm business management education among farmers through the DEA linkages with farmers to update them on effective and efficient use of major inputs. Hence, this understanding would presumably provide them with the ability to manage both labour and finances. They should be provided with greater options to enter the formal credit system in conjunction with such educational completion and government facilitation since the industry still has opportunities for local and global expansion.

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