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Article

Data Envelopment Analysis (DEA) to Estimate Technical and Scale Efficiencies of Smallholder Pineapple Farmers in Ghana

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Abstract: The study focused on the technical and scale efficiency of smallholder pineapple farmers in the Central Region of Ghana. The input-oriented Data Envelopment Analysis (DEA) was used to estimate technical, pure and scale efficiencies of the smallholder pineapple farmers, of which a random sampling procedure was used to select 320 respondents. The study revealed that the farmers were technically inefficient with mean technical efficiency under Constant Returns to Scale (CRS), pure efficiency under Variable Returns to Scale (VRS) and the Scale Efficiency levels of 0.505, 0.641 and 0.772, respectively, due to farmers' inability to exploit fully the available technology while experiencing evident post-harvest losses resulting from low adoption of post-harvest technologies. Such findings are meaningful and could help the farming communities and relevant policymakers to understand the issues in farming production and hence undertake necessary actions to potentially improve farmers' technical and scale efficiencies in the study area.

Keywords: data envelopment analysis; technical efficiency; scale efficiency; farming production

Introduction

The food and agricultural sector is fundamental to the Ghanaian economy because it contributes to sustain national growth and reduce poverty. Agricultural growth weighs heavily on Ghana's Gross Domestic Product (GDP) while improving livelihood of most Ghanaians as it is essential to meet the aggregate food needs and provides various employment opportunities generating income to over 60% of the Ghanaian working population from the rural areas (Asante & Kuwornu, 2014). Given its vital role, advance in the agricultural sector is often a goal and part of the developmental strategy in Ghana. Since 2002, agricultural policies were instituted aiming to enhance the overall economic growth including improving access to markets and financial services, developing infrastructure and agrarian society, expanding farming human resources and institutional capacity, and reducing non-performing lands due to unsustainable management coupled with low productivity (MoFA, 2002).

In reality, one of the major reasons for low agricultural productivity in Ghana is the inability of farmers to exploit fully the available technologies in farming, resulting in lower efficiencies. Over the years, Ghana's GDP attributed to agrarian production has been on a decline largely owing to lower productivity lacking technological use from major agricultural commodities such as pineapple. To this result, an increase or improvement in farming efficiency tied to effective farm-tech adoption would assume greater benefit for higher attainable output (Kathiravan, et al., 2018).

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Given the prevailing but limited farming technology and resource endowment, many Ghanaian farmers also face unfavorable gap between the potential and actual farm yields. Technical efficiency (TE) is an important measure of productivity differences across crops. It helps explore the capacity of existing farming technologies to improve or correct the disequilibrium in production, while the scale efficiency (SE) is equally important which allows farmers to apply and target the most productive scale so as to optimize farm yields (see Kathiravan, et al., 2018). As the efficiency check may most likely improve crop receipt, such as in pineapple farming, it is critical and strategic as a mechanism to reduce the productivity loss, close the production gap, and maximize farming output for the consumption demand. Given the importance and applicability of both efficiency measures, this study utilizes TE and SE to assess the smallholder pineapple farming across the Central Region of Ghana. Employed on the Data Envelopment Analysis (DEA), a mathematical programming used to estimate the production efficiency, its primary goal is to uncover the analytical findings upon the overall farming efficiency in the region, in hopes of suggesting policy instruments to foster future farming improvement.

Literature Review

Relevance of Efficiency and Productivity in Pineapple Farming

The agricultural sector is critical for achieving global economic growth and development in parallel with the 2030 Agenda for Sustainable Development Goals (SDG). Despite the importance of the agricultural sector, there is often a significant disparity in productivity between the primary sector and other industries and services. Many countries are taking measures to enhance productivity in regions where agriculture is a significant contributor to the economy. Improving productivity in the agriculture sector is essential for addressing poverty, ensuring food security, and increasing farmers' income. The global community recognizes the need for action to support the agricultural sector and has implemented various initiatives to support sustainable agriculture and rural development. In recent years, the importance of efficiency has become more prominent in various fields, especially agriculture, owing to the growing interest in productivity spillovers. Efficiency evaluation is a critical prerequisite for the sustainable allocation of scarce resources (Bansal et al., 2023; Haider & Mishra 2019; Paul, 2023).

Efficiency is defined as the capacity to perform a task in minimal time and effort. The origins of the concept can be traced back to economics, in which resource scarcity and the output gap serve as primary motivators. The literature on efficiency's definition and measurement dates back to pioneering works such as Debreu (1951) and Koopmans (1951). Farrell (1957) further contributes to the understanding of efficiency by defining it as the ability to attain a desired outcome with minimal resources. According to Farrell (1957), this is also reflected in the production unit's ability to effectively transform inputs into outputs and maximize output with a specific set of inputs and production technologies. In the microeconomic theory, efficiency is a crucial factor in determining the optimal output that can be achieved from a given set of inputs using the existing technology available to firms (Battese, 1992; Hidalgo, 2015). Hidalgo (2015) argues that efficiency is not solely dependent on the availability of resources but also on the effective management of these resources. Efficiency entails several dimensions such as technical, economic, and allocative factors, and examining these elements offers valuable insights into overall performance level (Adams et al., 2020).

However, Kelly et al. (2016) identified a significant challenge in measuring agricultural efficiency in developing countries, especially in sub-Saharan Africa, which is the underestimation of output and yields due to the failure to account for secondary crops and by-products. Horticultural crops are often excluded from farm output measurements because of their relatively small area compared with cereal or cash crops (Kelly et al., 2016). This is particularly relevant for farmers who are just beginning to diversify their product offerings to include fruit and vegetables. As indicated by Kelly et al. (1996), it is essential to estimate the efficiency of horticultural products, given the potential high value and importance of the revenue generated by farmers. The interest in smallholder pineapple farming has been increasing in Ghana in recent times due to its considerable impact on the

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livelihood of farmers and the economy as a whole (Boakye, 2020; De-Graft Acquah & Kumashie, 2016).

Although pineapple export and processing companies have increased, low yields continue to persist. Various factors contribute to this problem, including limited access to technology, inadequate credit availability, insufficient extension services, adverse weather conditions, and improper plant spacing. It is crucial to enhance production efficiency to meet the growing demand for pineapples (Rahim & Othman, 2019). Therefore, evaluating the technical and scale efficiencies of smallholder pineapple farmers as part of Ghana's agricultural policies is essential, especially when considering the increasing impact of climate change. However, there is a scarcity of empirical evidence estimating these efficiencies in smallholder pineapple farming, as highlighted from a methodological perspective.

Indicators for Measuring Efficiency and Productivity

In many respects, productivity and efficiency measurements for agriculture mirrors that of other industries. Notwithstanding this, several characteristics of the agricultural sector make it significantly different and, therefore, worthy of special consideration. A better understanding of efficiency in agriculture is required, especially in the context of lower availability of key resources and production factors. The burgeoning interest in the measurement of efficiency in agriculture has birthed various frameworks and indicators that can be broadly classified into parametric and non-parametric methods (Chen et al., 2020; Luo et al., 2017; Qiao et al., 2019; Shen et al., 2018; Zhao and Tang, 2018). Efficiency can be achieved using either parametric or non-parametric methods. Parametric methods such as the Stochastic Frontier Approach (SFA) proposed by Aigner et al. (1977) are proficient in distinguishing inefficiency from noise. Data envelopment analysis (DEA) is a non-parametric approach. Charnes et al. (1978) expanded Farrell's (1957) presentation on the concept of efficiency to encompass multiple output conditions by employing a linear programming-based data envelopment analysis methodology.

However, measuring efficiency is at the centre of many of the debates, policies and measures concerning the farming sector. It is crucial to account for the distinct characteristics of the agricultural subsector. This is because previous research has identified the difficulties associated with evaluating efficiency and productivity in the agricultural subsectors. Particularly in relation to smallholder farmers, the challenges are compounded by the fact that smallholder farmers, especially in developing countries, exhibit certain traits, such as a lack of profit motivation and limited production technology knowledge, which makes measuring their efficiency and productivity more intricate. The literature suggests that measuring efficiency and productivity in smallholder agriculture requires specific behavioral assumptions. Measurement techniques are generally classified as parametric and non-parametric, depending on their reliance on assumptions about the shape of the production frontier. Parametric methods are based on assumptions, whereas non-parametric methods do not make such assumptions.

Data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are commonly used techniques for efficiency analysis that do not require the specification of specific production functions or inefficiency terms in advance. As opined by several studies (Li et al., 2017; Shen et al., 2019; Adetutu and Ajayi, 2020; Benedetti et al., 2019; Gong, 2018) and in various industries (Błączęntis & Sun, 2020; Gao et al., 2021; Jin et al., 2019; Shi & Li, 2019; Wen et al., 2018), the use of DEA and SFA have become more prevalent due to their immunity to subjective influences. They are extensively applied for evaluating technical and scale efficiencies in agriculture. However, the SFA models possess features for measuring efficiency and productivity in agriculture, it has been criticized for its reliance on a predetermined production function and distribution form for the technical inefficiency component (Gong, 2020).

DEA models do not demand a predetermined functional form and establish a piecewise linear production boundary by comparing it with the most effective observed practices (Chen et al., 2021; Shen et al., 2018). DEA is particularly well-suited for gathering data on farm-level productivity and requires information on all outputs, inputs, and production factors to be collected. DEA has been

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extensively studied by the academic community. However, to the best of our knowledge, empirical studies on the application of DEA in Ghana remain elusive, as reflected in smallholder pineapple farming. In Ghana, studies on the efficiency of smallholder pineapple production have traditionally employed parametric methods (De-Graft Acquah & Kumashie, 2016; Essilfie et al., 2011; Mensah & Brummer, 2015), with only a few using DEA (Boakye, 2020; De-Graft Acquah & Kumashie, 2016). To bridge this methodological gap, this study employs DEA to estimate the technical and scale efficiencies of smallholder pineapple farmers in Central Ghana.

An Overview of Data Envelopment Analysis

DEA is a non-parametric method introduced by Charnes et al. (1978), which incorporates noise into their final outcomes. Unlike the parametric statistical approach of stochastic frontier analysis (SFA), which imposes a specific form on the production function to estimate the efficiency frontier, DEA is a non-parametric technique that assesses the relative efficiency of a decision-making unit (DMU) in comparison to similar DMUs on the "best practice" frontier (Paul, 2023). This method has broad applications in measuring technical efficiency, productivity, cost, and allocative efficiency (Sarkar, 2017). Additionally, DEA does not require assumptions about the relationship between inputs and outputs, unlike SFA, which may introduce uncertainty into the results (Watto & Mugera, 2019). In the agricultural sector, DEA is widely used because of its ability to handle multiple inputs and outputs, unlike conventional SFA models that can handle only a single input, output, or multiple inputs or outputs.

A recent study categorizing academic literature into DEA and non-DEA studies found DEA to be effective and flexible for estimating efficiency and production performance (Castro & Frazzon, 2017). As Adams et al. (2020) emphasised, current research on efficiency primarily focuses on the use of DEA as it does not necessitate assumptions about the functional form and distribution of errors, which is a prerequisite for stochastic frontier analysis (SFA). Building on this rationale, the DEA method has the potential to significantly improve productivity and efficiency in the agricultural sector. DEA can support the growth of the pineapple industry and contribute to the development of Ghana's agricultural sector. By focusing on the input-output data of smallholder pineapple farmers in this context, DEA can provide valuable insights into ways to optimize production processes, ultimately leading to increased productivity and profitability, particularly for smallholder pineapple farmers in the Central Region of Ghana.

Theoretical Structure of Efficiency Measurement

Efficiency Analysis

Theoretically, efficiency measures can be structured under the study of Leibenstein (1966). It starts with a producer who uses a non-negative vector of N inputs, denoted $x = (x_1, \dots, x_N) \in R_+^N$ to produce a non-negative vector of M outputs. This output vector is denoted $y = (y_1, \dots, y_M) \in R_+^M$. The technology set (T), or the collection of all feasible input and output vectors, is defined as:

$$T = \{(y, x): x \ can \ produce \ y\} \in R_+^{M+N} \tag{1}$$

Normally, production technology can be represented using the output or input sets. However, it can equivalently be defined using just the set of output. That is, for each input vector x, P(x) is defined as the set of feasible outputs, in the expression of:

$$P(x) = \{y: x \ can \ produce \ y\} = \{y: (y, x) \in T\} \in R_+^N \tag{2}$$

Here, the output set, P(x), is defined in terms of T. Since T is assumed to satisfy certain properties: *feasibility of observed data, free disposability, and selective convexity* (Olesen et al., 2022), it follows that P(x) can satisfy the corresponding properties. Importantly, the property of *free disposability* is a simple variation under the standard assumption of strong disposability of all inputs and outputs used, which have been adjusted for the requirement that the ratio of inputs and outputs should be within the input-output bounds.

Likewise, technology can also be defined by the input set, L(y), represented as:

$$L(y) = \{x: x\ can\ produce\ y\} = \{y: (y, x) \in T\} \in R_+^M \quad (3)$$

where the input set consists of all input vectors x that can produce a given output vector, y. Technically, as with P(x), L(y) is assumed to satisfy similar properties corresponding to T.

The above efficiency technique is useful and relevant to this study, as it allows the inspection of both technical and scale efficiencies over the smallholder pineapple farming, based on the technological component. That is, with the endogeneity of technology, it is likely to assess Central-regional Ghanaian farmers who were technically efficient when their counterparts were not.

Production Frontiers

In theory, the single-output case of production technology is useful in illustrating a production function. Its specification is used to describe a technology which produces only a single output, or more likely multiple outputs can be produced under the same technology which are aggregated into a single composite output $y = g(y_1, \dots, y_M)$. Definitions (2) and (3) above can then be converted to the following definition:

$$f(x) = max\{y: y \in P(x)\} = max\{y: x \in L(y)\} \quad (4)$$

where x is a vector of sources of information (inputs) and y is a scalar amount of output produced from the inputs used. The production frontier *f(x)* portrays the most yield (output) that can be produced with a vector of random information (inputs) to describe the upper limit of the possible output. Normally, producers work at or beneath this limit. The measurement of the distance from each producer's production input-output combination to the production frontier characterizes the assessment of technical efficiency.

In production theory, commonly, multiple-inputs are used to produce multiple-outputs with which a joint production possibilities frontier is used to describe the upper boundary of feasible production. This frontier involves defining a subset of both the input and output vectors each with an un-scalable maximum and minimum, respectively. Joint production frontiers are mostly and only utilized in observational examination since the upper limit of a production function in the multiple-input-multiple-output case is more often obtained by the distance functions (D). That is, an input distance function involves the scaling of the input vector as it measures distance from one production point to the boundary of production possibilities. Thus, the input distance function can be defined following the input set L(y):

$$D_1(x: y) = max\{p: x/p \in L(y)\} \quad (5)$$

Technical Efficiency

Koopmans (1951) provided a definition of technical efficiency for a multiple-input and multiple-output production; a producer is said to be technically efficient if an increase in any output is possible only by decreasing at least one other output or increasing at least one input. Alternatively, a reduction in an input is possible by reducing at least one output, or by increasing at least one other input. Accordingly, a technically inefficient producer could improve efficiency by using less of at least one input to produce the same level of output or could use the same inputs to produce more of at least one output.

Koopmans' definition of technical efficiency provides a way to differentiate between efficient and inefficient states of production. It does not, however, provide a measure of the degree of inefficiency or the tools for the comparison between inefficient and efficient input vectors. Alternatively, Debreu (1951) presented a radial measure of technical efficiency addressing such deficiency. In general, radial measures are convenient as they focus on the maximum feasible equi-proportionate reduction of variable inputs, or the converse maximum feasible expansion of all outputs. They are meanwhile useful to be independent of a unit of measurement. Nonetheless, one major drawback is identified when technical efficiency is measured by radial contraction of the input vector or expansion of the output vector, it may understate the degree of inefficiency under the given technology due to slack in the status of inputs or outputs. In other words, the radial measure of efficiency fails to consider the reallocation of one input over the other. Thus, a producer may be efficient in Debreu's measure, but inefficient following Koopmans'.

Farrell (1957) expanded on the work of Debreu by proposing that efficiency is made up of two components: technical efficiency and allocative, or price, efficiency. Technical efficiency refers to the producer being able to achieve maximum output from a given set of inputs. Allocative efficiency refers to the producer being able to select the appropriate proportion or combination of inputs based on their input prices and the available technology. Note that Farrell's analysis uses the assumption of cost minimization in production under a competitive market, where the measure of allocative efficiency implies the production to be economic-efficient. Together, the attainment of both efficiencies in output maximization and cost minimization would achieve the overall production efficiency.

Measurement of production efficiency requires the empirical approximation of the true production frontier. Once the frontier has been estimated, the measurement of efficiency based on distance from the frontier becomes straight-forward. Though the challenge lies in estimating the production frontier, two major contrasting techniques have been frequently employed; one based on mathematical programming and the other based on econometrics.

In summary, the econometric approach, characterized by Stochastic Frontier Analysis (SFA), seeks to estimate the production frontier and meanwhile to distinguish the effects of noise from inefficiency (Ghorbani, et al., 2010). It requires the specification of a production function and estimation of the distributional form of the inefficiency term. In a simple multiple-input and single-output case, the functional relationship is given as $y_i = f(x_i, \beta) + e_i$, where y_i is the scalar output of the producer, i is the producer being evaluated, and β is a vector of parameters to be estimated. The residual term, e_i, is decomposed into a random error component v_i and an inefficiency component u_i.

Alternatively, Data Envelopment Analysis (DEA) is a mathematical programming used to define a piecewise linear, quasi-convex hull over the data. To be technically efficient, production must occur on the frontier. In the case of DEA, the frontier is defined by the best practice compared among observed producers. Each producer's inputs and outputs are weighted, and the model aims to minimize the weighted input-output ratio subject to the constraint that all weights are non-negative and that one bound below the weighted sample (Ghorbani, et al., 2010).

Methodology

The Central Region of Ghana was purposefully selected in this study since it is one of the major pineapple growing areas in Ghana. The sampling process includes 15 smallholder pineapple farmers from the Abura-Asiebu-Kwamankese district, 875 farmers from the Komenda-Edina-Eguafo-Abirem district and 1051 from the Ekumfi district as designated by Ghanaian Department of Agriculture across the Central Region.

The technique on sample size determination for a given population was suggested in Krejcie and Morgan (1970) which was used to delineate the current sample size based on the sampling frame(s). As a result, 320 smallholder pineapple farmers were used. Due to uncertainty and constraints or unavailability of survey respondents, Marc, et al., (2005) advised the rationale for keeping provision of 10% of the sample to reflect the non-responses and errors occurred in the process of data collection.

Tools of Analysis

Technical efficiency is the ratio of output per input in production, along with the scale efficiency which indicates the ability of a farm in producing maximal output (or, scale-size production) under available farming technology and resources. Here, the Data Envelopment Analysis (DEA) was used to determine the technical and scale efficiencies of smallholder pineapple farmers as it would help identify any possible issues of farming ineptness. DEA is a non-parametric model which does not make use of the production function and the error term assumptions are treated following the Stochastic Frontier Analysis (SFA). Both techniques are purposed as the benchmarking tool to evaluate the production efficiency (Ghorbani, et al., 2010). DEA is the production frontier method not centered on the specification of a functional or distributional form, whereas it allows the relaxation of assumption on the 'constant returns to scale' production (Cooper, et al., 2007 & 2011; Fried, et al., 2008; Kathiravan, et al., 2018; Khomeini, et al., 2013).

Model Specification

The Data Envelopment Analysis (DEA) technique was appropriate for this study because it is used to estimate both technical and scale efficiencies in Ghanaian smallholder pineapple farming. It is a linear programming model which measures the relative performance of organizational units especially when multiple inputs and outputs are present making comparisons difficult.

To properly specify the procedure, first, assuming a total of *n* Decision Making Units (DMUs), of which each is with *m* inputs and *x* outputs. As the goal is to maximize the output with given inputs, the relative efficiency score of a test on DMU *p* would then be obtained by solving the following model suggested by Charnes, et al. (1978):

$$Max \sum_{k=1}^{s} v_k\, y_{kp} \Big/ \sum_{j=1}^{m} u_j x_{jp}$$
$$\sum_{k=1}^{s} v_k\, y_{ki} \Big/ \sum_{j=1}^{m} u_j x_{ji} \leq 1 \forall_i \tag{6}$$

Where

$k = 1$ to s; $j = 1$ to m, and $i = 1$ to n

y_{ki} = Amount of output *k* produced by DMU$_i$, x_{ji}= Amount of input *j* utilized by DMU$_i$.

v_k = Weight given to output *k*; u_j = Weight given to input *j*

To solve the model, it is needed to convert equation (6) into a linear programming formulation. It is given by:

$$Max \sum_{k=1}^{s} v_k\, y_{kp}$$
$$s.t. \sum_{j=1}^{m} u_j\, x_{jp} = 1$$
$$\sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0 \ \forall_i \tag{7}$$
$$v_k, u_j \geq 0 \ \forall k, j$$

The dual problem can therefore be specified as follows:

$$\text{Min } \theta$$
$$\sum_{i=1}^{n} \lambda_i\, x_{ji} - \theta x_{jp} \leq 0 \ \forall j$$
$$\sum_{i=1}^{n} \lambda_i\, x_{ki} - y_{kp} \geq 0 \tag{8}$$
$$\lambda_i \geq 0 \ \forall i$$

Where

θ = Efficiency score, and λi = Dual variables

According to Khoveyni, et al. (2013), there is an alternative model to estimate the maximized production by Most Productive Scale Size (MPSS) based on the optimal solution of Constant Return to Scale (CRS) also known as the Charnes-Cooper-Rhodes (CCR) model (Charnes, et al., 1978), and Variable Return to Scale (VRS) also known as the Banker-Charnes-Cooper (BCC) model (Banker, et al., 1984) as the frontier scale in the procedure of DEA.

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Constant Return to Scale (CRS)

$$\begin{gathered} Max \sum_{k=1}^{s} v_k\, y_{kp} \\ s.t. \sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0 \\ \sum_{j=1}^{m} u_j\, x_{jp} - 1 \\ v_k, u_j \geq 0 \end{gathered} \tag{9}$$

Variable Return to Scale (VRS)

According to Wang and Lan (2013), the linear model of BCC is expressed as follows:

$$\begin{gathered} Min\theta - \epsilon\left(\sum_{k=1}^{m} S_k^- + \sum_{j=1}^{m} S_j^+\right) \\ s.t. \sum_{i=1}^{n} \lambda_i\, x_{ji} + S_i^- = \theta x_{ji} \quad j = 1, \dots\dots, m \\ \sum_{i=1}^{n} \lambda_i\, x_{ki} + S_i^+ = \theta x_{ki} \quad k = 1, \dots\dots, s \\ \lambda_i \geq 0 \quad i = 1, \dots\dots, n \end{gathered} \tag{10}$$

$$\text{Scale Efficiency} = {}^{Efficiency\ in\ CRS}\!/_{Efficiency\ in\ VRS} \tag{11}$$

where CRS is 'Constant Returns to Scale' and VRS is 'Variable Returns to Scale'.

Empirical Results and Discussion

The results for the technical efficiency and scale efficiency of the smallholder pineapple farming in the Central Region of Ghana were presented in Table 1. It reveals that only 30 (equivalent to 9.18%) of the farmers, at the efficiency range of 0.9 < E < 1 and E = 1, operated with the overall technical efficiency of 0.90 or above under Constant Returns to Scale (CRS), whereas about 90.82%, equivalent to 100% minus 9.18%, of their counterparts were technically inefficient with respect to the allocation of inputs at the farm. The mean efficiency was 0.505 with the overall technical efficiency scores ranging from 0.079 to 1.000. In sum, 90.82% of the pineapple farmers who were not operating at the maximum level of efficiency could reduce their usage of inputs by 49.5% (=1 – 0.505) and presumably still maintain the same level of production as achieved by the 9.18% technically efficient farmers. That is, the technically inefficient farmers should avoid wasting farming resources to maintain their current output level.

Table 1. Technical and Scale Efficiencies of Smallholder Pineapple Farming in the Central Region of Ghana.

Efficiency	Technical Efficiency under CRS		Technical Efficiency under VRS		Scale Efficiency	
(E) Range	Frequency	%	Frequency	%	Frequency	%
0 < E < 0.1	2	0.61	-	-	-	-
0.1 < E < 0.2	9	2.75	-	-	2	0.61
0.2 < E < 0.3	79	24.16	2	0.61	5	1.53
0.3 < E < 0.4	38	11.62	13	3.98	5	1.53
0.4 < E < 0.5	31	9.48	67	20.49	13	3.98
0.5 < E < 0.6	85	25.99	95	29.05	36	11.01
0.6 < E < 0.7	13	3.98	53	16.21	27	8.27
0.7 < E < 0.8	31	9.48	22	6.73	79	24.16
0.8 < E < 0.9	9	2.75	13	3.98	53	16.21
0.9 < E < 1	25	7.65	8	2.45	100	30.6
E = 1	5	1.53	54	16.51	7	2.14

Summary of Technical Efficiency under CRS					
Min.	1st Qtr.	Median	Mean	3rd Qtr.	Max.
0.079	0.293	0.530	0.505	0.624	1.000
Summary of Technical Efficiency under VRS					
Min.	1st Qtr.	Median	Mean	3rd Qtr.	Max.
0.288	0.503	0.584	0.641	0.766	1.000
Summary of Scale Efficiency					
Min.	1st Qtr.	Median	Mean	3rd Qtr.	Max.
0.115	0.687	0.789	0.772	0.915	1.000

Source: Field survey, Boakye (2019).

Alternatively, under the Variable Returns to Scale (VRS) model, the pure technical efficiency ranged from 0.288 to 1.000 with mean efficiency score of 0.641. Relaxation of the assumption on constant returns following the use of convexity assumption on VRS revealed that technical efficiency improves or is value-added more than 117%, reflected the growth from 9.18% to 20% (or, 10.82% more farmers became technically efficient) with higher mean technical efficiency increasing from 0.505 to 0.641. The corresponding higher efficiency of VRS is linked to and corrected for the scale effect, which is derived from the ratio of the technical efficiency under CRS to the technical efficiency under VRS, as known as Scale Efficiency (or, see equation (11)).

Meanwhile, about 32.74%, at the efficiency range of $0.9 < E < 1$ and $E = 1$, of the pineapple farmers were found with scale efficiency of more than 90 percent. The scale efficiency scores ranged from 0.115 to 1.000 with an average of 0.772. In short, it shows that farmers who were scale inefficient (67.26% = 100% – 32.74%) could increase their production and reach higher efficiency by 0.228 or 22.8% to operate in optimal scale under existing technology. By operating in an optimal production scale, these farmers would be expected to potentially increase farming productivity in turn generating higher income to their farms.

Of the entire study, it is rather evident that currently most of the smallholder pineapple farmers in Central Region of Ghana are technically inefficient with relatively low mean efficiencies under CRS, VRS, and production scale at 0.505, 0.641 and 0.772, respectively. Such results reliably agree on the findings of Balogun, et al. (2018) witnessing Nigerian farms' sub-optimal production with the efficiency score of 0.603. In addition, the study by Lubis, et al. (2014) affirmed the underperforming farmers in Indonesia who were inefficient in growing pineapples suffering from low mean efficiencies over technical, allocative, and economic measures at 70.1%, 34.1%, and 24.1%, respectively. These comparable findings attested that production inefficiency in farming is likely a global issue. A pragmatic design and relevant agricultural policy-setting seem in need and appropriate to improve farming technique and technology as well as the allocation of farming resources. Once the efficiency challenge is resolvable, the yields across crops, not just pineapples, would most likely augment to support the welfare of farmers.

Conclusions and Recommendations

This study sought to assess the technical and scale efficiency of smallholder pineapple farmers in the Central Region of Ghana. A total of 320 respondents were chosen through random sampling technique and employed an input-oriented Data Envelopment Analysis (DEA) approach to evaluate the technical efficiency, purity, and scale of these farmers. The results revealed a significant issue concerning the suboptimal efficiency levels that most farmers operate. This underscores the need to improve resource allocation and production practices. Only a small number of farmers work at or near the optimal efficiency levels, presenting a significant opportunity to boost productivity and income in the crucial agricultural sector. To address the inefficiencies identified in this study, a comprehensive approach combining policy interventions and on-the-ground agricultural practices is necessary. Policymakers must acknowledge the systemic challenges faced by smallholder farmers and tailor policies to provide support in areas such as access to credit, education on modern farming techniques, and infrastructure development. These policies should aim to facilitate the adoption of

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efficient practices and technologies to increase productivity and reduce waste. Furthermore, agricultural extension services should be strengthened to equip farmers with the necessary knowledge and skills to optimize resource utilization and enhance efficiency. Improving smallholder pineapple farmers' productivity and sustainability can be achieved by targeted training in crop management, irrigation, and pest control. To address scale inefficiencies, cooperation or farmer associations should be encouraged. A comparative study of Nigeria and Indonesia has shown widespread production inefficiencies, highlighting the need for regional and international collaboration to share knowledge and resources. Drawing inspiration from this, it is essential for policymakers, practitioners, and stakeholders across the agricultural value chain to collaborate in implementing interventions that enhance both technical and scale efficiency in Ghana's pineapple sector. Such efforts can result in increased productivity, income, and overall welfare for smallholder farmers.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org.

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