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

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Abstract: This study focuses on evaluating the technical and scale efficiencies of smallholder pineapple farmers in Ghana's Central Region. We surveyed 320 participants selected using random sampling and applied an input-oriented Data Envelopment Analysis (DEA) method to gauge their technical, pure, and scale efficiencies. Our findings indicate that the mean technical efficiency among these farmers is 0.505, with individual scores ranging from 0.079 to 1.000. Notably, 90.82% of the farmers are operating below maximum efficiency levels, suggesting a potential input reduction of up to 49.5% while maintaining current production levels. Relaxing the assumption of constant returns under Variable Returns to Scale (VRS) conditions reveals a notable improvement in technical efficiency, with 10.82% more farmers achieving optimal efficiency levels. Furthermore, our analysis highlights scale inefficiencies, with 67.26% of farmers operating below optimal scale levels. By increasing production by 22.8%, these scale-inefficient farmers could enhance their efficiency and productivity within existing technological frameworks. These findings underscore the importance of collaborative efforts among policymakers, practitioners, and stakeholders within the agricultural value chain to implement interventions such as improving access to technology and innovation for smallholder farmers and making necessary investments in farmer education and training programs to enhance both technical and scale efficiencies in Ghana's pineapple sector. Such initiatives can drive sustainable growth, improve farmers' livelihoods, and bolster the sector's overall competitiveness.

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

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1. Introduction

Smallholder agriculture is crucial for ensuring global food security, particularly in Africa, where subsistence farming is more prevalent [1]. Among smallholder crops, pineapple cultivation is a significant contributor, fulfilling dual roles as a primary source of income for farmers and a significant export commodity across various tropical regions [1]. Similarly, the food and agricultural sectors are fundamental to most African economies, including Ghana, because they contribute to sustaining national growth and reducing poverty. Agricultural growth weighs heavily on Ghana's Gross Domestic Product (GDP) while improving the livelihood of most Ghanaians, as it is essential to meet the aggregate food needs and provide various employment opportunities to generate income for over 60% of the Ghanaian working population from rural areas [1]. Given its vital role, advances in the agricultural sector are often a goal and a part of Ghana's developmental strategy. Since 2002, agricultural policies have aimed to enhance overall economic growth by improving access to markets and financial services, developing infrastructure and an agrarian society, expanding farming, human resources, and institutional capacity, while simultaneously reducing non-performing lands due to unsustainable management and low productivity [2].

One of the major reasons for low agricultural productivity in Ghana is the inability of farmers to fully exploit the available technologies, resulting in low efficiency. Over the years, Ghana's GDP attributed to agrarian production has been declining, largely owing to low productivity and lack of technological advancement in major agricultural commodities, such as pineapple. Thus, an improvement in farming efficiency tied to effective farm-tech adoption can result in higher output and associated benefits [3].

Given the prevailing but limited farming technology and resource endowment, many Ghanaian farmers face an unfavorable gap between potential and actual farm yields. Technical efficiency (TE) is an important measure of the productivity differences across crops. It helps explore the capacity of existing farming technologies to improve or correct the disequilibrium in production, while scale efficiency (SE) is equally important, which allows farmers to apply and target the most productive scale to optimize farm yields (see [3]). As the efficiency checks are likely to improve crop yield, such as in pineapple farming, they are critical and strategic as a mechanism to reduce productivity loss, close the production gap, and maximize farming output for consumption demand. Given the importance and applicability of both efficiency measures, this study utilized TE and SE to assess smallholder pineapple farming across the Central Region of Ghana.

The novelty of this study is reflected in two aspects. First, it addresses the lack of comprehensive analysis of the technical and scale efficiencies of smallholder pineapple farmers in Ghana's agricultural landscape. Second, it employs the DEA within a non-parametric framework to investigate the complex factors affecting pineapple productivity, making it pioneering work in estimating technical and scale efficiencies. This study aims to improve resource allocation and enhance the sustainability and competitiveness of smallholder pineapple farmers in Ghana and beyond. By applying DEA, a mathematical program used to estimate production efficiency, the primary goal of this research is to uncover the analytical findings on the overall farming efficiency in the region and to suggest policy initiatives that foster future farming improvement.

The results of this study are expected to provide valuable insights to agricultural policymakers, researchers, development practitioners, and stakeholders involved in improving the productivity and sustainability of small-scale pineapple farming in Ghana. By understanding the factors that impact the efficiency of pineapple production, stakeholders can formulate targeted interventions, provide extension services, develop policies to improve agricultural productivity and farmers' livelihoods, and promote inclusive rural development.

2. Literature Review

The agricultural sector is critical for achieving global economic growth and development, in line 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 [4–6].

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 the definition of efficiency and its measurement dates to pioneering works such as [7,8]. Ref. [9] further contributes to the understanding of efficiency by defining it as the ability to attain a desired outcome with minimal resources. According to [9], 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 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 [10]. Ref. [11] 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 the overall performance level [11].

However, Ref. [12] 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 [12]. This is particularly relevant for farmers who are just beginning to diversify their product offerings to include fruit and vegetables. As indicated by [13], 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 livelihood of farmers and the economy as a whole [14,15].

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 [16]. 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.

The pineapple sector is important to Ghana's agricultural economy, and smallholder farmers play a crucial role. This study adds to the existing literature on agricultural efficiency in developing countries and provides specific insights into the challenges and opportunities faced by smallholder farmers in Ghana. By assessing the efficiency of these farmers, policymakers and stakeholders can gain insight into the sector's productivity and growth potential. This study used the DEA technique to evaluate the technical and scale efficiencies of smallholder pineapple farmers in Ghana. DEA is a rigorous quantitative framework that helps identify both the best practices and areas for improvement, allowing for targeted intervention and resource allocation [5,6]. Ultimately, this study can help inform policies and interventions aimed at enhancing the sustainability and competitiveness of Ghana's pineapple industry.

3. Materials and Methods

3.1. Sampling and Sample Procedure

Pineapple was chosen for this study because of its considerable economic influence in tropical areas, including Ghana. By analyzing the intricacies of pineapple farming, economists can assess its contributions to employment, income generation, and trade balances within these regions. Furthermore, given the global trade significance of pineapples and their intricate supply chains involving production, processing, distribution, and marketing, studying pineapple farming provides valuable insights into supply chain dynamics, logistics, quality control, and market access, thereby benefiting researchers in various fields.

Additionally, 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 the Ghanaian Department of Agriculture across the Central Region.

The technique of sample size determination for a given population was suggested in [17], which was used to delineate the current sample size based on the sampling frame(s). As a result, 320 smallholder pineapple farmers were selected for this study. Due to the unavailability of survey respondents, [18] supported the rationale for keeping the provision of 10% of the sample to reflect the non-responses and errors that occurred in the process of data collection.

3.2. Indicators for Measuring Efficiency and Productivity

In many respects, productivity and efficiency measurements for agriculture mirror those 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 spawned various frameworks and indicators that can be broadly classified into parametric and non-parametric methods [19–21]. Efficiency can be achieved using either parametric or non-parametric methods. Parametric methods, such as the Stochastic Frontier Approach (SFA), proposed by [22], are proficient in distinguishing inefficiency from noise. DEA is a non-parametric approach. Ref. [23] expanded [9]'s 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 center 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 concerning smallholder farmers, the challenges are compounded by the fact that they, 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.

DEA and SFA are frequently employed methods for assessing efficiency without the need for predefining production functions or inefficiency terms. According to multiple research studies [24–28] spanning various industries [29–32], the popularity of DEA and SFA has increased because they are unaffected by subjective biases. They are extensively applied for evaluating technical and scale efficiencies in agriculture. However, although the SFA models possess features for measuring efficiency and productivity in agriculture, they have been criticized for their reliance on a predetermined production function and distribution form for the technical inefficiency component [28].

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 [19,25]. 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 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 [15,33,34], with only a few using DEA [14,15]. To bridge this methodological gap, this study employs DEA to estimate the technical and scale efficiencies of smallholder pineapple farmers in Central Ghana.

3.3. An Overview of Data Envelopment Analysis

The DEA method, first introduced by [23], is a non-parametric approach that considers noise in the outcomes. Unlike the parametric statistical approach of SFA, which imposes a specific form on the production function to estimate efficiency, DEA is non-parametric method that evaluates the relative efficiency of a decision-making unit (DMU) in comparison to similar DMUs on the "best practice" frontier [6]. DEA is widely applicable and can measure technical efficiency, productivity, cost, and allocative efficiency [35] without assuming any relationship between inputs and outputs. This is in contrast to SFA, which may introduce uncertainties in the results [36]. In the field of agriculture, DEA's versatility is particularly notable, as it can effectively manage multiple inputs and outputs, whereas traditional SFA models are limited to handling only single 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 [5]. As [11] emphasized, 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 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.

3.4. Efficiency Analysis

Efficiency measures can be theoretically organized according to the framework presented in [37]. The process begins with a producer utilizing a non-negative vector of N inputs, represented as $x = (x_1, \ldots, x_N) \in R_+^N$, to generate a non-negative vector of M outputs, denoted as $y = (y_1, \ldots, y_M) \in R_+^M$. The technology set (T) encompassing all viable input and output vectors is defined as follows:

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

Typically, production technology can be depicted using either the output or input sets. However, it can also be defined equivalently using only a set of outputs. In this alternate representation, denoted as P(x), each input vector x encompasses a set of feasible outputs, as expressed by the following:

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

In this context, the output set P(x) is delineated in terms of T. Given that T is presumed to adhere to specific criteria, such as the feasibility of the observed data, free disposability, and selective convexity [38], it logically follows that P(x) can also adhere to these corresponding properties. It is worth noting that the property of free disposability is essentially a straightforward adaptation under the standard assumption of strong disposability of all inputs and outputs utilized, duly adjusted to ensure that the input–output ratio remains within the prescribed bounds. Similarly, technology can be defined using the input set, denoted as L(y), expressed as follows:

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

where the input set encompasses all input vectors x capable of generating a specific output vector y. Functionally akin to P(x), L(y) is presumed to adhere to properties analogous to T.

The efficiency technique described above is pertinent and valuable to this study, as it facilitates the examination of both technical and scale efficiencies within smallholder pineapple farming, focusing on the technological aspect. This approach enables the evaluation of Central-regional Ghanaian farmers who may be technically efficient, while their counterparts are not, considering the endogeneity of technology.

3.5. Production Frontiers

In theory, the single-output case of production technology serves as a useful tool for illustrating the production function. This specification describes a technology that generates either a single output or, more commonly, multiple outputs that can be aggregated into a single composite output $y = g(y_1, \ldots, y_M)$ under the same technology. Definitions (2) and (3) can then be transformed into the following definitions:

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

In this context, x represents a vector encompassing various sources of information (inputs), whereas y denotes a scalar quantity of output produced from the utilized inputs. The production frontier, denoted by f(x), signifies the maximum yield (output) achievable with a vector of random information (inputs), delineating the upper boundary of the potential output. Producers typically operate at or below this threshold. Evaluating technical efficiency involves measuring the distance from each producer's input–output combination to the production frontier, elucidating their degree of efficiency.

In production theory, it is common to utilize multiple inputs to generate multiple outputs, whereby a joint production-possibility frontier is employed to delineate the upper limit of feasible production. This frontier entails defining a subset of both input and output vectors, each with an unscalable maximum and minimum, respectively. Joint production frontiers are primarily utilized in observational examinations, as the upper limit of a production function in a multiple-input–multiple-output scenario is typically determined by distance functions (D). Specifically, an input distance function involves scaling the input vector to measure the distance from a production point to the boundary of the production possibilities. Hence, the input distance function can be defined using the input set L(y):

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

3.6. Technical Efficiency

According to [8], the technical efficiency of a multiple-input and multiple-output production setting can be explained as follows: A producer is considered technically efficient if increasing any output can only be achieved by reducing at least one other output or increasing at least one input. Conversely, reducing the input is only possible by decreasing at least one output or increasing at least one other input. Therefore, a technically inefficient producer has the potential to improve efficiency by using fewer resources of at least one input to maintain the same output level, or by maintaining input levels while increasing at least one output.

Koopmans' concept of technical efficiency provides a means to differentiate between efficient and inefficient production processes. However, it does not offer a method for quantifying the extent of inefficiency or for comparing inefficient and efficient input vectors. To address this limitation, Ref. [7] proposes a radial measure of technical efficiency. Radial measures of efficiency are advantageous because they focus on achieving the greatest feasible reduction of variable inputs or the maximum feasible expansion of all outputs, without being influenced by a specific measurement unit. However, there is a significant drawback in assessing technical efficiency using the radial contraction of the input vector or expansion of the output vector. This approach may underestimate inefficiency owing to slack in the status of inputs or outputs. In other words, the radial measure of efficiency does not consider the redistribution of one input over others. Therefore, a producer may be considered efficient according to Debreu's measure but inefficient according to Koopmans.

The work in [9] expands upon Debreu's theoretical framework by proposing that production efficiency consists of two components: technical efficiency and allocative efficiency, which is also known as price efficiency. Technical efficiency refers to the producer's ability to achieve the highest level of output from a specified set of inputs. By contrast, allocative efficiency is concerned with the producer's capacity to determine the appropriate combination or proportion of inputs based on their respective prices and available technology. It is crucial to note that Farrell's analysis presupposes cost minimization for production within a competitive market. In this context, allocative efficiency refers to economic efficiency. Achieving both forms of efficiency, namely, output maximization and cost minimization, results in overall production efficiency.

The measurement of production efficiency requires an empirical approximation of the true production frontier. Once estimated, the efficiency measurement based on distance from the frontier becomes relatively straightforward. However, the main challenge lies in estimating the production frontier itself, for which two major contrasting techniques are commonly used: one based on mathematical programming and the other on econometrics.

In conclusion, the econometric methodology of the SFA determines the production frontier and differentiates between the effects of random fluctuations and inefficiency [39]. This requires defining a production function and estimating the shape of the distribution of the inefficiency term. In a basic model with multiple inputs and a single output, the functional relationship is expressed as $y_i = f(x_i, \beta) + e_i$, where y_i represents the producer's total output, i refers to the producer being evaluated, and β represents a vector of parameters to be estimated. The residual term e_i is separated into random error component vi and an inefficiency component.

Alternatively, the DEA is a mathematical programming technique employed to delineate a piecewise linear quasi-convex hull over a dataset. For a producer to be deemed technically efficient, production must occur precisely at this frontier. In DEA, the frontier is established by comparing observed producers with best practices. Each producer's inputs and outputs are assigned weights to, and the model aims to minimize the weighted input–output ratio while ensuring that all weights are non-negative and that one is bound below the weighted sample [39].

3.7. Tools of Analysis

Technical efficiency assesses the output–input ratio in production, whereas scale efficiency gauges a farm's ability to attain maximum output using the available technology and resources. To evaluate the technical and scale efficiencies of smallholder pineapple farmers, the DEA was applied. This approach enables the identification of inefficiencies in farming practices, without relying on specific production function assumptions [39]. Non-parametric in nature, DEA aligns with the error term assumptions of the SFA, making it an effective benchmarking tool for evaluating production efficiency. Unlike other methods, DEA does not require a functional or distributional form specification and allows for the relaxation of the assumption of 'constant returns to scale' production [3,40–42].

3.8. Model Specification

The utilization of the DEA technique in this study was suitable, as it enabled the estimation of both technical and scale efficiencies within Ghanaian smallholder pineapple farming. DEA, functioning as a linear programming model, facilitates the assessment of organizational units' relative performance, particularly in scenarios involving multiple inputs and outputs, where direct comparisons pose challenges.

To properly outline the procedure, let us start by considering a total of n DMUs, each equipped with m inputs and x outputs. Since the objective is to maximize output with given inputs, the relative efficiency score of a test on DMU p can be determined by solving the following model, proposed by the following [21]:

$$\begin{gathered} Max\sum_{k=1}^{s} v_k y_{kp} / \sum_{j=1}^{m} u_j x_{jp} \\ \sum_{k=1}^{s} v_k y_{ki} / \sum_{j=1}^{m} u_j x_{ji} \le 1\forall_i \end{gathered} \tag{6}$$

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 the following:

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

The dual problem can therefore be specified as follows:

$$\begin{gathered} \text{Min } \theta \\ \sum_{i=1}^{n} \lambda_i x_{ji} - \theta x_{jp} \le 0\forall j \\ \sum_{i=1}^{n} \lambda_i x_{ki} - y_{kp} \ge 0 \\ \lambda_i \ge 0\forall i \end{gathered} \tag{8}$$

where

θ = efficiency score, and λi = dual variables.

As per [42], an alternative model is available to estimate maximized production by the Most Productive Scale Size (MPSS) based on the optimal solution of Constant Returns to Scale (CRS), also referred to as the Charnes–Cooper–Rhodes (CCR) model [21], and Variable Returns to Scale (VRS), also known as the Banker–Charnes–Cooper (BCC) model [43], serving as the frontier scale in the DEA procedure.

3.8.1. Constant Returns to Scale (CRS)

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

3.8.2. Variable Returns to Scale (VRS)

According to [44], the linear model of BCC is expressed as follows:

$$Min\theta - \epsilon\left(\sum_{k=1}^{m} S_k^- + \sum_{j=1}^{m} S_j^+\right) \tag{10}$$

$$\begin{gathered} s.t.\sum_{i=1}^{n} \lambda_i x_{ji} + S_i^- = \theta x_{ji}\ j = 1, \ldots\ldots, m \\ \sum_{i=1}^{n} \lambda_i x_{ki} + S_i^+ = \theta x_{ki}\ k = 1, \ldots.., s \\ \lambda_i \ge 0\ i = 1, \ldots.., n \end{gathered} \tag{11}$$

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

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

4. Results

Table 1 displays the results for the technical efficiency and scale efficiency of smallholder pineapple farming in the Central Region of Ghana. As can be seen from the table, only 30 farmers (9.18% of the total) achieved an overall technical efficiency of 0.90 or higher under CRS. These farmers fell within the efficiency range of 0.9 < E < 1 and E = 1. However, approximately 90.82% of farmers were technically inefficient in terms of input allocation to the farm. The mean efficiency was 0.505, and the technical efficiency scores ranged from 0.079 to 1.000 across all farmers. In conclusion, the majority (90.82%) of pineapple farmers did not operate at their maximum efficiency levels. This suggests that they could potentially reduce their input usage by 49.5% (1 − 0.505), while maintaining the same production levels as 9.18% of the technically efficient farmers. This highlights the importance of technically inefficient farmers optimizing resource usage to sustain their current output levels.

Table 1. Technical and scale efficiencies of smallholder pineapple farming in the Central Region of Ghana.

Efficiency (E) Range	Technical Efficiency under CRS		Technical Efficiency under VRS		Scale Efficiency	
	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 (2020) [14].

Under the VRS model, technical efficiency ranged from 0.288 to 1.000, with an average efficiency score of 0.641. By relaxing the assumption of constant returns and utilizing the convexity assumption for VRS, it was found that technical efficiency improved by more than 117%. This improvement is demonstrated by an increase in the percentage of farmers achieving technical efficiency ranging from 9.18% to 20% and a higher mean technical efficiency ranging from 0.505 to 0.641. The enhanced efficiency under VRS is attributed to and adjusted for the scale effect, which is derived from the ratio of technical efficiency under CRS to technical efficiency under VRS, also known as scale efficiency, as shown in Equation (11).

According to the research, 32.74% of pineapple farmers who were found to operate within the efficiency range of 0.9 < E < 1 and E = 1 had a scale efficiency of more than 90 percent. These farmers had scale efficiency scores ranging from 0.115 to 1.000, with an average score of 0.772. This suggests that farmers who were scale inefficient (67.26% = 100% − 32.74%) could potentially increase their production and achieve between 0.228 and 22.8% higher efficiency by operating at an optimal scale under existing technology. By operating on an optimal production scale, these farmers are expected to improve their farming productivity and generate higher incomes for their farms.

5. Discussion

This research aims to evaluate the technical and scale efficiencies of smallholder pineapple farmers in the Central Region of Ghana. Using the DEA model, we computed the efficiency levels of these farmers, utilizing conventional models, such as the CRS and VRS models to ascertain both pure and scale efficiency. Of the entire study, it is rather evident that currently, most of the smallholder pineapple farmers in the Central Region of Ghana are technically inefficient, exhibiting relatively low mean efficiencies under CRS, VRS, and production scales at 0.505, 0.641, and 0.772, respectively.

The efficiency of farmers and other production agents has been studied in different countries, which showed similar or contradictory findings to the ones in this study. For instance, the results reliably agree with the findings of [45], witnessing Nigerian farms' suboptimal production, exhibiting an efficiency score of 0.603. In addition, the study by [46] affirmed the underperforming farmers in Indonesia, who were inefficient in growing pineapples, suffering from low mean efficiencies across technical, allocative, and economic measures, at 70.1%, 34.1%, and 24.1%, respectively.

Similarly, [6], in his study on the technical efficiency of chemical-free farming in India showed that farmers can reduce their input use by 34% without reducing output. A study by [11] on the efficiency of small-scale irrigation farmers in the Northern Region of Ghana using the DEA technique found that less than 50% of vegetable farmers in the Northern Region of Ghana are technically inefficient, which aligns with the findings in this study.

These comparable findings attested that production inefficiency in farming is likely a global issue. A pragmatic design and relevant agricultural policy setting seem needed and appropriate to improve farming techniques, technology, and the allocation of farming resources. Once the efficiency challenge is resolved, the yields across crops, not just pineapples, would most likely augment, supporting the welfare of farmers.

6. Conclusions and Implications

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 a random sampling technique, and an input-oriented DEA approach was employed 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 at.

Thus, our results show that less than 10% of the farmers are efficient, exhibiting an overall technical efficiency of 0.90 and above under the CRS assumption. This implies that more than 90% of the farmers are technically inefficient. By relaxing the CRS assumption, more of the farmers became technically efficient. Thus, 10% more farmers became efficient under the VRS assumption. Finally, about 32.74% of the pineapple farmers were scale efficient. This means that farmers who are scale inefficient can increase production and operate at the optimal level, reducing input use by 22.8%.

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. This finding presents 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 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, policymakers, practitioners, and stakeholders across the agricultural value chain need 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.

6.1. Theoretical Implications

The significance of employing Data Envelopment Analysis (DEA) is underpinned by its non-parametric nature, which provides a reliable structure for evaluating the technical and scale efficiencies of agricultural systems. The DEA results can be utilized by policymakers to formulate data-driven policies tailored to specific agricultural contexts. Through a comprehensive analysis of DEA findings, policymakers can pinpoint the drivers of inefficiency and design targeted interventions to enhance resource allocation, production practices, and access to support services. By identifying the systemic challenges within agricultural systems, DEA offers valuable insights to policymakers to address broader issues, such as access to credit, education, and infrastructure development. Policymakers can work toward sustainable improvements in agricultural efficiency and productivity by aligning policy interventions with on-the-ground practices and incorporating DEA insights.

6.2. Policy Implications

This study reveals considerable inefficiencies among smallholder pineapple farmers in Ghana's Central Region, with many of them operating below maximum efficiency. Targeted policy interventions should be implemented, including enhancing resource allocation, improving production practices, providing access to credit, and offering modern farming education. Strengthening extension services and fostering farmer associations can further optimize efficiency. Policymakers must address these systemic challenges by tailoring policies to improve access to credit, education, and infrastructure. A comprehensive approach integrating policy interventions and on-the-ground practices is crucial. Collaboration across the agricultural value chain is vital for enhancing technical and scale efficiency in Ghana's pineapple sector. These efforts promise increased productivity, income, and welfare for smallholder farmers, demonstrating the importance of addressing inefficiencies in agricultural production through coordinated policy and practical measures.

6.3. Limitations of This Study

Despite the diligent efforts invested in this study, certain constraints remain unavoidable. Firstly, this study used the survey technique, where respondents are likely to provide inaccurate or incomplete information. Additionally, since this study aimed to collect purely quantitative data, it is difficult to provide in-depth information to understand the complexities surrounding the inefficiencies of the farmers. It is anticipated that future research endeavors will consider these crucial factors to alleviate the limitations identified in this research.

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