Scientific African 14 (2021) e01003

Contents lists available at ScienceDirect

Scientific African

journal homepage: www.elsevier.com/locate/sciaf

Technical and resource-use efficiencies of cashew production in Ghana: implications on achieving sustainable development goals

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ARTICLE INFO

Article history:
Received 4 August 2021
Revised 27 September 2021
Accepted 7 October 2021

Editor: DR B Gyampoh

Keywords:
Cashew
Double bootstrap DEA
Ghana
Resource-use efficiency

ABSTRACT

The expansion of Ghana's cashew industry is expected to be a watershed moment in the country's diversification of agricultural export commodity trade. In Ghana's cashew farms, however, there is a significant difference between observed and potential farm yield. As a result, empirical study is required to serve as policy guidelines in order to improve farmer's productive efficiency and, as a necessary consequence, contribute to the achievement of the Sustainable Development Goals (SDGs) of no poverty and zero hunger. The study explores farm-level productive efficiency and factors that can lead to variations in farmer's technical efficiency in the Bono East region of Ghana. The single-stage double bootstrap Data Envelopment Analysis (DEA) was used to estimate technical efficiency and its determinants. The estimated results indicate that the average bias-corrected technical efficiency score (33%) was lower than the original average score (51%), suggesting that the original efficiency scores had been skewed upwards. Some of the primary factors that have been reported as having a significant effect on technical efficiency include the gender of respondents, educational attainment, and membership of farmer groups. Results of the resource-use efficiency analysis suggest that cashew farmers in Ghana do not escape the criticisms of inefficient resource allocation. Farm-level policies should be skewed towards enhancing resource-use efficiency through effective capacity-building to improve farmer's management and technical capabilities, improve farm productivity, and consequently contribute to Ghana's quest to meet the sustainable development goals.

Introduction

Cashew has probably emerged as the most popular nut on the global market today. Global cashew consumption increased by 25% between 2011 and 2015 and is expected to increase further for the top 20 consuming countries due to health benefits [17]. Gro Intelligence [15] noted that the shift in consumer taste to tree crops (e.g., cashew) and alternative milk products

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https://doi.org/10.1016/j.sciaf.2021.e01003

such as cashew milk accounts for high cashew demand, particularly in the developed economy. Cashew production in Ghana is becoming a very profitable industry, leading to extensive cashew cultivation by many farmers. In Ghana, cashew export has received considerable attention due to its ability to push non-traditional agricultural exports [40]. ISSER [19] noted that exports of cashew nuts contributed about 53% of the total export earnings of $371.1 million from non-traditional agricultural exports in Ghana in 2016. Rabany et al. [33] indicated that Cashew has become Africa's (including Ghana) second major cash crop. Cashew production in Ghana is primarily intended to meet unique niche demand (for export) and not household consumption, although a small proportion of nuts are processed for local consumption.

Ghana registered the first export of a total of 15 tonnes of raw cashew nuts. This increased considerably to 3.571 tonnes in 1997 [32]. In 1998, Ghana's Ministry of Food and Agriculture (MoFA) described cashew as a potential non-traditional export commodity [35]. As a result, the Cashew Development Project (CDP) started in 2002, which was the first attempt by the Government of Ghana to improve and coordinate activities in the cashew sector. Production of raw cashew nuts increased considerably from 6.333 tonnes in 2003 to approximately 34.633 tonnes in 2006 and increased to 81.190 tonnes in 2008 [35]. In 2015, Ghana exported some 232,834 tonnes, contributing more than $200 million [30]. MoFA [30] estimates show that Ghana has 13,600,000 ha of land available for agriculture and 634,930 ha (4.66%) of land under cultivation.

World Bank [41] indicated that the economic success of developing countries depends mostly on the success of their agricultural sector and that the increase in per capita and overall socioeconomic well-being depends largely on the overall productivity factor. Therefore, efficient use of resources and improved technologies to increase total factor productivity is necessary to boost sustainable income and general wellbeing of farmers. Sustainability is concerned with environmental and socioeconomic problems that affect present and future generations [16]. In agricultural policy debates, effcient allocation of resources has become increasingly vital and has led many agricultural stakeholders to take the issue of evaluating agrarian practices into consideration. Recently, productivity and efficiency in Ghana's agricultural production have attracted considerable attention largely due to the inefficiency that exists within the sector. Report from World Bank [42] concluded that the agricultural sector in Ghana is mostly characterized by low yields for both cash and staple crops. World Development Indicators [43] report also revealed that yields of cereals are projected at 1.7 t/ha compared to the regional average of 2 t/ha and with potential yields in excess of 5 t/ha. Also, COCOBOD [7] report shows that the average yield of cocoa in Ghana is estimated at 400 to 450 kg/ha, and is part of the lowest in the world. With cashew production, the global demand for cashew nuts have increased by 6.1% and the consumption demand is expected to increase substantially by 2025 [13]. However, Ghana's productivity has only increased from 530 kg/ha in 2010 to about 638 kg/ha in 2016 [10], and the reason could be that producers are not producing efficiently with the resources available. The average yield of cashew in Ghana is 0.5 t/ha against the potential yield of 1.8 t/ha [30]. Ghana achieved only 27.78% of the potential yield. However, the first step in meeting the challenge of the sustainable use of natural resources is to increase productivity and efficiency in agricultural inputs. As a result, if inefficiencies in farm productivity are not well addressed, Ghana may fall short of meeting the SDGs.

Monteiro et al. [31] noted that while West African countries, including Ghana, have seen substantial improvements in cashew production over the last decade, the increase has been due to land expansion committed to cashew cultivation rather than increased output per hectare (yield). Consequently, the only way to improve output is for farmers to maximize and assign their resources efficiently. While some studies [1,11] have tried to address agricultural efficiency issues in Ghana, few studies [27,38] are on cash crops, especially cashew. The contribution of this study is to expand the scope of the literature on efficiency in two areas: (1) estimating the efficiency of farmers and the determinants of their efficiency variations by means of a statistically based and state-of-the-art technique called the double bootstrap Data Envelopment Analysis (DEA) procedure and (2) exploring how efficient cashew farmers are in the allocation of their resources.

Furthermore, we included three variables that, in our opinion, can help Ghana's cashew industry achieve sustainable growth, enhancing Ghana's chances of fulfilling SDG targets. These variables include membership of farmer's organisations, regular access to extension services and access to farm loans. We believe that these variables are critical in meeting the SDGs, ensuring that farmers and other rural people live productive and fulfilling lives. For example, agriculture is vital to the lives of more than half a billion rural populations, and extension service is one of the main institutions that provide advice and other services to those individuals. It is crucial to pay attention to farmers because they are the keepers of the land and the producers of food from the land. They are also important in supporting the SDGs because they help to ensure the stability of agriculture, which provides food for people around the world. Farmer's associations are strong players in acknowledgment of the fact that farmers are advancing sustainable development by continually working to improve on the three pillars of sustainability: economic, social, and environmental. In addition, an important step in promoting the growth of a rural farming economy is to aid farmers in accumulating financial capital, which encourages the growth of income for farmers over time. As a result, agricultural loans play a critical role in sustainable development through accummulation of funds for the purchase of farming equipment and inputs. Finally, assessing the sustainability of agricultural systems through effective resource use is an important issue in adopting policies and practices aimed at supporting the development of a sustainable farming system that has a beneficial impact on the objectives of sustainable development. The findings of this study are designed to provide empirical direction for farm-level initiatives aimed at improving the productivity of cashew farmers.

Materials and methods

The study area and data collection procedure

The data for this study were collected with the purpose of assessing the efficiency of production and resource use among smallholder farmers in the Nkoranza north district of the Bono east region, Ghana. The district is mainly rural, where agriculture is the main occupation of the people, and cashew is the main cash crop that serves as the dominant source of household income. The study used multi-stage sampling where stratified and random sampling were the main techniques. First, the district was subdivided into four strata based on council areas using stratified sampling and five communities were randomly selected from each stratum or council area. Second, 15 farming households were randomly selected from each group. The total sample size of the study was 300 farming households. The study used primary data for its analysis, and the primary data were obtained using a semi-structured questionnaire via face-to-face interviews.

Theoretical framework and estimation technique

The empirical framework on which the objectives of the study are theorized is discussed in this section of the study. The study followed two main approaches to achieving its goals. First, we applied a single-stage double bootstrap DEA procedure to estimate the technical efficiencies of individual farming households and identify the factors explaining differences in efficiency. Second, the marginal value product – marginal factor cost approach was adopted to evaluate the allocative efficiency of each of the inputs employed in cashew production during the 2018/19 production year.

Technical efficiency estimation using DEA approach

The parametric and non-parametric methods are the two main approaches for estimating efficiency. The parametric method which is commonly known as Stochastic Frontier Analysis (SFA) was used to discover comparative levels of efficiency by theorizing a functional form. Data Envelopment Analysis (DEA) is a non-parametric method that employs mathematical programming that requires no functional form. The popularity of the DEA is attributed to its ability to use multiple inputs and outputs for relative efficiency calculation. DEA is known to be an approach that was first developed by Charnes et al. [6] to compute the relative efficiency of production set and/or management units now known as decision-making units (DMUs). The main idea behind this is to relatively estimate how these units produce outputs while mobilizing the inputs. DEA permits multiple inputs and outputs to be measured at the same time without any assumption on the data or information distribution. In DEA efficiency study, we have two main orientations: input-oriented DEA, which tends to decrease the quantity of input to generate a constant output, and output-oriented DEA which seeks to upsurge the output while maintaining the input level [11,24].

Generally, agricultural production and cashew production specifically is such that farmers do have more control over the amount of inputs they use but have little or no influence on the output. Therefore, the study employs an input-oriented efficiency model to estimate the technical efficiency scores. As indicated by Coelli et al. [9], the decision on which orientation to employ depends on which production system (input or output) the DMU has more influence on. Various studies such as Solomon et al. [37] and Ullah and Perret [39] employed input-oriented DEA in the Agricultural production system. Based on the assumption of constant return to scale, Charnes et al. [6] developed the input-oriented DEA, which is also known as CCR-model. The model was named after the initials of the developers.

Following Ji [20], the technical efficiency (TE) or constant return to scale can be calculated using the DEA model;

Minimize $\theta, \lambda\theta$

Subject to

$$\begin{aligned} &-y_i + Y\lambda \geq 0 \\ &\theta x_i - X\lambda \geq 0, \\ &\lambda \geq 0 \end{aligned} \tag{1}$$

where θ is a scalar and represents the efficiency score of the ith cashew farm household, X and Y are inputs and output matrix, respectively, where X_i is an input vector of the ith cashew farm household and Y_i is an output vector of the ith cashew farm household, λ is a $N \times 1$ vector of constant, that is, the intensity vector of the efficient cashew farmer's weight. If $\theta = 1$ it indicates a technically efficient cashew farm and if $\theta < 1$ then it indicates cashew farms that are not technically efficient. The linear programming mentioned above will be solved N number of times, once for every DMU, providing θ value for each DMU.

Eq. (1) represents constant return to scale (CRS), also refered to as the overall technical efficiency (OTE); hence, will be indicated by OTE_{CRS}. The OTE_{CRS} assumption is suitable in cases where all DMUs operate at an ideal scale level. The OTE_{CRS} comprises of two components: pure technical efficiency (PTE), which represents the management practices under asumption of variable return to scale (VRS) [henceforth indicated by PTE_{VRS}][1] and scale efficiency (SE), which is the ratio of

[1] Henceforth, we represent OTE under CRS and VRS as OTE_{CRS} and OTE_{VRS} respectively, and PTE under CRS and VRS as PTE_{CRS} and PTE_{VRS}, respectively.

OTE to PTE ($SE = OTE/PTE$). The SE measures the scale of operations of the farm. Nevertheless, there might exist constraints on DMUs which do not permit them to operate at the optimal scale. Using CRS for such DMUs will yield TE scores, which are affected by SE scores. Therefore, one has to use the VRS model of DEA. VRS implies that a rise in inputs may result in either additional or less than proportionate increase in the output. The VRS model includes the CRS model, with an extra convexity constraint imposed on λ [8]. The VRS can be specified as:

Minimize $\theta, \lambda\theta$

Subject to

$$-y_i + Y\lambda \geq 0 \tag{2}$$

$$\theta x_i - X\lambda \geq 0,$$

$$N1\lambda = 1$$

$\lambda \geq 0$ where $N1$ is a $N \times 1$ vector of one

Determinant of DEA using Simar and Wilson bootstrapped-based truncated regression. Even though DEA has a plethora of advantages, it also has some limitations. Since the purpose of the DEA technique is to estimate the efficiency of the DMUs, it fails to take into account the error term, which indicates that the errors in the variables are included in the efficiency estimation. Furthermore, DEA scores have no statistical significance because of its non-parametric nature and their inability to determine variables that could account for variations in the technical efficiency scores across the DMUs. To address this issue, Coelli et al. [9] suggested the operationalization of a two-stage analysis, with the second stage being a regression analysis, where the estimated efficiency scores ($\hat{\theta}$) are regressed on a vector of explanatory variables. Many studies [23,34] employed Tobit regression for the second stage of DEA in efficiency analysis, with the assumption of censored distribution error terms since the exogenous variable ($\hat{\theta}$) lies between zero (0) and one (1). In addition, other studies [3,18] have employed a bootstrapped truncated regression based on criticism of the well-known Tobit regression model for its potential bias in efficiency scores. This is because DEA scores are susceptible to estimation and sampling errors due to the fact that they create efficiency scores for the sampled population instead of the entire population [36]. The argument put forward by Simar and Wilson [36] was that the DEA's estimated efficiency scores rely heavily on each other; thus, they could run counter to the underlying assumption of regression models, making censored regression models not suitable. At the same time, they proposed a statistically grounded bootstrapped-based truncated regression procedure as a workaround for the weakness of the censored regression models, resulting in a consistent inference in the second stage. The method for generating consistent and unbiased estimates can be discussed in two key DEA estimation procedures: Algorithm # 1 and algorithm # 2. Algorithm # 1 does not include DMUs for which efficiency scores equal unity in the regression analysis, which are products of finite sample bias. The remaining efficiency scores enter a truncated regression model as a dependent variable. The algorithm # 2 approach relies more on the bias-corrected DEA scores as a dependent variable in the left-truncated regression model with bootstrapping procedure.

Following Simar and Wilson [36], this study adopted the double bootstrap algorithm # 2 procedure, where the bias-corrected efficiency scores are regressed on a set of hypothesized variables that can affect farm-level technical efficiency using the following regression model;

$$\hat{\theta} = a_0 + \beta z_i +_i \delta SD + \varepsilon_i \tag{3}$$

where $\hat{\theta}$ represents the efficiency score of each DMU, a_0 is a constant term, z_i denotes the vector of farmer's socioeconomic variables (e.g., gender, age, household size, etc.), SD_i is a vector of sustainable development variables (i.e., FBOs membership, credit accessibility and extension contacts), β and δ are the set of unknown parameters, and ε_i is the error term with $N(0, \sigma^2)$ and left-truncated $1 - \beta z_i$. The double bootstrap truncated regression algorithm #2[2] has been employed in many efficiency studies such as Işgın et al. [18], Danso-Abbeam et al. [11], Long et al. [24], Anang et al. [2], Lopez-Penabad [24], among others. The double bootstrap approach uses a data generation process to address the challenges of estimating Eqs. (2) and (3). The following steps were followed to estimate the efficiency scores with the double bootstrap algorithm # 2. (i) After calculating efficiency scores for each farm using Eq. (2), (ii) truncated regression was estimated using Eq. (3), (iii) and bootstrap estimates were calculated. (iv) Using these results, the efficiency scores adjusted for bias were calculated as the response variable in a truncated regression for estimating factors affecting efficiency scores. (v) We then carry out a series of bootstrapping operations to provide bootstrap estimates; and (vi) finally, we used the bootstrap estimates to derive new confidence intervals.[3]

[2] In estimating with algorithm #2, we used 1500 bootstrap replications to estimate the confidence interval and the standard errors for regression coefficient, while 2000 bootstrap replications were used for the bias correction of the DEA scores.

[3] A detailed mathematical description of the Simar and Wilson [36] algorithm # 1 and algorithm # 2 can be found in page 7 of Badunenko and Tauchman [4]; long et al. [24], Lopez-Penabad et al. [25], among others.

Resource-use efficiency analysis

The Resource Use Efficiency (RUE) starts with the classic assumption of profit maximization, which states that the producer is rational and therefore distributes resources in a way that maximizes profits. RUE may be determined by estimating an output function, which is assumed to satisfy the condition that the marginal physical product (MPP) of any input is positive but decreasing (the second stage of the production function). The rationality of the cashew producers, taking into account their variable input usage, is assessed using the elasticity scale and their RUE is determined using the marginal value productivities (MVPs) for each resource at their respective price ratio. Miah et al. [28] concluded that, in ideal competition, farmers could maximize profit and make optimal use of resources at a level where their marginal value product is comparable to their marginal factor cost.

As stated by Goni et al. [14], resource use efficiency is given as;

$$RUE = \frac{MVP}{MFC} \tag{4}$$

where, RUE = Efficiency coefficient, $MVP = Marginal\, Value\, Product$, and $MFC = Marginal\, Factor\, Cost\, of\, inputs$ Specifying the econometric model using the double-log Cobb-Douglas production function, we obtain;

$$\ln Y = \ln \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + ... + \beta_k \ln X_k \tag{5}$$

where Y is output of cashew, $X' s$ are the inputs to be used in other to obtain the output, ln is the natural logarithm, $\beta' s$ are the parameters to be estimated (they are elasticity coefficients in the case of a Cobb- Douglas specification of the production function). From the Cobb-Douglas production function;

$$MVP_x = \frac{\partial Y}{\partial X}.P_y = \beta_x \frac{y}{x}.P_y \tag{6}$$

where $Y = mean\, value\, of\, output$, $x = mean\, value\, of\, input\, employed\, in\, the\, production\, of\, a\, product$, $\frac{\partial Y}{\partial X} = partial\, derivative$ of Y and X and $\beta_x = output\, elasticity\, of\, input$ Thus, the marginal value product (MVP) of the input is identified by multiplying the output elasticity of that input, mean output to mean input values ratio and the unit output price. Further, marginal factor cost (MFC) reflects the average unit price of the input. An input is considered to be efficiently allocated based on the following conditions: if $RUE = 1$ input is efficiently used. If $RUE > 1$ the input is underutilized and that both output and profit would appreciate if more of that input is employed.

Finally, if $RUE < 1$ the input was underutilized and that both output and profit would appreciate if less of that input is employed.

Following Mijindadi [29], the relative percentage in MVP of each input required in other to obtain optimal input/resource allocation of RUE =1 or MVP = MFC was calculated using;

$$R = \left(1 - \frac{MFC}{MVP}\right) \times 100 = \left(1 - r^{-1}\right) \times 100 \tag{7}$$

where R is the relative percentage change in MVP

Results and discussions

This section discusses the empirical findings of the study. First , the socioeconomic factors of the respondents are presented. Second, the findings of empirical assessments of efficiency scores are well tabulated and discussed. Third, the determinants or factors responsible for differences in efficiency amongst cashew producers using Simar and Wilson bootstrapped-based truncated regression are discussed. Finally, resource-use efficiency are also discussed.

Description of data

Table 1 reports some basic summary statistics for the sampled farmers. All the selected variables assumed to influence efficiency at farm level is mainly pivoted on some past and recent review of empirical literature of efficiency. These include Awunyo-Vitor et al. [1], Kabwe et al. [21], Solomon et al. [37], among others.

The average age for cashew plot managers in the study area is approximately 52 years. This confirms the findings of Wongnaa and Ofori [40], which show that a higher proportion (74.3%) of cashew farmers in the Brong Ahafo region are over 40 years old. Averagely, there are seven people per household and the percentage of plot managers who are married among respondents interviewed is 65%. On average, cashew producers had nine years of schooling, indicating a lower level of educational attainment among farmers. Cashew plot managers typically had 11 years of experience in cashew production. In addition, cashew farmers had at least four agricultural extension service contacts in the last cashew season. The average walking distance from farmer's home to their field is approximately four kilometers. With regards to our sustainable development variables, the proportion of cashew producers in the study are who are members of FBO and had access to credit facilities are 0.39 and 0.57, respectively. Moreover, on average, farmers received extension services 4 times in the past three years. About 35% of households are male plot managers belong to other social groups (e.g., funeral committee, local government, etc.). Table 1 also shows that the average quantity (output) of cashew collected by the producers in the study

Table 1
Descriptive statistics of variables used in the models.

Variables	Description/unit of measure	Mean	SD
Output/ha	Quantity of cashew nuts in kg per hectare (ha)	415.61	355.12
Farmer socioeconomic factors			
Gender	Proportion of farmers who received credit	054	
Age	Age of Famers (Years)	52.39	13.16
Household size	Number of members in the household	7.07	3.52
Marital status	Proportion of farmers who are married	0.65	
Education	Educational level of farmer in years	9.05	5.52
experience	cashew farming experience of farmers (yrs)	11.09	5.87
socioeconomic group	membership of any socioeconomic group (e.g., local government committee)	0.35	
Distance	Distance from home to farm site in km	2.19	
Sustainable development factors			
Extension service	Number of times farmers received extension service in the past 3 years.	3.70	4.00
FBO membership	Proportion of farmers who are members of FBO	0.39	
Credit access	Proportion of farmers who received credit	0.44	
Inputs for DEA analysis			
farm size (matured cashew)	cashew farm size in acres	2.28	3.99
labour per ha	man-days per ha (8 h/man-day)	394.77	330.78
Age of matured cashew farm	Age of matured cashew farms in years		
Chemical application per acre	Quantity of herbicides and insecticides in liters per ha	13.21	10.26

SD indicates standard deviation.

Table 2
Summary results of original and bias-corrected DEA estimates.

Efficiency range	Bias-corrected estimates CRS %	Raw estimates (not corrected) VRS %	SE %	CRS %	VRS %	SE %
0 – 0.10	33.33	1.00	6.00	10.67	0.33	4.67
0.11 – 0.20	37.67	10.67	7.00	22.67	1.00	4.67
0.21 – 0.30	23.00	33.00	11.00	23.67	10.00	6.00
0.31 – 0.40	5.00	27.67	14.00	21.67	22.67	11.00
0.41 – 0.50	1.33	14.67	14.67	10.00	25.67	9.67
0.51 – 0.60	1.33	9.00	16.33	5.00	14.33	12.33
0.61 – 0.70	0.33	3.33	12.00	2.67	9.33	11.00
0.71 - 0.80	0.00	0.67	9.67	1.00	5.00	13.00
0.81 – 0.90	0.00	0.00	6.33	1.67	2.00	15.33
0.91 – 0.99	0.00	0.00	3.00	0	3.33	11.0
Efficient (= 1)	0.00	0.00	0.00	1.00	6.33	1.33
Efficiency measures						
Mean score	0.16	0.33	0.48	0.29	0.51	0.59
Standard deviation	0.10	0.13	0.23	0.18	0.21	0.26
Minimum	0.01	0.05	0.02	0.01	0.07	0.03
Maximum	0.60	0.76	0.99	1.00	1.00	1.00
Return to scale (%)						
Increasing RTS	28					
Constant RTS	1					
Decreasing RTS	71					

region is approximately 415 kg/ha, whereas the average farm size of the cashew producers is approximately 2.38 ha. Dubbert [12] reported the average yield of 522.98 kg/ha for contract cashew farmers and 411.18 kg/ha for non-contract farmers, which can be compared with the results obtained in this study.

On average, cashew producers aim to employ 395 man-hours per ha in the 2018/2019 cashew season. This hired labour was obtained by adding the quantity of labour used for weeding, spraying insecticides and herbicides, as well as harvesting per season and changing it to the equivalent of 8 h per man-day. In addition, cashew farmers had their farm sprayed on average 13 liters of chemicals (both herbicides and insecticides) in the 2018/2019 production season.

DEA analysis of efficiency scores

The distribution of the technical efficiency score for bias-corrected and the original DEA for farm managers in the study area is shown in Table 2 and Fig. 1. Both the original and the bias-corrected efficiency scores based on the assumptions of OTE_{CRS}, PTE_{VRS} and SE are all described in Table 2. Any farm manager with an efficiency score of less than one (1) is considered to be inefficient. OTE_{CRS}, as noted by Kumar and Gulati [22], predicts the inefficiency resulting from the configuration of input or output and the scale of the activity. PTE_{VRS} enables one portion of the overall efficiency score to be calculated,

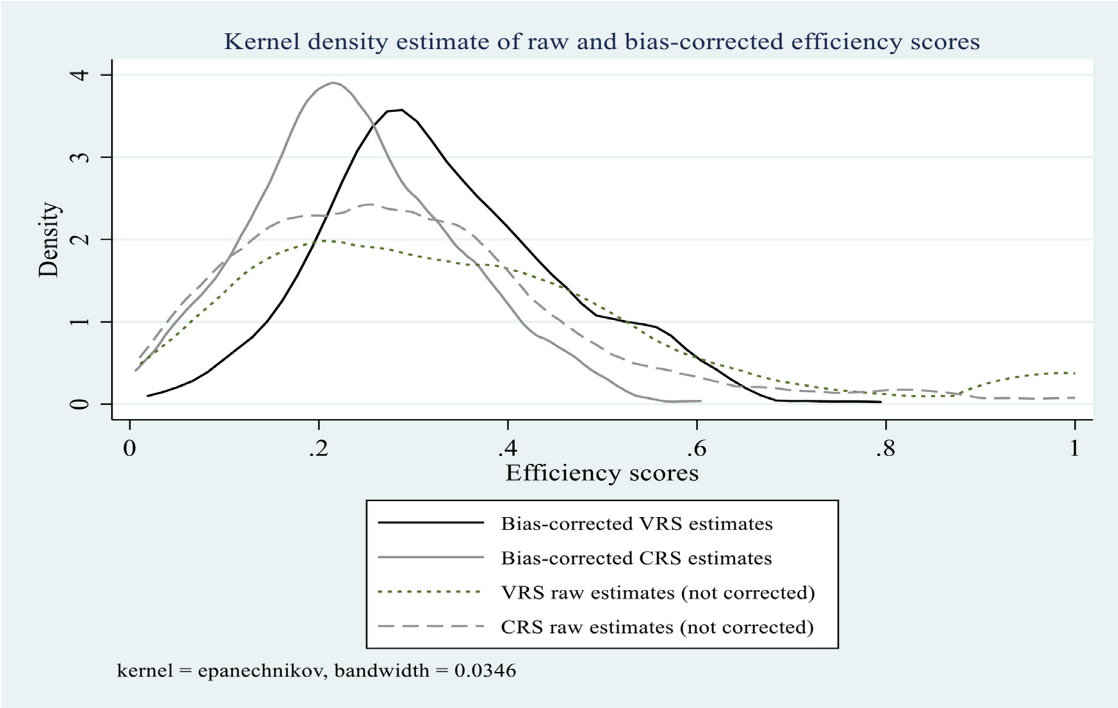

Fig. 1. Kernel density distribution of raw and bia-corrected OTECRS and PTEVRS.

taking care of inefficiencies arising from underperformance by farm managers. In addition, the SE, which is the ratio of OTE_{CRS} to PTE_{VRS}, indicates whether the farmer performs within the ideal size of the field. The OTE_{CRS} score ranges from 0.01 to 0.60 for bias-corrected efficiency with a mean efficiency of 0.16 and the original OTE_{CRS} efficiency ranges from 0.01 to 1.00 with a mean efficiency of 0.29 (Table 2 and Fig. 1). The average efficiency score tends to be lower for bias-corrected than for the original efficiency score. These are analogous to the kernel density distributions of original and bias-corrected efficiency scores shown in Fig. 1. The distributions of bias-corrected efficiency scores (OTE_{CRS} and PTE_{VRS}) are fairly similar, whereas the distributions of the original efficiency scores (OTE_{CRS} and PTE_{VRS}) are very different. There was a statistically significant difference between the original OTE_{CRS} and the bias-corrected OTE_{CRS}, as well as the original PTE_{VRS} and the bias-corrected PTE_{VRS}, using the paired *t*-test for equality of distributions.

These estimated mean efficiencies suggest that the average farm produces 16% of the potential output when the bias adjustment is made in the estimates and 29% in the original estimates. This means that there is potential to increase cashew output by about 84% and 71% for the bias-corrected and original scores, respectively, in the short term, if inefficient groups of farmers migrate to the efficiency frontier or adopt the technologies or practices used by the few productive farmers among them. In other words, farmers can produce up to 6.24 times (1/0.16) and 3.44 times (1/0.29) of their current output under bias-corrected and original efficiency score respectively, without altering their inputs.

The results further showed that only 1% of the cashew producers are at the frontier of the cashew production system under the original DEA procedure. However, no farmer was found to be efficient when efficiency scores were bias-corrected. This indicates that the proportion of plot managers who were technically inefficient under the CRS assumption of the original DEA estimation and the bias-corrected DEA estimation were 99% (297 farms) and 100% (300 farms), respectively. The result is consistent with the study by Işgın et al. [18] in which cotton farmers were technically more efficient under the original CRS technology but massively reduced when the bias-corrected DEA estimator was applied.

With regard to PTE_{VRS}, Banker et al. [5] suggested that some farmers would be efficient but not at the CRS frontier and thus added VRS efficiency, making it possible to disintegrate OTE into PTE and SE in DEA estimation processes. The average farm efficiency score improved from 0.29 to 0.51 when the PTE_{VRS} uncorrected bias estimation was used, while the bias-corrected DEA had an average score of 0.33, which reflects an improvement of more than 100% (from 16% to 33%) compared to the mean under OTE_{CRS}. The higher efficiency of the VRS assumption relative to that of the CRS assumption is expected because Kumar and Gulati [22] claimed that "the BCC model is a convex hull of intersecting planes that encapsulates data points more tightly than the CRS conical hull and provides efficiency scores that are greater than or equal to those obtained using the CCR model." In addition, when the VRS assumption was introduced, farmers who were efficient under OTE_{CRS} increased significantly to 6.33% for the original DEA score. However, under PTE_{VRS}, no farmer was efficient for bias-corrected scores. The VRS scores also vary from 0.07 – 1 and 0.05 – 0.76 for the original and bias-corrected DEA estimations, respectively. The findings further suggest that under PTE_{CRS}, technical inefficiency could be due to an inappropriate size rather

Table 3
Determinants of technical efficiency of cashew plot managers.

Variable	Coefficient	Bootstrap S.E
Household socioeconomic characteristics		
Gender	−0.056***	0.017
Marital status	−0.029*	0.016
Age of farmer	−0.001	0.001
Household size	−0.005**	0.002
Educational attainment	0.003*	0.001
experience in cashew farming	−0.001	0.001
socioeconomic group membership	−0.015	0.015
Distance from house to farm	−0.020***	0.005
Sustainable development variables		
Extension service	0.021	0.017
Membership of FBO	0.038***	0.015
Credit access	0.006	0.014
Sigma	0.117	0.005

***, ** and * denote significant levels at 1, 5, and 10%.

than managerial weakness or inefficient use of resources. That's why the 16 farms that were inefficient under the CRS have now become efficient under the original VRS DEA estimation.

Taking into account the calculated SE, the average scale efficiency obtained from the uncorrected DEA estimation is approximately 59% but reduced to 48% when the efficiency scores were bias-adjusted. The results show that, under both assumptions, plot managers do not perform at their optimum operating size. The share of farmers who were technically efficient under the uncorrected DEA was 1.33%, but decreased to 0% under the corresponding bias-corrected DEA. The estimated results further indicate the proportions of farms experiencing decreasing returns to scale (DRS), constant returns to scale (CRS) and increasing returns to scale (IRS). In order to maximize profits, each production unit would like to work on the most profitable scale, thereby acting on a constant return to scale. However, only 1% of the producers witnessed CRS while working on a more profitable scale. This implies that output increases in proportion to the increase in input. The result is mainly skewed to a decreasing return to scale (DRS) for farmers (71%), indicating that farmers are working above their optimum size. This indicates that there is a potential for farmers to reap the size of their economies by decreasing their size of cashew production. In other words, reducing their scale of operation is a great way to increase their level of performance. In addition, 28% of producers were producing under increasing returns to scale (IRS), which means that farmers are working below their optimum level.

Determinants of technical efficiency

Following Simar and Wilson [36], Table 3 presents the findings of the second part of the double bootstrap DEA estimation, which describes the determinants of farm technical efficiency under PTE_{VRS}. Factors that have a major effect on PTE_{VRS} include household size, marital status, number of years of formal schooling, distance from home to farm, FBO membership and the gender of the farmer.

Gender of plot managers negatively affects technical efficiency and statistically significant at 1% level. This indicates that male cashew plot managers are less technically efficient than their female counterparts. This finding contradicts the belief that male plot managers are technically more efficient than their female counterparts. It could be the outcome of female plot managers in the study area benefiting from special programs aimed at minimizing the gap between male and female in access to agricultural inputs and services. Although this evidence has not been presented by our data, many government policies nevertheless support the need to reduce the gender gap in access to agricultural inputs and services. This finding commensurate with the study of Kabwe et al. (2016) in which male cotton farmers were technically less productive than female cotton farmers. The marital status is statistically significant and has a negative effect on technical efficiency. This suggests that unmarried (either single, divorced or widowed) plot managers are technically more efficient than their married counterparts. This may be due to the fact that married farmers have various commitments, such as paying school fees; expenditure on utility bills, feeding, medications, among others, and that cash resources available for farm production maybe diverted to these commitments. This is in contrast to our a priori assumptions, which suggested a positive relationship between marital status and efficiency, given that most married farmers receive labor assistance or cash support from their spouses or children. Household size also exerts a negative and significant effect on efficiency. This indicates that a household with small members is more efficient than a household with more members, and this contradicts our a priori expectations that farmers with larger family size appear to have more family labor, which could contribute to an increase in their level of efficiency.

However, this could be as a result of increased pressure exerted by the size of the household on the fewer resources available. In addition, the cash resources available for farm activities are competed for by more household members, leading to a minimal or no allocation of productivity-enhancing inputs and subsequently leads to inefficiency. The findings are consistent with the analysis by Mango et al. [26], which conducted a study on the technical efficiency of smallholder farm-

Table 4
Input use efficiency and adjustments in MVP for optimal input use.

Inputs	β	MVP	MFC	MVP/MFC	Efficiency indicator	% Divergence
Hired labour	0.45	3.01	44.33	0.07	over-utilized	1392.50
Family labour	0.26	23.47	28.23	0.83	over-utilized	20.19
Quantity of insecticides	0.16	8127	7.60	1069.40	under-utilized	99.91
quantity of herbicides	0.33	47.20	10.12	4.77	under-utilized	78.62

β indicates the coefficient of the inputs from the Cobb-Douglas production function in Eq. (5).

ers in Zimbabwe. However, it contradicts the findings of Tanko [38], which showed a positive correlation between the size of the household and the profit efficiency of the Shea butter processors. The coefficient of educational level was positively signed and significant, which indicates that farmers who had more years of formal education were more technically efficient than their counterparts with fewer years of formal education. Thus, a higher educational level enhances technical efficiency. Farmer's level of education upsurges his ability to understand and evaluate information on new production technologies which subsequently, enhances productivity. Education enables farmers to better understand the socioeconomic conditions controlling their farming activities and also help them learn how to assemble, retrieve, analyze and disseminate information. Extension agents' recommendations are better understood by farmers with higher educational attainment and hence, contribute to the enhancement of their technical efficiency as indicated by the positive coefficient of extension service even though not statistically significant.

The role of sustainable development variables such as FBOs in the technical and managerial development of farmers cannot be overemphasized. Our findings show that farm managers who are members of FBO tend to achieve a higher degree of efficiency relative to farm managers who do not engage in FBO activities. FBOs in Ghana's farming communities are typically self-help groups for farm workers, credit and, more importantly, information on new farm practices or technologies. FBOs, therefore, allow farmers to reduce labour costs and provide them with the ability to purchase additional inputs, which could contribute to increased productivity. Moreover, small-scale farmer cooperatives have the potential to amplify their voices and promote sustainable development by making their voice heard and exerting pressure on key investment in order to help farmers become more productive. In addition, agricultural extension agents from both government and non-government agencies typically tend to work with farmers in groups rather than individuals in order to minimize their operating costs. The distance from home to the farm has shown a negative and significant relationship with the technical efficiency of the plot managers. This indicates that farmers who have their farms farther away from home are less technically efficient than their counterparts who have their farms closer to home, and this is consistent with the study's a priori expectation of a negative relationship between farm efficiency and farm distance. The explanation is that farms that are far from the farmer's home need more walking time or higher costs in terms of transporting inputs such as herbicides, insecticides, among others, to the farm and also a lot of energy to walk from the farmer's home to the farm, thereby reducing productivity.

Marginal value product-marginal factor cost (MVP – MFC) analysis

This section provides a comprehensive explanation of input (resource) use efficiency of cashew producers and adjustment in MVPs for optimal input usage. The RUE is calculated as each input's MVP ratio used to its corresponding factor price (MFC). Inputs are considered to be optimally distributed under purely competitive market conditions where there is no difference between MVPs and their corresponding unit cost. Thus, when MVP-to-MFC ratio is equal to unity. Table 4 illustrates how farmers in the study region distribute their inputs according to unit price and the percentage of divergence. Results on input usage efficiency in Table 4 indicate that cashew farmers in the study region are inefficient in allocating all the inputs used in the production year 2018/2019.

The efficiency indicator for hired and family labour, respectively, was 0.07 and 0.83, suggesting over-use of both hired and family labor in the study field. This implies decreasing the amount of labor employed would increase the quantity of cashew fruits produced. On the contrary, MVP / MFC values for insecticides and herbicides were greater than one (1), indicating that these two inputs were underutilized. Farmers need to increase these two inputs to improve performance. The results on divergence from optimal level of resource use shows wide divergence of hired labour followed by insecticides application. Family labour had the least (20%) percentage of divergence from its optimal use.

Conclusions

This study estimated the technical and resource-use efficiency of cashew production in the Nkoranza north district of Bono east region, Ghana. The results of the double bootstrap DEA estimates showed that only 1% of the cashew producers are at the frontier of the cashew production system with a mean PTE_{VRS} of 51%. However, when the efficiency estimate was bias-corrected, no farmer hit the frontier and the mean PTE_{VRS} decreased to 33%. This suggests that the original scores were skewed upwards; hence, the DEA double bootstrap technique is important for estimating the efficiency of cashew production in the study area. Factors that significantly affect the technical efficiency of cashew farmers in the study area include gender, household size, marital status, educational attainment, distance from home to farm, and FBO membership. For efficient utilization of resources, labour (family and hired) should be reduced, whereas insecticides and herbicides should be increased in order to boost productivity.

Some important policy recommendations can be outlined from the above findings. First, government and other stakeholders should step up strategies to enable farmers to increase the use of insecticides and herbicides to manage pests and weeds, respectively. These techniques may be in the form of technological and managerial training in the application of inputs. In addition, ensuring that farmers have convenient access to inputs through an effective distribution system such as FBOs is recommended in order to increase the productive use of inputs. Second, agricultural extension agents should make a deliberate effort to persuade farmers to join FBOs. In communities where there are no FBOs, extension officers can promote the creation of one. This is because FBOs serve as an important platform for the dissemination of information on agricultural technologies and the right input combinations. Farmers who are members of FBOs are more likely to have knowledge of agricultural technologies and effective use of resources. As Ghana strives to meet the SDGs targets, optimizing productivity and resource use is critical to boosting the cashew industry, which will have a trickle-down effect on improving the incomes of the actors (e.g., farmers, input dealers, buyers, processors, etc.) in the cashew value chain, improving food security, and aiding in the fight against poverty.

Declaration of competing interest

The authors report no conflicts of interest.

Availability of data and materials

The data set and the analytical codes that support the findings of this study are available upon reasonable request from the corresponding author.

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