Determinant of Technical Efficiency of Sugarcane During the Covid 19 Pandemic in Malang Regency East Java Indonesia

A Santosa[11], *E S* Rahayu[2], *J* Sutrisno[3], and Kusnanda*r*[4]

[1]Doctoral Program of Agriculture Science, Faculty of Agriculture, Universitas Sebelas Maret, Kentingan, Surakarta 57126, Indonesia
[1]Department of Agribusiness, Faculty of Agriculture, Universitas Pembangunan Nasional, Yogyakarta 55283, Indonesia
[2]Department of Agribusiness, Faculty of Agriculture, Universitas Sebelas Maret, Kentingan, Kentingan, Surakarta 57126, Indonesia
[3]Department of Agribusiness, Faculty of Agriculture, Universitas Sebelas Maret, Kentingan, Kentingan, Surakarta 57126, Indonesia
[4]Department of Agribusiness, Faculty of Agriculture, Universitas Sebelas Maret, Kentingan, Kentingan, Surakarta 57126, Indonesia

Abstract. Sugarcane farmers in sugar-producing countries are experiencing an economic crisis due to the Covid 19 pandemic. Restrictions on transportation and a scarcity of labor have delayed sugarcane harvesting, increased production costs, decreased productivity, and decreased income. Therefore, our research aims to measure the technical efficiency and the influence of environmental factors on the technical efficiency of sugar cane farming in Malang Regency. The results of the research using the multiple bootstrap regression approach show that the efficiency values based on the VRS and CRS assumptions are 0.854 and 0.834. This value means that sugarcane farmers in Malang Regency must reduce the use of inputs by 16.6% and 14.6% respectively to make sugarcane farming more efficient. The variable age of the head of household reduces technical efficiency, while the variables of sugarcane training experience, organizational experience, ratoon cane, and increases in input prices have the potential to increase technical efficiency. The Covid 19 pandemic has become a momentum for policy makers to create training programs that aim to utilize natural resources to overcome scarcity and rising input prices, as well as realize agricultural sustainability.
Keywords: Technical efficiency, Sugarcane Farming, Development Envelope Analysis, Covid-19, Multiple Bootstrap Regression

1 Introduction

The United Nations introduced the Sustainable Development Goals (SDGs) in 2015 to tackle the pressing global issues arising from our evolving environment until 2030. These goals encompass a wide range of challenges, such as poverty, inequality, economic

[1] Coresponding author: agussantosa110871@gmail.com

© The Authors, published by EDP Sciences. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

prosperity, promoting good health, and enhancing overall well-being. The agriculture sustainable sector leads to food security solutions and is critical to eradicating hunger and poverty [1]. The importance of the sustainable agriculture sector, this effort is expected to be one of the main solutions in achieving sustainable development goals. Within the agricultural sector, A majority of the global population includes staple foods as part of their daily diet. [2]. Therefore, it is essential to assess the efficiency and sustainability of staple food commodities [3].

The government determines nine agricultural commodities in Indonesia as a staple food, including sugar cane [4]. As a sugar-producing country, Indonesia produces around 2 million tons per year, and Malang Regency is the largest sugar-producing region in Indonesia [5]. However, although it is a sugar-producing country, Indonesia needs to meet domestic consumption, so sugar imports are increasing yearly. The insufficient sugarcane productivity at the farm level is the primary reason for the production's inability to meet consumption demands. [6].

The inefficient use of inputs causes the low productivity of sugarcane. Inefficiency in the agricultural sector refers to the excessive use of resources by farmers to achieve a certain level of production compared to the utilization of resources by the most efficient farmers [7]. The ability of a farm manager to transform inputs into outputs using specific technology is often influenced by the environmental conditions under which production takes place [8]. These environmental factors include specific aspects of agriculture, such as managerial skills, institutional limitations, risk attitudes, or hard-to-measure innovations, which can be partly represented by observable variables such as age, experience, involvement in agricultural improvement initiatives, and educational background. [9]. Inefficient agricultural practices waste valuable resources, damage the environment, and create unsustainable agricultural systems. Addressing this through sustainable farming methods is critical to conserving resources, increasing food production, and ensuring agricultural resilience. Understanding and considering environmental variables in agricultural strategies can lead to more effective interventions and improved productivity and well-being of farmers in the long run.

The environment for sugar cane farming is increasingly complex after the Covid 19 pandemic. Almost all countries implement a lockdown policy to forestall the spread of the Covid 19 outbreak. In addition, specifically in Indonesia, the government implements a policy involving significant restrictions on social activities at a large scale. Supply chain disruptions occurred because the Indonesian government a policy involving significant restrictions on social activities at a large scale during the Covid 19 pandemic [10]. For instance, transportation restrictions during the COVID-19 pandemic caused delays in distributing fertilizers to farmers and sugarcane from the field to the sugar factory [4], [11]. Furthermore, the scarcity of labour in the sugarcane business because of restrictions on social mobility [12]. As a result, sugarcane harvesting activities are delayed, production costs increase, sugarcane productivity declines, and income decrease [4], [12], [13].

Measuring the disparities in efficiency and pinpointing their root causes can offer valuable insights for farm managers, taxpayers, consumers, policymakers, and planners who aim to assist farmers in enhancing their productivity and income [9]. One way to assess technical efficiency is through stochastic frontier analysis (SFA) [14], [15], and data envelopment analysis (DEA) [16], [17], where the actual production is compared to the best practice (or 'frontier') production. With techniques such as stochastic frontier analysis and data wrapping analysis, farm managers and policymakers can identify areas where inefficiencies occur. This analysis enables a thorough evaluation of factors affecting farm performance, such as suboptimal resource allocation, inadequate technology, or ineffective management practices. With this understanding, interventions and support programs can be developed to improve agricultural productivity and economic sustainability for farmers and the agricultural sector as a whole. Several research studies have investigated the technical efficiency of sugar cane farming in Indonesia, utilizing the DEA (Data Envelopment Analysis) and SFA (Stochastic Frontier Analysis) methods. [18]–[22]. This study uses the DEA model because this model is well-known for assessing the operational and environmental performance of various entities in the public sector. The input targets in the DEA model are used to transform inefficient farming into efficient farming [23]. According to Simar and Wilson [24], the traditional non-parametric DEA method lacks a strong statistical foundation, making it difficult to draw robust statistical conclusions. Therefore, bootstrap techniques must be incorporated into the DEA framework so that the weaknesses of the conventional DEA model are overcome [24]–[26].

Based on the description above, our study aims to measure technical efficiency and environmental factors' influence on sugarcane farming's technical efficiency in Malang Regency. Therefore, we adopt a double bootstrap approach to answer the research objectives.

2 Material and methods

2.1 Data envelopment analysis (DEA)

The DEA model is categorized into two types based on assumptions: CCR-DEA estimate constant returns to scale, while BCC-DEA considers variable returns to scale [27]. Additionally, the DEA model can be classified as input-oriented and output-oriented. The input-oriented DEA model seeks to minimize the input needed to achieve a specific level of output, whereas the output-oriented DEA model aims to maximize the output achieved with a given set of inputs. [28]. In this research, the input-oriented DEA model is utilized because it effectively tackles the concern of limited resources by establishing input targets and addressing the problem of increasing input costs. The conventional DEA model used to evaluate technical efficiency can be represented as follows. [29]. The usage of the input-oriented DEA model in this research allows for a thorough evaluation of the efficiency of using inputs to achieve specific output levels, thus providing valuable insights into potential areas of improvement and resource optimization for the agricultural sector:

$$Min_{\theta,\lambda}\theta_i \tag{1}$$

Subject to :

$$\begin{gathered} -y + Y\lambda \geq 0, \\ \theta_{xi} - X\lambda \geq 0, \\ \sum_{i=1}^{N} \lambda_i = 1 \\ \lambda \geq 0 \end{gathered}$$

Where θ_i is technical efficiency (TE) quantified on a scale from 0 to 1, representing the extent to which a system or process is performing optimally and effectively, a TE value equal to 1 implies that a sugarcane farmer is technically efficient. In contrast, TE value below 1 (0<TE<1) means that a sugarcane farmer is technically inefficient. The vector λ, a constant weight vector with dimensions Nx1, is used to determine the linear combination of the ith Decision Making Unit (DMU) counterparts, where N represents the total number of farmers involved in the analysis. Y denotes the vector representing the number of outputs, while X represents the vector of observed inputs. For the ith Decision Making Unit (DMU) among N farmers, y is the output vector compared to the output vector of the theoretically efficient DMU (Yλ). Similarly, Xλ represents the minimum input required from a theoretically efficient DMU to achieve the level of output produced by the ith DMU. Meanwhile, Xi represents the input level of the ith DMU. [28], [29]. Equation (1) represents constant returns to scale (CRS), also known as overall technical efficiency (OTECRS), which implies that farmers are operating at an optimal scale. OTECRS can be broken down into two components: pure technical efficiency (PTE), denoted as PTEVRS, which reflects management practices considering variable returns to scale (VRS), and the remaining part referred to as scale efficiency (SE). To ensure efficiency under variable returns to scale (VRS), convexity constraints are introduced, ensuring production possibilities and input-output relationships have a convex shape, optimizing resource allocation across different scales of operation. ∑ λ_i=1 The VRS frontier is generated as a result of implementing these additional convexity constraints. [30]. This constraint ensures that the ratio of inefficient farms in the region to the provisions of farm size must be equal [31]. SE is used to determine the scale of farm operations, which is the ratio of OTE to PTE(SE=OTE/PTE). SE is an important component in assessing the efficiency of farm operations, as it provides insight into how effectively a farm operates at current scale compared to optimal scale, thus helping to identify opportunities for scale adjustment and improving overall productivity.

2.2 Second stage bootstrap truncated regression

The next stage is to explain the sources of farms level efficiency, in which the socioeconomic and farm characteristics are associated with technical efficiency. Many previous studies used the Tobit method to look at the relationship between explanatory variables and efficiency scores, which is why this method is suitable for estimating the nature of censored efficiency scores [32]–[34]. However, the procedure for using the Tobit model was criticized by Simar and Wilson [26] because several problems were found, such as this method needing to describe the consistency of data-generating processes and problems related to invalid inference due to serial correlation arises. Simar and Wilson [26] propose an alternative double-bootstrapped procedure that allows valid inference while generating standard errors and confidence intervals for the efficiency estimates. This method addresses the issue of accurate statistical inference in efficiency analysis. Hence, we utilize the double bootstrap method, where we first calculate bias-corrected efficiency scores. Then, these scores are regressed on a set of explanatory variables to analyze their relationship and understand the factors affecting efficiency :

$$(\theta\_i)\hat{}\hat{} = z\_i\,\beta + \varepsilon\_i \qquad (2)$$

The bootstrapped truncated regression procedure (Algorithm 2) using STATA software provides a comprehensive approach to investigating the impact of socioeconomic and agricultural characteristics (z_i) Starting with a dataset containing these key variables and error terms, For each bootstrap sample, a truncated regression analysis is performed, with δ as the dependent variable and z_i as the explanatory variable. It produces parameter estimates (β) showing the relationship between δ and z_i for each sample. By combining parameter estimates from all bootstrap samples, researchers derive an overall estimate of β, allowing them to draw statistically valid conclusions about factors affecting efficiency in the context of socioeconomic and agricultural characteristics. STATA software facilitates the implementation of this methodology, making it a powerful tool for efficiency analysis in various fields with operational procedure is as follows [35]:

Step 1: Calculate the value $\hat{\theta}_i$ for each DMU i=**1**,...,***N*** using the DEA method with Equation (1).
Step 2: Select one reference DMU (e.g. DMU M) from the N DMUs calculated in the previous step, based on its efficiency $\hat{\theta}_i > 1$. Use the selected reference DMU and perform truncated regression on the input variable z_i. To obtain an estimate of the β coefficient and an estimate of the variance parameter $\hat{\sigma}$. using the maximum likelihood method.
Step 3: Bootstrap B-1 times by repeating steps 3.1-3.4 B_1 times to get B_1 bootstrap approximation $\hat{\theta}_i^b$ for each DMU $i = 1, ..., N$,.
3.1. In each DMU $i = 1, ..., N$, add a made-up error $\tilde{\epsilon}_i$ derived from the distribution $N\left(0, \hat{\sigma}\right)$ with left traction at $1 - z_i\hat{\beta}$
3.2. Calculate the artificial efficiency $\tilde{\theta}_i$ As a result of $z_i\hat{\beta} + \tilde{\epsilon}_i$ fo each DMU $i = 1, ..., N$**.**
3.3. Generate $i = 1, ..., N$ artificial DMUs with input quantities $\tilde{x}_i = x_i$ and output quantities $\hat{\theta}_i^b$ for each DMU $i = 1, ..., N$
3.4. Use the reference DMU generated in step 3.3 as a reference in calculating bootstrap efficiency $\tilde{y}_i = \left(\frac{\hat{\theta}_i}{\tilde{\theta}_i}\right) y_i$ for each DMU $i = 1, ..., N$.

Step 4 : Calculate the corrected efficiency score $\hat{\theta}_i^b$ in each DMU $i = 1, ..., N$ that produces artificial KRL $i = 1, ..., N$ with yield quantity $\hat{\theta}_i^{bc}$ and the sum of output $\left(\frac{1}{B_1}\sum_{b=1}^{B_1} \hat{\theta}_i^b - \hat{\theta}_i\right)$
Step 5 : Use the N-made KRL, generated in step 4, as the reference set for the DEA that produces $\hat{\theta}_i^{bc}$ in each DMU $i = 1, ..., N$
Step 6: At DMU $i = 1, ..., N$ calculate can be calculated bias corrected efficiency score $\hat{\theta}_i^{bc}$
6.1. Perform truncated regression on the variable z_i by using a bias-corrected efficiency score $\hat{\theta}_i^{bc}$ as a dependent variable to obtain the estimation of the coefficient $\hat{\hat{\beta}}$ and the estimation of the variance parameter $\hat{\hat{\sigma}}$ using the maximum likelihood method. Bootstrap B_2 again by repeating step 5 B_2 times to get B_2 bootstrap approximation $\hat{\hat{\beta}}^b$, and $\hat{\hat{\sigma}}^b$ At DMU $i = 1, ..., N$ add artificial error z_i derived from the distribution $N\left(0, \hat{\hat{\sigma}}\right)$ with left truncation at $z_i\hat{\hat{\beta}} + \tilde{\tilde{\epsilon}}_i$

6.2. Calculate the artificial efficiency score of $\hat{\hat{\theta}}_i$ As a result of $z_i\hat{\hat{\beta}} + \tilde{\tilde{\epsilon}}_i$ fo for each DMU $i = 1, ..., N$

6.3. Perform truncated regression on the variable z_i. Using the artificial efficiency score $\hat{\hat{\theta}}_i$ as a dependent variable to obtain an estimate of the $\hat{\hat{\beta}}^b$, coefficient. and estimated variance parameters $\hat{\hat{\sigma}}^b$ using the maximum likelihood method.

Step 7 : Calculate the standard confidence and error intervals for the estimation of the $\hat{\hat{\beta}}$ coefficient and the estimation of the $\hat{\hat{\sigma}}$ variance parameters that have been generated from the previous steps.

2.3 Study sites and data

Malang Regency was chosen as the research location because this area is Indonesia's largest sugar cane producer. Sugarcane production in Malang Regency is equivalent to 18.09% of the total sugarcane production in Indonesia. Next, we chose the Gondanglegi and Bantur Districts as the research locations. Then, four villages were selected from the two sub-districts and 50 sugarcane farming households from each village through a simple random sampling technique. We surveyed 200 sugarcane farming households, but only 144 were willing to be interviewed.

The data collected consists of three parts: (1) input and output variables, (2) socioeconomic variables, and (3) farm characteristics variables. Land, seeds, ZA fertilizer, PO fertilizer, herbicides, fuel, and labor are the input variables, while the quantity of sugar cane is the output variable. The socio-economic variables used in this study are age, gender, education, number of households, dependency ratio, farming experience, training, organizational experience, distance to input markets, access to credit, input subsidies, and input prices. Farm characteristic variables include access to irrigation, number of ratoons, and crop diversification.

Our study uses the Herfindahl–Hirschman index (HHI) to measure crop diversification. HHI is the sum of the square of the area of each type of plant to the total area of the plant, where the HHI equation is as follows [36]:

$$Herfindahl–Hirschman\ Index\ (HHI) = \sum\_J\hat{}N\ A\_j\hat{}2 \quad (3)$$

Increasing diversification leads to a decrease in the Herfindahl-Hirschman Index (HHI), a measure of crop acreage concentration, where A_j is the proportion of the j-th crop's acreage in the total cropped area. An HHI index equal to one indicates specialization, and an HHI index equal to zero implies diversification.

3 Result and discussion

Our study uses Max DEA and Stata 16 to answer the efficiency problem in sugarcane farming. We entered the input and output variables into Max DEA software for a technical efficiency score. The score we obtained is still based on the conventional DEA model, in which this score needs to be statistically validated. Therefore, we used STATA 16 software to double bootstrap to obtain statistically valid technical efficiency scores and regression results that policymakers can trust. This approach aims to bootstrap the regression coefficients and the DEA efficiency score. We used 2000 replications to estimate the regression coefficients. Specifically for bootstrap DEA efficiency scores, Simar and Wilson [26] suggest 100 replications, Badunenko and Tauchmann [35] and suggest 1000 replications for bootstrap DEA efficiency scores. Our study uses 200 replications to bootstrap the DEA efficiency score.

3.1 Summary of descriptive statistics

Table 1 Provided information presents a summary of the data's statistical measures collected in the study. Each farmer produces a sugar cane of 125,547.9 kg per planting season (min. 18,000 kg: max. 1,500,000 kg). The average sugarcane harvesting land is 8483.68 m2 (min. 1,000 m2: max. 100,000 m2).

The labor input variable represents the total working hours for sugar cane production, including hired and family labor, assuming an 8-hour workday. On average, farmers spend 291.53 hours per planting season, ranging from 34.43 to 3,345.71 hours. The seed variable measures the quantity of sugarcane ratoon in kilograms per planting season. On average, there is 10729.03 kg per planting season. Farmers use two fertilizers, the average ZA fertilizer of 945.49 kg per planting season, while the average PO fertilizer is 421.01 kg per planting season. The average herbicide used in sugarcane production is 1.82 liters per planting season. Fuel is measured as the cost of sugarcane transportation to a sugar factory converted at the price of fuel per liter. The average fuel for transportation is 138.31 liters.

Regarding socio-economic variables, the average age of the head of the sugarcane farmer household is 47.03 years old, 95.83 % of the heads of sugarcane farmer households are men, 24,30 % have access to credit, and 75 % of farmers have access to input subsidies. The average head of a family attends school for nine years. The average sugarcane farmer has experience in farming and organization for 21.53 years and 15.41 years, respectively. Sugarcane farming households have an average number of family members and a dependency ratio of 3.97 and 1.95, respectively. The average distance from the house to the market is 1390.08 meters. We use the input price variable due to increased input prices during the Covid-19 pandemic. The measurement of input prices is based on the growth of input prices after the government reduced the input subsidy 85.42 % of sugarcane farmers have access to irrigation, most farmers use sugarcane ratoons, and the average diversification index is 0.813.

Table 1. Summary statistics of variables in the models

Variable name	Mean	Std dev	Min	Max
First Stage Variables (DEA Model)				
Sugarcane (kg)	125547.9	207394	18000	1500000
Land (meters)	8483.681	14830.2	1000	100000
Seed (kg)	10729.03	18094.8	1450	130000
ZA fertilizer (kg)	945.493	1583.517	100	12000
PO fertilizer (kg)	421.006	741.041	50	5500
Herbicide (liter)	1.820	3.333	0.1	30
Fuel (liter)	138.306	58.381	66	465
Labor (hours worked per day)	291.532	499.149	34.429	3345.714
Second Stage Variables (Model Determinant of Efficiency)				
Age (years)	47.028	10.292	23	70
Education (years)	9.354	3.352	0	17
Gender (1:male;0:female)	0.958	0.201	0	1

Household size (number)	3.972	1.206	1	7
Dependency (ratio)	1.953	1.390	0	6
Farm experience (years)	21.535	9.046	3	50
Training (numbers in last years)	3.326	1.294	0	6
Organization (years)	15.417	3.402	3	20
Distance (meters)	1390.083	1994.515	0	12000
Ratoon (1:plant cane;2-8:ratoon cane)	3.903	1.543	1	8
Credit (1:yes;0:no)	0.243	0.430	0	1
Irrigation (1:yes;0:no)	0.854	0.354	0	1
Subsidies (1:yes;0:no)	0.75	0.434	0	1
Input price (percent)	22.809	20.215	0	86.573
Diversification (ratio)	0.813	0.215	0.346	1

3.2 Technical efficiency estimation

Table 2 shows efficiency scores calculated based on CRS and VRS assumptions. Based on conventional DEA model measurements, the average technical efficiency score of sugarcane farming in Malang District based on both assumptions (CRS and VRS) is 0.879 and 0.907, respectively. These results mean that, on average, inefficient sugarcane farmers would have to reduce their inputs by 12.1% and 9.3%, without changing their output levels.

Table 2. Conventional and double bootstrap TE estimates.

Variables	Mean		t-Ratio	Kolmogorov Smirnov test
	Conventional	Double bootstrap		
TE CRS	0.879	0.834	17.002***	0.222 ***
TE VRS	0.907	0.854	18.559***	0.354***

*** Significant at 1%

We also compare the value of conventional technical efficiency and the value of technical efficiency based on the double bootstrap approach. The two-sample Kolmogorov-Smirnov test and paired t-test showed that the value of technical efficiency based on the double bootstrap approach significantly differs from that of conventional technical efficiency. The two tests show that the double bootstrap technical efficiency is lower than the conventional technical efficiency for the two assumptions (CRS and VRS). Applying the corrected bias to the technical efficiency value causes the double bootstrap technical efficiency value to be lower than the technical efficiency conventional DEA for the two assumptions. These results indicate that the potential for increasing technical efficiency suggested by the double bootstrap method in this study is undoubtedly greater than conventional DEA. The potential for increasing technical efficiency can be seen from the input savings that can be made by producers, in which sugarcane farmers in Malang Regency are advised to reduce inputs by 16.6% and 14.6%, on both assumptions for a double bootstrap approach. The more significant input savings in the DEA bootstrap approach were found in [17], [37] study. The findings of this study highlight the importance of using a double bootstrap approach in assessing technical efficiency, as this method uncovers greater potential for input savings and increased efficiency among sugarcane farmers in Malang District compared to conventional DEA methods.

3.3 Determinant of technical efficiency analysis

In this study, the efficiency value of each sugarcane farming operation was used as the dependent variable. The independent variables with positive and negative coefficient signs indicate their positive and negative effects on efficiency measures, respectively. The findings, as presented in Table 3 using the truncated regression with a double bootstrap approach for technical efficiency under CRS and VRS assumptions, revealed that the age of the household head had a negative and statistically significant impact on both TE CRS and TE VRS. Specifically, for every 1% increase in the age of the household head, the technical efficiency of sugarcane farmers decreased by 0.00166% and 0.00170%, respectively. Elderly sugarcane farmers are worried about getting Covid 19 if they leave their homes. Fear of disease causes old farmers not to take care of their sugarcane plants. This behaviour has an impact on reducing sugarcane productivity and reducing technical efficiency. The studies [38] support our findings.

Table 3. Determinants of technical efficiency double bootstrap on both assumptions

Variable	TE CRS		TE VRS	
	Coefficient	z-value	Coefficient	z-value
Age	-0.00166***	-2.59	-0.00170***	-2.88
Education	-0.00256	-1.60	-0.00184	-1.23
Gender	0.02412	1.02	0.02585	1.17
Household size	0.00029	0.07	-0.00222	-0.63
Farm experience	-0.00039	-0.05	-0.00068	-1.03
Distance	2.60e-06	-1.03	2.73e-07	0.11
Credit	0.00749	-0.66	-0.01227	-1.14
Training	0.05195***	12.97	0.04704***	12.45
Irrigation	0.00536	0.41	-0.00345	-0.28
Organization	0.00395**	2.25	0.00242	1.43
Ratoon	0.003555	1.16	0.00792***	2.71
Subsidy	-0.00509	-0.46	0.00124	0.12
Dependency	-0.00518	-1.53	-0.00298	-0.98
Diversification	-0.02446	-1.17	-0.02355	-1.17
Input Price	0.00042*	1.76	0.00027	1.20

***,**,*Significant at 1%, 5% and 10% levels, respectively.

We found different results for the coefficients on the variables training, organization, sugarcane ratoon, and input prices, which can potentially increase technical efficiency. Despite the Covid-19 pandemic in Malang Regency, sugarcane farmers are still enthusiastic about participating in sugarcane training, on average, have attended three trainings in the past year. They wear masks and keep their distance during training. Training materials on sugarcane cultivation per health protocols help prevent them from getting sick with Covid 19 and can increase sugarcane production. Dessale's study [39] also found that training can increase technical efficiency. The sugarcane training was organized by the Sugarcane Farmers Cooperative (KPTR). Farmers who join organizations such as KPTR make it easy to obtain additional capital (credit) and production facilities (tractors) and exchange information to overcome production constraints.

These logical reasons indicate that the organization can increase technical efficiency. Similar results were found in the Olagunju study [40]. Transportation restrictions during the Covid 19 pandemic caused a scarcity of inputs [4]. Farmers use sugarcane ratoons to overcome input scarcity, reduce production costs, and increase productivity. These logical reasons indicate that sugar cane ratoons can increase technical efficiency. Similar results were found in Ullah's study [41]. Transportation restrictions during the COVID-19 pandemic also caused input prices to increase. Based on information from the field, the average increase in input prices is 22.80%. Rising prices and scarcity of inputs have become a momentum for farmers to utilize natural resources as organic inputs. Organic inputs benefit cost savings, increased productivity and technical efficiency.

4 Conclusion

Our study found that the value of technical efficiency with the double bootstrap approach is lower than that of conventional DEA technical efficiency. Lower values indicate that sugarcane farmers can save more inputs. Based on the double bootstrap approach, sugarcane farmers are expected to reduce input use by 16.6% and 14.6% based on the CRS and VRS assumptions. The potential for higher input savings demonstrated by the double bootstrap approach emphasizes the importance of implementing more efficient and sustainable agricultural practices for sugarcane farmers in Malang District, with the aim of achieving better resource management and economic sustainability within the agricultural sector.

Based on the truncated regression double bootstrap, we found that the age of the head of the household decreases technical efficiency. Old farmers are very worried about getting sick with Covid 19, so they stay home more than they go outside, including to their sugar cane fields—lack of maintenance of sugarcane leads to low sugarcane production and decreased technical efficiency. As a result of their concerns related to COVID-19, reduced activity and lack of maintenance in their sugarcane fields not only led to low sugarcane production but also contributed to a decrease in overall technical efficiency among older farmers. Variables of training, organization, ratoon of sugar cane, and increase in input prices have the potential to increase technical efficiency. Farmers joining organizations such as KPTR can quickly obtain information about production facilities and training. Farmers who attend training can obtain information on how to deal with scarcity and rising input prices. Using sugarcane ratoons and organic inputs for cost savings, increased productivity, and increased technical efficiency. The Covid 19 pandemic has become a momentum for policymakers to create training programs that aim to utilize natural resources to overcome scarcity and rising input prices and realize agricultural sustainability.

The authors would like to thank the financial support and technical assistance from Universitas Pembangunan Nasional Yogyakarta.

References

[1] United Nations, "The Sustainable Development Goals Report 2022," New York, 2022. Accessed: Mar. 26, 2023. [Online]. Available: https://unstats.un.org/sdgs/report/2022/The-Sustainable-Development-Goals-Report-2022.pdf.

[2] A. C. Ribeiro-Duthie, F. Gale, and H. Murphy-Gregory, "Fair trade and staple foods: A systematic review," J Clean Prod, vol. 279, p. 123586, Jan. 2021, doi: 10.1016/J.JCLEPRO.2020.123586.

[3] H. D. Nguyen, T. Ngo, T. D. Q. Le, H. Ho, and H. T. H. Nguyen, "The Role of Knowledge in Sustainable Agriculture: Evidence from Rice Farms' Technical

Efficiency in Hanoi, Vietnam," Sustainability 2019, Vol. 11, Page 2472, vol. 11, no. 9, p. 2472, Apr. 2019, doi: 10.3390/SU11092472.
[4] USDA, "Indonesia: Sugar Annual," Apr. 2022. Accessed: Oct. 08, 2022. [Online]. Available: https://fas.usda.gov/data/indonesia-sugar-annual-5.
[5] Directorate General of Estate Crops, "Statistical of National Leading Estate Crops Commodity 2019-2021," Jakarta, Indonesia, Dec. 2020. Accessed: Aug. 11, 2022. [Online]. Available: https://drive.google.com/file/d/1ZpXeZogAQYfClNBOgVLhYi8X_vujJdHx/view.
[6] A. Toharisman and Triantarti, "An Overview of Sugar Sector in Indonesia," Sugar Tech 2016 18:6, vol. 18, no. 6, pp. 636–641, Nov. 2016, doi: 10.1007/S12355-016-0490-6.
[7] H. T. Huy and T. T. Nguyen, "Cropland rental market and farm technical efficiency in rural Vietnam," Land use policy, vol. 81, pp. 408–423, Feb. 2019, doi: 10.1016/J.LANDUSEPOL.2018.11.007.
[8] T. J. Coelli, D. S. Prasada Rao, C. J. O'Donnell, and G. E. Battese, "An introduction to efficiency and productivity analysis," An Introduction to Efficiency and Productivity Analysis, pp. 1–349, 2005, doi: 10.1007/B136381/COVER.
[9] H. Alem, G. Lien, and J. B. Hardaker, "Economic performance and efficiency determinants of crop-producing farms in Norway," International Journal of Productivity and Performance Management, vol. 67, no. 9, pp. 1418–1434, Nov. 2018, doi: 10.1108/IJPPM-01-2018-0026/FULL/PDF.
[10] Z. Rozaki, "Food security challenges and opportunities in Indonesia post COVID-19," Advances in Food Security and Sustainability, vol. 6, pp. 119–168, Jan. 2021, doi: 10.1016/BS.AF2S.2021.07.002.
[11] R. Wardianingsih and Dahiri, "Upaya Mewujudkan Swasembada Gula Nasional," Buletin APBN, Jakarta, Indonesia, pp. 3–6, Oct. 20, 2021. Accessed: Oct. 23, 2022. [Online]. Available: https://berkas.dpr.go.id/puskajianggaran/buletin-apbn/public-file/buletin-apbn-public-136.pdf.
[12] S. Solomon, G. P. Rao, and M. Swapna, "Impact of COVID-19 on Indian Sugar Industry," Sugar Tech , vol. 22, no. 4, pp. 547–551, May 2020, doi: 10.1007/S12355-020-00846-7.
[13] H. K. Sachan and D. Krishna, "Fiji Sugarcane Industry Amidst COVID-19 Pandemic," Sugar Tech, vol. 23, no. 3, pp. 473–475, Jun. 2021, doi: 10.1007/S12355-020-00929-5/METRICS.
[14] K. P. Mnisi and A. L. Alhassan, "Financial structure and cooperative efficiency: A pecking-order evidence from sugarcane farmers in Eswatini," Annals of Public and Cooperative Economics, vol. 92, no. 2, pp. 261–281, Jun. 2021, doi: 10.1111/APCE.12295.
[15] M. Wollni and B. Brümmer, "Productive efficiency of specialty and conventional coffee farmers in Costa Rica: Accounting for technological heterogeneity and self-selection," Food Policy, vol. 37, no. 1, pp. 67–76, Feb. 2012, doi: 10.1016/J.FOODPOL.2011.11.004.
[16] L. K. Long, "Cost efficiency analysis in aquaculture: Data envelopment analysis with a two-stage bootstrapping technique," https://doi.org/10.1080/13657305.2021.1896605, vol. 26, no. 1, pp. 77–97, 2021, doi: 10.1080/13657305.2021.1896605.
[17] L. K. Long, L. Van Thap, N. T. Hoai, and T. T. T. Pham, "Data envelopment analysis for analyzing technical efficiency in aquaculture: The bootstrap methods," https://doi.org/10.1080/13657305.2019.1710876, vol. 24, no. 4, pp. 422–446, 2020, doi: 10.1080/13657305.2019.1710876.
[18] Fahriyah, Hanani Nuhfil, Koestiono Djoko, and Syafrial, "Technical Efficiency AND Scale Efficiency of Sugarcane Production," Russ J Agric Socioecon Sci, vol. 77, no. 5,

pp. 304–308, May 2018, Accessed: Aug. 12, 2022. [Online]. Available: https://rjoas.com/issue-2018-05/article_36.pdf.
[19] M. T. Yusuf, J. Jamhari, and I. Irham, "Technical Efficiency of State-Owned Sugarcane Production in East Java," Agro Ekonomi, vol. 31, no. 1, pp. 1–15, Sep. 2020, doi: 10.22146/AE.50004.
[20] W. Setyaningrum, T. Ekowati, and B. Kristanto, "The efficiency of sugarcane (Saccharum officinarum) farms using the dea (data envelopment analysis) approach in Purworejo Regency," Agrisocionomics: Jurnal Sosial Ekonomi Pertanian, vol. 4, pp. 330–335, Mar. 2020, doi: 10.14710/agrisocionomics.v4i2.5833.
[21] Nanda Anggiadita and Sujarwo Sujarwo, "Technical Efficiency Analysiss of Sugarcane Production in Sutojayan Village, Pakisaji Sub-Distric, Malang, East-Java, Indonesia," Agricultural Socio-Economics Journal, vol. 16, no. 2, pp. 45–51, 2016, doi: 10.18551/rjoas.2018-05.36.
[22] A. Suwandari et al., "The Impacts of Certified Seed Plant Adoption on the Productivity and Efficiency of Smallholder Sugarcane Farmers in Indonesia," Sugar Tech 2020 22:4, vol. 22, no. 4, pp. 574–582, Apr. 2020, doi: 10.1007/S12355-020-00821-2.
[23] P. K. Nkegbe, "Credit access and technical efficiency of smallholder farmers in Northern Ghana: Double bootstrap DEA approach," Agricultural Finance Review, vol. 78, no. 5, pp. 626–639, Sep. 2018, doi: 10.1108/AFR-03-2018-0018/FULL/XML.
[24] L. Simar and P. W. Wilson, "Statistical Inference in Nonparametric Frontier Models: The State of the Art," Journal of Productivity Analysis 2000 13:1, vol. 13, no. 1, pp. 49–78, 2000, doi: 10.1023/A:1007864806704.
[25] L. Simar and P. W. Wilson, "Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models," http://dx.doi.org/10.1287/mnsc.44.1.49, vol. 44, no. 1, pp. 49–61, Jan. 1998, doi: 10.1287/MNSC.44.1.49.
[26] L. Simar and P. W. Wilson, "Estimation and inference in two-stage, semi-parametric models of production processes," J Econom, vol. 136, no. 1, pp. 31–64, Jan. 2007, doi: 10.1016/J.JECONOM.2005.07.009.
[27] T. T. T. Nguyen et al., "Efficiency Analysis of the Progress of Orange Farms in Tuyen Quang Province, Vietnam towards Sustainable Development," Sustainability 2020, Vol. 12, Page 3170, vol. 12, no. 8, p. 3170, Apr. 2020, doi: 10.3390/SU12083170.
[28] A. Ton Nu Hai, T. Bui Dung, and S. Speelman, "Analyzing the variations in cost-efficiency of marine cage lobster aquaculture in Vietnam: A two-stage bootstrap DEA approach," https://doi.org/10.1080/13657305.2018.1429032, vol. 22, no. 4, pp. 458–473, Oct. 2018, doi: 10.1080/13657305.2018.1429032.
[29] T. Coelli, "A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program," 96/08, 1996. Accessed: Aug. 14, 2022. [Online]. Available: http://www.une.edu.au/econometrics/cepa.htm.
[30] G. Danso-Abbeam, L. J. S. Baiyegunhi, and T. O. Ojo, "Gender differentials in technical efficiency of Ghanaian cocoa farms," Heliyon, vol. 6, no. 5, p. e04012, May 2020, doi: 10.1016/J.HELIYON.2020.E04012.
[31] T. Işgın, R. Özel, A. Bilgiç, W. J. Florkowski, and M. R. Sevinç, "DEA Performance Measurements in Cotton Production of Harran Plain, Turkey: A Single and Double Bootstrap Truncated Regression Approaches," Agriculture 2020, Vol. 10, Page 108, vol. 10, no. 4, p. 108, Apr. 2020, doi: 10.3390/AGRICULTURE10040108.
[32] Effendy et al., "Factors influencing the efficiency of cocoa farms: A study to increase income in rural Indonesia," PLoS One, vol. 14, no. 4, p. e0214569, Apr. 2019, doi: 10.1371/JOURNAL.PONE.0214569.
[33] J. Haji, "Production Efficiency of Smallholders' Vegetable-dominated Mixed Farming System in Eastern Ethiopia: A Non-Parametric Approach," J Afr Econ, vol. 16, no. 1, pp. 1–27, Jan. 2007, doi: 10.1093/JAE/EJL044.

[34] T. Ngo, H. V. Vu, H. Ho, T. T. T. Dao, and H. T. H. Nguyen, "Performance of Fish Farms in Vietnam–Does Financial Access Help Improve Their Cost Efficiency?," International Journal of Financial Studies 2019, Vol. 7, Page 45, vol. 7, no. 3, p. 45, Aug. 2019, doi: 10.3390/IJFS7030045.
[35] O. Badunenko and H. Tauchmann, "Simar and Wilson two-stage efficiency analysis for Stata:," https://doi.org/10.1177/1536867X19893640, vol. 19, no. 4, pp. 950–988, Dec. 2019, doi: 10.1177/1536867X19893640.
[36] K. Ogundari, "Crop diversification and technical efficiency in food crop production: A study of peasant farmers in Nigeria," Int J Soc Econ, vol. 40, no. 3, pp. 267–287, 2013, doi: 10.1108/03068291311291536/FULL/XML.
[37] H. ; Zhang, U. ; Nisar, Y. Mu, H. Zhang, U. Nisar, and Y. Mu, "Evaluation of Technical Efficiency in Exotic Carp Polyculture in Northern India: Conventional DEA vs. Bootstrapping Methods," Fishes 2022, Vol. 7, Page 168, vol. 7, no. 4, p. 168, Jul. 2022, doi: 10.3390/FISHES7040168.
[38] W. Alwarritzi, T. Nanseki, and Y. Chomei, "Analysis of the Factors Influencing the Technical Efficiency among Oil Palm Smallholder Farmers in Indonesia," Procedia Environ Sci, vol. 28, pp. 630–638, Jan. 2015, doi: 10.1016/J.PROENV.2015.07.074.
[39] M. Dessale, "Analysis of technical efficiency of small holder wheat-growing farmers of Jamma district, Ethiopia," Agric Food Secur, vol. 8, no. 1, pp. 1–8, Jan. 2019, doi: 10.1186/S40066-018-0250-9/TABLES/2.
[40] K. O. Olagunju, A. I. Ogunniyi, Z. Oyetunde-Usman, A. O. Omotayo, and B. A. Awotide, "Does agricultural cooperative membership impact technical efficiency of maize production in Nigeria: An analysis correcting for biases from observed and unobserved attributes," PLoS One, vol. 16, no. 1, Jan. 2021, doi: 10.1371/JOURNAL.PONE.0245426.
[41] A. Ullah, S. R. Perret SR, S. H. Gheewala, and P. Soni, "Eco-efficiency of cotton-cropping systems in Pakistan: an integrated approach of life cycle assessment and data envelopment analysis," J Clean Prod, vol. 134, no. Part B, pp. 623–632, Oct. 2016, doi: 10.1016/J.JCLEPRO.2015.10.112.