J. ISSAAS Vol. 29, No. 2: 1-12 (2023)

TECHNICAL EFFICIENCY, HOUSEHOLD INCOME, AND DEFORESTATION MITIGATION AMONG OIL PALM SMALLHOLDER IN SOUTH TAPANULI, INDONESIA

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(Received: December 23, 2022; Accepted: June 10, 2023)

ABSTRACT

Oil palm smallholders usually have low yield encouraging them to extend land areas. Some studies suggested increasing yields can lead to higher income and prevent smallholders from extending land areas. This paper aims to analyze the correlation between oil palm smallholders' Technical Efficiency (TE), income, household expenditure and deforestation mitigation potential. Research was conducted in July 2021, involving 160 smallholders, selected using the disproportionate stratified random sampling method. South Angkola and Batang Toru in South Tapanuli, Indonesia were selected as the research locations. Data was analyzed using the stochastic frontier analysis. The mean of TE level of smallholders (0.8) implies that the yield level of oil palm only reaches 80% of potential yield. Landholding size, farmers' education, and group involvement influence significantly TE level. At current production level, farmers get an income about IDR 49 million/year. An additional income of IDR 6.3 million/year is needed to cover household expenditure, which is equal to 0.2 ha. With 4,142 oil palm smallholding households in South Tapanuli, the total reduction in land needs will be around 838 ha. At optimal level of production (TE=1), the income could increase to IDR 64.5 million/year. It is higher than the household expenditure, thus no additional land is needed.

Key words: Good Agricultural Practices, household income, independent smallholders, stochastic frontier

INTRODUCTION

Indonesia is the largest palm oil-producing country, with a total plantation area of more than 16.3 million hectares (Kementerian Pertanian RI 2019). The significant increase in the global demand for crude palm oil has driven the large-scale development of plantations. In 2009, the Indonesian Minister of Agriculture planned to double the oil palm plantation area from 9.7 million ha to 18 million ha by utilizing 53% of the degraded areas and 47% of the most suitable land for oil palm, least suitable for food cultivation, and containing the lowest carbon stock (Koh and Ghazoul 2010). However, a decade later, in 2020, Purwanto et al. (2020) found that the spread of oil palm plantations to forest areas is around 15-20%, and Kehati (2020) estimated that around 36% of the total independent smallholding plantations area are operated illegally as they are located in forest areas. In other words, the increase in oil palm production was likely still significantly come from the land expansions.

Many argued that land expansion could be avoided by increasing the productivity of oil palm plantations. Intensification programs have been applied nationwide to inhibit deforestation (Tomich et al. 2001; Angelsen 2010; Garrett et al. 2018). The average Indonesian oil palm plantation only realizes around 60-70% of its potential productivity (Siahaan 2017). Among oil palm producers, smallholdings are considered the group with the highest potential improvement, as they show the lowest productivity. On average, oil palm smallholdings in Indonesia still faced land inefficiency (Sari et al. 2021; Dalheimer et al. 2022). In 2020, the average productivity of smallholdings was 2.56 tons CPO/ha/year (equal to 13.49 tons FFB/ha/year), while the state and private companies were 4.09 (equal to 21.51 ton FFB/ha/year) ton CPO/ha/year and 3.50 ton CPO/ha/year, respectively (equal to 18.43 ton FFB/ha/year) (Directorate General of Estates 2021). With low productivity, smallholders need more land to earn more income for covering their household expenses (Sari et al. 2021; Rhebergen et al. 2018).

The oil palm smallholders‘ technical efficiencies lead to low productivity. stochastic frontier analyses (SFA) and Data Envelopment Analyses (DEA) are two models that are widely used in estimating TE. SFA is a parametric model that accommodates the stochastic term, while DEA is a non-parametric one that uses a deterministic model. In SFA, both producers' inefficiencies and random elements are considered in the estimation, while DEA only includes the producers' inefficiencies (Sultana et al. 2023). The decision to choose the SFA or DEA models depends on the choice of input and output variables and the characteristics of the data analyzed. The SFA model is introduced to address the argument that not all the deviation in production should be only associated with pure TE. This is most important in agricultural products, in which some influencing production factors are unpredictable or random (Bai et al. 2007). Using generated data, it was argued that cross-sectional SFA holds no advantages over DEA (Ruggiero 2007). In contrast, using empirical data in both models, SFA fits better with the observed data estimation in potato production (Sultana et al. 2023). When the unpredictability reduces with the greenhouse microclimate, deterministic and stochastic models are feasible for modeling agriculture products (Yang et al. 2019).

Besides the unpredictable error, the inefficiency error from SFA is also influenced by the given existing technology of the sample data. TE results from various studies are affected by farm heterogeneity due to region-specific characteristics, thus, are not always comparable (Wang and Hockman 2012). Previous studies in several smallholders' oil palm centers found low TE, between 0.65 to 0.85 (Hasnah et al. 2004; Fariani et al. 2018; Varina et al. 2021; Ismiasih 2018; Latzko 2020). In contrast, an average TE of 0.95 was revealed in North Mamuju, West Sulawesi, which is not an oil palm center in Indonesia (Puruhito et al. 2019). Therefore, additional information about the technical potential of each location is also important.

Low TE stems from a lack of knowledge, financial support, and economies of scale. Many smallholders still use illegitimate seedlings, improper fertilizers, and only own 2 - 4 ha of land (Woittiez 2017; Folefack et al. 2019; Harsono et al. 2011; Soliman et al. 2016). On average, high-quality seedlings can reach 9 tons of CPO/ha/year compared to the current CPO productivity of only 3 tons of CPO/year (Baskett et al. 2008). In addition, the current fertilizer application methods and doses cause the productivity of smallholders to reach less than 50% of its potential (Woittiez 2017; Soliman et al. 2016). Most smallholdings were still facing increasing returns to scale. Oil palm smallholders with larger land sizes tend to be more efficient than the smaller ones (Dalheimer et al. 2022; Hernández 2020). If smallholders can correct their inconsistencies in agricultural practices, yield improvement can reduce land use of oil palm smallholdings. Field schools (FS) are among the alternatives that have been chosen and are still widely proposed to improve agricultural practices and productivity, including among the oil palm smallholders (van den Berg et al. 2020; Chalil et al. 2020; Pramudya et al. 2022). Previous studies estimated that a 2% yield improvement can reduce land use of oil palm smallholdings by 1 Mha. In total, the CPO supply can increase by 75%, or 15–20 MT/year, and reduce up to 4-6Mha or 17% to 58% of the total smallholding land (Folefack et al. 2019; Woittiez 2017; Van der Laan et al. 2017). Interestingly, intensification and high TE do not always lead to a reduction in new land use. Higher land efficiencies result in low production costs, which gives incentives (substitution effect) and purchasing power (income effect) for producers to obtain more land (Paul et al. 2019). Such conditions can be seen in the U-shape TE, in which both less and more efficient farms use more land for their agricultural activities, increasing deforestation (Marchand 2012).

While issues of oil palm smallholdings in the forest areas stemming from poor agricultural practices and low income still exist, studies that analyze the correlation between the smallholders' land needs and their household expenditure and the potential to increase production through TE improvement are very limited. This study was conducted in South Tapanuli District, North Sumatra, Indonesia. From 2000 to 2018, South Tapanuli recorded 45,000 hectares of deforestation, with the highest factor being plantation activities at 16,181 hectares. If there is no change in management (business as usual), estimations show that smallholders reach less than 50% of their potential, and by 2037, an additional 3,578 hectares of forest area will be converted to plantations (Pravitasari 2020). Findings from this study are expected to contribute to the literature on the TE of smallholders, household expenditure needs, and deforestation. In particular, the purposes of this paper are to (i) estimate the TE level of smallholdings, (ii) estimate factors that cause low levels of TE in smallholdings, and (iii) estimate the potential reduction in land needs with increased smallholding efficiency.

METHODOLOGY

This research was conducted in 2021 in the South Tapanuli District, one of the oil palm centers in north Sumatra, with a total area of 9,536 hectares involving 4,142 households. This district was selected as it had approximately 82% high conservation value and high carbon stock value in its total area. All the smallholding plantations in South Tapanuli were owned and managed by independent oil palm smallholders, developing their plantations with little to no assistance. Improper use of seeds and poor plantation maintenance negatively impact the average productivity of smallholdings in South Tapanuli, averaging only 80% compared to the average of North Sumatra (Chalil and Barus 2021). Two sub-districts, namely Batang Toru and South Angkola, were selected as they were classified as Special Cultivation Areas (Kawasan Budidaya Khusus), and the smallholders had received the GAP improvement FS Program. Batang Toru is located close to the city, with a dominant of S3 land suitability, while South

Angkola is close to the forest, with a mix of S2 and S3 land suitability (IOPRI 2009). Therefore, this study selected these two locations to observe their possible impact on productivity and deforestation.

The FS participants consist of 700 smallholders from four sub-districts. Sample smallholders were selected using a clustered sampling method based on their location and participation in the FS. The total samples involved in this study were 160 smallholders, consisting of 80 samples from each sub-district representing FS participants and non-participants. The sample size was determined by Yamane's formula with a margin of error of 10%, giving 40 samples for each sub-district (Al-Subaihi 2003). For comparison purposes, 40 additional non-participants were randomly selected from each sub-district.

The smallholdings' TE level was analyzed using the stochastic frontier production function. The method of measuring TE of a firm by estimating production function of firms at frontier production function was proposed by Farrel (1957). The stochastic frontier production function was then developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) to capture the measurement error in production function. Battese and Coelli (1995) developed the stochastic frontiers and models for the TE effects that can estimate all the parameters involved simultaneously, particularly for panel data. The stochastic frontier production function was defined as:

$$Yi = f(x_{ik};\ \beta_k)\ \exp\ (V_i - U_i) \tag{1}$$

where: Y_i is the productivity of oil palm in kg/ha/year; F (x; β) is a Cobb-Douglas production function of vector X (nitrogen in kg/ha/year, phosphor in kg/ha/year, potassium in kg/ha/year, harvesting labor in man hour, number of plants per hectare, crop age in year, and participation in the field school as dummy variable, 1 if involved in the field school, otherwise 0); Vector β (unknown parameter); V is random errors that were assumed to be independent and identically distributed (i.i.d.) N $(0, \sigma_v{}^2)$; U is a non-negative random variable associated with the technical inefficiency of production, which was assumed i.i.d. U was obtained by truncation at zero from the normal distribution with mean, zδ, and variance σ_u^2.

The stochastic frontier model for this study uses cross-sectional data from all samples to estimate a single equation; it was assumed to be time-invariant. The parameters of the stochastic frontier and the model for TE effects were estimated simultaneously using the maximum likelihood method. TE has a value between 0 and 1, which was calculated using the following formula:

$$TE_i = \frac{Y_i}{Y_{i*}} = \frac{E(Y_i|U_i, X_i)}{E(Y_t|U_i = 0, X_i)} = E\left[\frac{exp(-U_i)}{s_i}\right] \tag{2}$$

where: Y_i is the actual productivity, and Y_i^* is the potential productivity.

The smallholdings' TE influencing factors were estimated using multiple regression, with TE as the dependent variable and eight variables as the vector of possible influencing factors. Technical inefficiency effects, U, is defined as:

$$U_i = z_i\delta + W_i \tag{3}$$

Z is a vector (1 x m) of free variables, namely Z_1 = land size (ha), Z_2 = education (year), Z_3 = smallholder experience (year), Z_4 = group involvement (1 if involved in smallholder groups, otherwise 0), Z_5 = smallholders' age (year), Z_6 = land status (1 if certified, otherwise 0), and Z_7 = family labor (%); δ is the vector (m x 1) of the unknown coefficients.

The potential reduction in land needs was analyzed by comparing the oil palm smallholding income in the current average TE with household expenditures. The income from oil palm plantations at the current TE was calculated using the average production and price. All prices, income, and costs were presented in IDR, which currency rate is 14,200 IDR/USD. Values from low, normal, and high seasons were multiplied by 0.3, 0.6, and 0.3, respectively. Household expenditures were calculated using routine and non-routine household expenses per year. The difference between income and household expenditures was then converted into the additional land needed based on the oil palm smallholding average income per ha. Then, the steps were repeated by calculating income with TE =1. The required land size was calculated by dividing the household expenditure/year by the oil palm plantation income/year/ha for the current and maximum TE.

RESULTS AND DISCUSSIONS

The TE of smallholdings. This study uses the Cobb Douglas production function. The specification was justified by the Ramsey Reset test result with F-stat 0.00, showing that linearity on the logarithmic data cannot be rejected at 1% significance. Before estimating the SFA with MLE, equation specification and assumptions on normality, homogeneity, autocorrelation, and heteroscedasticity for the production function were tested with OLS.

The residual scatterplot and PP plot showed a negative skewness, and the Kolmogorov-Smirnov test and Jarque-Bera test have 0.073 and 9.98 stat values at 1% significance. Therefore, the normality assumption is rejected. However, skewness residuals often appear in SFA, which have one-sided errors coming from inefficiencies. Commonly, production inefficiency errors have positive skewness, while costs have positive skewness. This condition means that the existing productivity is lower than the optimal frontier while the cost is higher. In this case, the negative skewness, -0.21, might partly be explained by the high difference in productivity between samples, stemming from the different land suitability and fertilizer usage. Some smallholders in South Angkola, which have S2 land suitability and use fertilizers very close to the recommended level, have very high productivity compared to those in Batang Toru with S3 and suitability and low-level fertilizer usage. Using the half distribution is argued to correct the inconsistent parameters due to the unnormal error distribution in OLS. This one-sided distribution includes half-normal, truncated, exponential, and gamma distributions (Carree 2002; Hafner 2016). In this case, the half-normal distribution was chosen for the production frontier estimation.

The Glejser and Breusch-Pagan-Godfrey homogeneity tests showed that all independent variables for the production function have coefficient regressions t-stat less than one, showing that they did not significantly relate to the residuals. However, the crop age has a t-stat of -2.27 and -2.29, thus rejecting the homogeneity assumption. Empirically, this can be explained by the oil palm crop productivity pattern that usually increases at age 3 to 10, then stays at the maximum for about ten years until 20, and starts declining until the end of its economic age of 25. The Durbin-Watson test gives a t-stat value of 1.68, with dL and dU values of 1.64 and 1.83, respectively. This result brings inconclusive results for autocorrelation. Empirically, there is autocorrelation of crop yield data due to spatial dependence of in-site specific crop management (Koutsos 2021).

The MLE production frontier estimation results showed that two of seven explanatory variables significantly influenced productivity, including the number of harvesting labor and the involvement of smallholders in the field school (Table 1).

Table 1. MLE results on the land productivity regression estimation.

Variable	Coefficient	t-statistic
Nitrogen (kg/ha/year)	-0.01	-0.79
Phosphorus (kg/ha/year)	0.00	0.27
Potassium (kg/ha/year)	0.00	-0.54
Harvesting labor (%)	0.09	2.49***
Number of plants/ha	0.02	0.20
Crop age (year)	0.04	0.94
FS Participant (dummy)	0.10	2.35***
Constant	2.69	5.01

Note: ** and *** = significant at 5% and 1%
Source: Primary data analysis

The empirical model of the stochastic production function is as follows:

$$y_i = 2.69x_1^{-0.01}x_2^{0.00}x_3^{0.00}x_4^{0.09}x_5^{0.02}x_6^{0.04}x_7^{0.10} \quad (4)$$

The involvement of smallholders in field school proved to be an essential factor in improving the skill and knowledge of smallholders to manage their farms, leading to an increase in oil palm production. Unfortunately, smallholders with larger land sizes are often reluctant to participate in the FS.

In contrast to several empirical findings in this case, fertilizer usage, plantation density, and crop age did not significantly affect oil palm productivity (Alwarritzi et al. 2015; Nordin et al. 2017; Ismiasih 2018). The gap between the current and the recommended fertilizer usage may partly be explained by the insignificant fertilizer coefficients. The potassium fertilizer, crucial for generative growth, had a gap of 33.50% and 66.61% below the recommended amount in South Angkola and Batang Toru, respectively. The fertilizer gap could also be negative, as shown in the average phosphate usage of participants in South Angkola. Overall, FS participants (FS P) show less fertilizer gap than the non-participants (NP) (Table 2).

Table 2. Average fertilizer usage and the gap to the recommendation.

Fertilizer	South Angkola				Batang Toru			
	Mean (kg/ha/year)		Gap (%)		Mean (kg/ha/year)		Gap (%)	
	FS P	NP	FS P	NP	FS P	NP	FS P	NP
Nitrogen	133.56	121.60	9.76	17.84	82.29	108.33	44.40	26.81
Phosphate	98.46	70.66	-9.29	21.57	69.58	65.55	22.77	27.24
Potassium	134.23	99.86	10.60	33.50	72.64	50.13	51.62	66.61

Source: Primary data analysis
Note: Recommended fertilizers refer to IOPRI (2022) for each type of macro fertilizer at the crop age range of 9-15 years

In some cases, the number of trees has the highest effect on production (Abdul et al. 2022). In this case, there was not much variation in the number of plants and age among smallholders. The number of plants in South Angkola is 116 and 122 per hectare, and in Batang Toru is 129 and 120 per hectare for participants and non-participants, respectively. Depending on the plant variety, the optimum plant density is around 130 to 143 (IOPRI 2022). Besides the quantity, the quality of seedlings should also be considered. Most smallholders do not use certified seedlings. In South Angkola, non-participants did not use certified seedlings, while only 7.5% of the participants used them. In Batang Toru, 37.50% of participants utilized certified seedings, while 15% of the non-participants do. The numbers show another opportunity to increase the smallholders' productivity by up to 300% by replacing illegitimate seedlings (Basket et al. 2008). The change can only be made during the replanting period. Therefore, a well-planned replanting program is crucial.

The estimation results need to be interpreted with caution as the R^2 productivity function is only 0.090, showing that most of the variation in the function is not explained by the independent variables. Such a condition was then further tested using a simple OLS regression estimation, which shows that more than 95% of the production level is explained by land size. The function also shows heterogeneity issues. These issues might be related to the high variation in fertilizer usage at the same age. Many of the samples have limited knowledge of the recommended fertilizer usage. In addition, the insignificant fertilizer usage has a negative phosphate gap, indicating their random usage. This gap shows the possibility to increase productivity by improving good agricultural practices. A similar low R^2 issue appears in several agricultural production and stochastic frontier functions studies. They are considered empirical rather than econometric issues. Therefore, the estimation results are still used to explain related causes (Abdulai 2018; Butzer 2011; Tauer 2006; Vollenweider 2016; Wu 2011). The TE estimation also showed that the coefficient of land size is significant at 1%. As this paper focuses on TE, productivity estimation is still used with empirical situations as the explanation.

Under such conditions, all smallholder samples achieved a TE value of more than 40%. Using the SFA, oil palm smallholdings that follow the recommended oil palm cultivation have a higher TE than those that do not (Ariyanto et al. 2020). Previous studies show that FS can improve farmers' technical efficiencies by promoting pro-adaptive behavior (Oguntade 2012; Saddozai et al. 2013; Purwasih et al. 2020; Zubair et al. 2021; Tomlinson and Rhiney 2018). However, the results do not strongly conclude the impact of FS on TE. In South Angkola, almost 95% of the non-participant samples have TE $\geq$ 0.80, and none have less than 0.60. The increase in knowledge through FS does not necessarily have a linear relationship with the increase in technology adoption (Huluka 2015). The knowledge can be translated into adoption only if enabling factors and conditions exist. In Batang Toru, FS participants have a slightly higher percentage of TE > 0.80 than non-participants (Table 3).

Table 3. Technical efficiency distribution frequency (percentage of the sample).

Technical efficiency level	South Angkola		Batang Toru	
Index	FS P	NP	FS P	NP
$0.40 \leq TE < 0.60$	2.56	0.00	2.70	5.00
$0.60 \leq TE < 0.80$	71.79	5.26	24.32	35.00
$TE \geq 0.80$	25.64	94.74	72.97	60.00

Source: Primary data analysis

This result contradicts the MLE estimation results of the land productivity function (Table 1), which shows that FS significantly influenced productivity. Therefore, the productivity of FS participants was tested before and after training. The productivity in South Angkola and Batang Toru increased by 30.07% and 36.70%, respectively. This improvement stemmed from the increase in their nitrogen, phosphate, and potassium usage by 58.11%, 67.50%, and 174.77% in South Angkola and 38.81%, 49.00%, and 52.68% in Batang Toru. However, data on FS participants before training were not used in TE estimation as they violate the requirement for independent decision-making units in SFA. Time-varying technical inefficiencies exist, and panel data are needed to capture technical changes (Battese and Coelli 1995; Dhawan and Gerdes 1997). Therefore, further work with panel data is required to obtain a robust conclusion.

The TE influencing factors. Estimation results revealed that land size, level of education, and group involvement significantly influenced the TE of the samples (Table 4).

Table 4. Factors affecting technical inefficiency.

Variable	Coefficient	t-statistic
Land size (ha)	-0.09	-3.31***
Education (year)	-0.02	-2.03**
Experience (year)	0.00	-0.48
Group involvement (dummy)	0.25	2.72***
Smallholder age (year)	0.00	-1.56
Land status (dummy)	-0.11	-0.99
Family labor (%)	0.07	0.81
Constant	0.63	2.51

Note: ** and *** = significant at 5% and 1%
Source: Primary data analysis

The inefficiency effects equation is as follows:

$$IE = 0.63 - 0.09z_1 - 0.02z_2 + 0.00z_3 + 0.25z_4 + 0.00z_5 - 0.11z_6 + 0.07z_7 \quad (5)$$

The negative coefficient of the land area and level of education means that a larger land size and a higher level of education led to less technical inefficiency. This result is in line with previous studies that found oil palm smallholders with larger land sizes tend to be more efficient than the smaller ones. The size and technical efficiency are partially explained by technological factors, such machines, fertilizers, pest control, irrigation systems, and technical assistance (Dalheimer et al. 2022; Hernández 2020). The positive coefficient of group involvement showed that group members had higher inefficiency than those who did not join smallholder groups. This result contrasts with many empirical studies suggesting the contribution of farmer group participation in increasing agricultural productivity and efficiency (Baga et al. 2023; Abdul-Rahaman et al. 2018; Agarwal 2018). In this case, many non-participants did not join any smallholder group. They showed less interest in joining groups or participating in the FS, as they have not seen significant benefits. Smallholders would actively participate in a smallholder group only if higher benefits were perceived (Ibnu et al. 2018). Family workers provide a positive impact due to better motivation and low management costs but a negative impact with their limited technical and managerial capabilities (Kostov et al. 2018). In this study, however, family workers do not significantly impact the TE.

TE and land size additional need. Given the TE, this study estimated the smallholders' additional land needs based on land productivity, household income, and expenditure. The average non-participant productivity in South Angkola is higher than FS participants and vice versa for Batang Toru. However, all groups did not reach their potential productivity level (Table 5).

Table 6 shows the difference in the average production and income of each group. The average income of smallholders is around IDR 34.10 million to IDR 80.50 million/HH/year. Except for non-participants in South Angkola, all groups have larger HH expenditures than their income. They needed an additional IDR 13 million to IDR 25 million/year/HH. To fulfill their needs, the smallholders need an additional IDR13.08 million to IDR21.17 million/HH/year. This is equal to an additional 0.56 to 1.11 ha of land per HH, or an average 0.20 ha/ HH.

Table 5. The gap between current and potential productivity.

Description	South Angkola		Batang Toru	
	FS Participant	Non-Participant	FS Participant	Non-Participant
Productivity (FFB tonnes/ha)	20.42	23.43	22.38	18.92
Crop age (year)	12.98	15.59	10.38	9.60
Potential productivity (FFB tonnes/ha)*	30.00	27.75	28.50	27.50
Difference in current and potential productivity (%)	32	15	21	31

* IOPRI, 2009
Source: Primary data analysis

Table 6. Current production, income and additional land need (TE = 0.8).

Description	South Angkola		Batang Toru	
	FS Participant	Non-Participant	FS Participant	Non-Participant
FFB production (ton/year/HH)	43.76	127.25	39.62	33.21
Selling price (IDR/kg)	1,287.06	1,156.16	1,457.87	1,483.44
Revenue (IDR/year/HH)	56,320,246.17	147,122,583.73	57,756,313.38	49,267,184.53
Costs of production (IDR/year/HH)	17,091,145.31	66,637,344.34	15,574,697.69	15,172,270.31
Income per HH (IDR/year)	39,229,100.86	80,485,239.39	42,181,615.69	34,094,914.22
Difference between FFB income and HH expenditure (IDR/year)	-16,036,327.71	25,219,810.82	-13,083,812.88	-21,170,514.35
Income per ha (IDR/year)	18,112,031.25	14,422,300.79	23,523,635.31	19,019,670.63
Additional land needed (ha/HH)	0.89	-1.75	0.56	1.11
Average additional land need (ha/HH)				0.2025

Source: Primary data analysis

If smallholders can overcome their constraints and reach the maximum TE (TE=1), they could significantly increase the HH income (Table 7). The income could reach IDR43.948 million/year/HH to IDR109.909 million/year/HH, thus their additional income needs reduce to IDR 1,533 million/year/HH to IDR -11,317 million/year/HH. On average their income is higher than their household expenditure, therefore they no longer need additional land. The increase in TE can reduce the potential expansion of smallholdings by around 0.20 hectares/household. With 4,142 smallholder households in South Tapanuli, the total reduction of deforestation risk in South Tapanuli is approximately 828 hectares.

The use of certified seeds can be another potency to increase productivity. The data showed that the use of certified seeds was still very low. In South Angkola, none of the non-participant samples use certified seeds, and only 7.5% of participants use certified seeds. Batang Toru showed better conditions, with 15% and 37.5% of the non-participants and participants using the certified seeds, respectively. Therefore, replanting should be prioritized to improve this condition. Certified seeds can increase productivity by 31.5% (Ardana et al. 2022). In this regard, Indonesia implemented the Communities' Oil Palm Replanting (Peremajaan Sawit Rakyat) program since 2018 to support smallholders in using certified planting material.

Table 7. Potential production, income, and additional land need (TE = 1).

Description	Angkola Selatan		Batang Toru	
	FS Participants	**Non-Participants**	**FS Participants**	**Non-Participants**
FFB production (ton/year/HH)	52.51	152.70	47.54	39.85
revenue (IDR/year/HH)	67,584,295.41	176,547,100.48	69,307,576.05	59,120,621.44
Income per HH (IDR/year)	50,493,150.09	109,909,756.14	53,732,878.36	43,948,351.13
Difference between FFB income and HH expenditure (IDR/year)	-4,772,278.48	54,644,327.57	-1,532,550.21	-11,317,077.45
Income per ha (IDR/year)	23,371,912.50	20,083,323.96	30,017,272.38	24,621,799.75
Additional land needed (ha/HH)	0.20	-2.72	0.05	0.46
Average additional land need (ha/HH)				0

Source: Primary data analysis

CONCLUSION

Smallholders' productivity is significantly influenced by harvesting labor and FS participation. The improvement in their input usage and TE leads to higher productivity and income. However, almost all smallholder respondents have not reached the optimal TE. Land size, education, and involvement in smallholder groups influenced significantly the TE of smallholders. The income of these smallholders is smaller than their household expenditures. Therefore, they need additional land to increase their income. If all the smallholders' agricultural practices can be corrected and reach maximum TE, they can earn more income than their household expenditures and no longer need additional land. This study demonstrated that FS has a positive impact in improving TE and could mitigate deforestation. However, the result is not strong enough to show the difference between the participants and non-participants. On the other hand, the data show a strong impact of FS participants' fertilizer usage and productivity before and after trainings. Further work with panel data is required to explain the indication of technical change among the FS participants.

ACKNOWLEDGMENTS

The authors would like to express their deepest gratitude to extension workers, Conservation International staff members, and South Tapanuli Bappeda staff members who helped collect the required data amidst the pandemic. This work was supported by Penelitian Terapan 2021 from the Ministry of Education, Culture, Research and Technology, Republic of Indonesia 189/UN5.2.3.1/PPM/KP-DRPM/2021.

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