sustainability

MDPI

Article

The Effect of Good Agricultural Practices on the Technical Efficiency of Chili Production in Thailand

Wirat Krasachat

KMITL Business School, King Mongkut's Institute of Technology Ladkrabang, Bangkok 10520, Thailand; wirat.kr@kmitl.ac.th; Tel.: +66-8910-809-61

Abstract: While recognition of the positive influence of good agricultural practices (GAP) on reducing negative externalities due to conventional farming and providing more export opportunities is growing, there is some doubt about the effects of GAP on the economic performance of chili farms. In this regard, this study's principal objectives are to assess the impact of GAP and to examine farm-specific and environmental factors regarding the technical efficiency (TE) of chili farms in Thailand. This study employed a stochastic meta-frontier input distance function to measure and explore the effects of farm-specific and environmental factors on TE using 2018 farm-level survey data from Thai chili farms. The sample of 100 farms includes GAP and non-GAP farms. The empirical results highlight three critical findings. First, there is confirmation that GAP positively influence the TE of chili farms. Second, family labor intensity and small farm size also positively impact the TE of farms. At the same time, completion of a technical training course positively affects the TE of non-GAP farms only. Finally, education, experience, training courses, and crop diversification negatively affect the TE of GAP farms only. Thus, policymakers need to focus on GAP adoption and farm-specific factors to promote the sustainable development of Thai chili farms.

Keywords: chili farm; good agricultural practices; stochastic meta-frontier input distance function; technical efficiency; sustainability; emerging markets

Citation: Krasachat, W. The Effect of Good Agricultural Practices on the Technical Efficiency of Chili Production in Thailand. *Sustainability* **2023**, *15*, 866. https://doi.org/10.3390/su15010866

Academic Editors: Donato Morea and Antonio Boggia

Received: 20 July 2022
Revised: 27 November 2022
Accepted: 28 December 2022
Published: 3 January 2023

1. Introduction

The international fruit and vegetable markets were among the agro-food sector's first markets to truly embrace globalization [1]. The demand for fresh horticultural products (including fruits and vegetables) is continually rising in both domestic and international markets [2]. However, globalization has resulted in opportunities and pressures for domestic firms in emerging markets to innovate and increase their competitiveness. Domestic firms may put more effort into upgrading their technology, improving their product or service quality, or acquiring certification [3]. However, food safety problems and consumers' rising health consciousness have increased the demand for safe horticultural products [4]. Consumers are also becoming increasingly aware of environmental concerns and are interested in how farms produce food and farming practices [2].

Good agricultural practices (GAP) are quality standards for food safety of on-farm and post-farm activities, including management regulations on producing environmentally friendly and socially acceptable products [5]. GAP are the most crucial standards in global horticulture, and GlobalGAP standards have been a particular focus in the private sector [2]. Following Aldieri et al. [6], GAP also represent an environmental invention. Farmers who apply GAP guidelines by substituting chemical fertilizers for plant materials, animal manures, and food processing wastes produce better soil health and nutrients and less pollution and promote better well-being for themselves and the people nearby. If many farmers were to adopt GAP, essential natural resources could be conserved and maintained. Encouraging GAP adoption could also assist farmers in enhancing their production efficiency, creating a trade-off for farmers, buyers, and the country [7]. In addition, GAP may enrich farmed commodities for the export of the country [8]. Existing studies [2,9–12] indicate that GAP-certified farmers receive significantly more chances to trade more significant amounts, higher prices, and more income for their agricultural goods because of the confidence of exporters and the improvement of product quality and quantity.

The Ministry of Agriculture and Cooperatives of Thailand initiated the national GAP program, and this has been implemented as an effective tool to ensure the food safety of major agricultural products since 2003. Through this, farmers are encouraged to increase sustainable cultivation and competitiveness in global trade [13]. The GAP program focuses on food safety and standardized production systems of fruits and vegetables. It is equivalent to the GlobalGAP standards [14].

Chili is a costly crop and the main income basis for Thai smallholder farmers [15]. It is also a labor-intensive crop, and family labor is engaged in its enterprise activities, such as production, harvesting, and marketing preparation [16]. In 2019, 26,791 hectares of chili were cultivated [17]. However, in the past, pesticides have been overused in chili farms in both the before- and after-harvest periods to contain pests, save crops from disease, and satisfy high production levels [15,18–20]. Laosutsan et al. [14] reported that, in 2011, European countries barred Thai chilis because of pesticide contamination. In addition, the pesticide concentrations and practices harm farmers' health [21–23]. Possible dangers to human health related to pesticides comprise cancer, chronic neurodevelopmental impairment, reproductive dysfunction, acute neurologic poisoning, and possibly dysfunction of the immune and endocrine systems [22]. A high concentration of chemicals in blood samples of farmers and consumers has been reported repeatedly in Thai local media [24]. In addition, pesticides can damage the environment by contaminating water, turf, soil, and other vegetation. They can poison other organisms such as fish, birds, non-target plants, and useful insects [25].

For food safety, environmental conservation, sustainable cultivation, and competitiveness in international trade, GAP use for fruit and vegetable production systems (including chili) has been promoted in Thailand, as mentioned above. However, whether prime producers gain productive efficiency from applying GAP remains questionable. This is because improvements in the efficiency and productivity of chili farms are crucial for boosting the farm income of rural and urban residents involved in chili production [26]. In addition, López-Penabad et al. [27] stated that efficiency is one of the measures used to analyze whether achieving sustainable chili cultivation in Thailand is possible. However, knowledge about the impacts of GAP on firms' technical efficiency (TE) is relatively limited. A few studies have directly assessed the effects of GAP adoption on farms' TE (e.g., [7,28–33]). However, the results have been inconclusive, particularly regarding Thai chili farms.

This study has two main objectives. The first is to assess the impacts of GAP adoption on the TE of chili farms in Thailand, while the second is to examine farm-specific and environmental factors regarding the TE levels of chili production in different farms. We focused on chili because it is not only one of the most important crops to Thailand's economy, especially in rural areas, as mentioned above, but also one of Thailand's ethnic products and is used extensively in Thai cooking. A hundred chili GAP farms and non-GAP farms for the 2018 crop year were employed. Depending on their geographic location, these farms grow chili in the rainy or dry seasons. Conventional non-GAP farms use traditional farming methods and substantially apply pesticides and chemical fertilizers; thus, their chili produce is tainted with chemical remains.

In contrast, GAP-adopting farms apply GAP guidance to warrant the suitable quality, cleanliness, and safety of their products [14,34,35]. They are generally small but use modern agricultural methods. We scrutinized rainy-season and dry-season chili farms together to examine the impacts of GAP adoption and farm-specific factors on chili farms' TE.

This study provides at least three significant contributions to the related body of literature. First, previous studies have investigated TE in chili production at the farm level in Thailand (e.g., [7,30,31]). However, to the author's best knowledge, no study has applied the stochastic meta-frontier input distance function to quantify and describe TE in Thai farms. Second, in addition to investigating the main effects of GAP adoption on TE, we also analyzed the impacts of farm-specific characteristics such as farmers' ages, cultivation experience, and crop diversification on the efficiency of GAP and non-GAP farms. Villano et al. [36] revealed that when farms' characteristics (both observable and unobservable factors) are not considered, the results of a study can be biased, limiting the analysis of the actual influence of GAP adoption on farmers' performance. For example, farmers' production decisions, such as decisions to change from specialization to the adoption of a diversified cropping system, also affect farms' TE and overall productivity [37]. Diversified cropping systems help farmers to minimize production and price risk, increase profitability, and improve ecological sustainability in the long term [38,39]. Unfortunately, to the author's best knowledge, no study has explicitly evaluated the effects of crop diversification on the TE of GAP and non-GAP chili farms. Without consideration of these factors, in addition to the assessment of the impact of GAP adoption on farms' efficiency, incomplete and biased recommendations may be given to farmers, extension agencies, and policymakers. Finally, unlike previous studies (e.g., [30,31]), which assumed technological homogeneity for GAP farms and non-GAP farms in their analyses, this study tested a hypothesis on technological uniformity between GAP and non-GAP chili-growing farms. Through this, TE could be more realistically interpreted, as indicated by Madau [40].

Empirical results could help government and nongovernmental organizations (NGOs) to invent and execute policies and learning and training classes to effectively stimulate GAP adoption. GAP and non-GAP farmers could improve their production efficiency and quality to satisfy manufacturing and export requirements. As a result, chili grown with GAP would have increased competitiveness in the international market, thereby increasing the income of the farms at which it is grown. Therefore, the use of the GAP standards allows chili production to be sustainable. This study's results can also be used to help policymakers choose the proper direction for development planning to decrease the environmental impacts of production and consumption and increase resource productivity and food security. These findings also support the policy developed to move Thailand forward to a value-based economy for Thailand 4.0, which was initiated by the Thai government [41].

This paper is organized into five sections. Following this introduction, a literature review on the impact of GAP adoption on the efficiency of farms is presented in Section 2. Then, the data and TE measurement, as well as the empirical model, are described in Section 3. Section 4 introduces the hypothesis tests and presents the findings and discussion. Section 5 concludes the paper.

2. Literature Review

Previous studies focused on the impacts of GAP adoption, covering different products, regions, and aspects. For example, Dörr and Grote [42] stated that GlobalGAP-certified Bazilian grape farmers gain higher levels of productivity than those who are not endorsed. Purnamasari et al. [43] found that the GAP adoption rate significantly positively influences soybean productivity in the Indonesian Kulon Progo Regency district. In contrast, when comparing EurepGAP-certified tomato farms with uncertified farms in Turkey, the certified group was found to have lower productivity and lower production costs while having a higher net income. Certified farms were found to have a 2.8 times greater net gain per unit area and a higher selling price than uncertified producers [44]. Bairagi et al. [45] investigated the impact of GAP adoption on Nepalese farms. They also found that GAP adoption had a positive and significant relationship with farm income. In contrast, Lazaro et al. [46] found that the profit of GAP vegetable farms was not statistically different from that of non-GAP farms within the short time period investigated.

In a study conducted in Kenya, Asfaw et al. [47] indicated that EurepGAP vegetable farmers could substantially improve their financial performance by adopting standards and exporting certified products to the European Union market. Subervie and Vagneron [9] focused on GlobalGAP-certified lychee producers in Madagascar, while Fiankor et al. [11] concentrated on apples, bananas, and grapes from 45, 39, and 44 GlobalGAP-certified producing countries, respectively. They pointed out that GAP-certified producers had a greater chance of selling more significant amounts of their products due to exporters' confidence and their improved product quality and quantity. VietGAP is a public GAP program that was implemented by the Vietnamese government. Tran and Le [48] and Thanh Truc and Thuc [49] investigated the impact of the VietGAP program on vegetable and fruit farmers in Thua Thien Hue Province and the Mekong Delta region, Vietnam. The empirical results indicated that the program significantly improved VietGAP farmers' revenue and health and moved the farmers towards the use of environmentally friendly production methods, thereby encouraging health protection and environmental sustainability.

In a study conducted in Thailand, Lippe and Grote [50] pointed out that mango farmers may be aware of higher prices because of GAP certification. In contrast, most orchid farmers did not recognize higher prices as a significant benefit of GAP adoption. However, they noticed that increased product quality, improved farm management, and improved health and safety of farmers were extra benefits of GAP adoption. Pongvinyoo et al. [51] and Krause et al. [2] revealed that the adoption of GAP production techniques could increase farm income more than the use of conventional farming methods for mangosteen and mango products, but not orchid products. This could be because the farmers can demand a higher price for these products. However, farmers who adopt GAP methods have to cope with higher costs [51]. Conformity with GAP guidelines for small farms requires increased investment in variable inputs and long-term structures [47]. Farms' GAP certification costs and the time required for record keeping and training have been shown to be the main obstacles to the adoption of GAP [52].

Few studies have directly examined the impact of GAP adoption on farms' TE. For example, Charamba and Thomas [33] indicated that Namibian maize farmers trained in the use of good horticultural practices are likely to have farms with higher TE. De Silva and Rathnayaka [29] showed that GAP adoption positively and significantly affects Sri Lankan tea smallholders' TE. Taraka et al. [28] found that GAP adoption positively contributes to rice farm TE in Thailand. Thang and Dung [32] indicated that GAP participation does not impact the TE of grape and apple production in Ninh Thuan Province, Vietnam. Previous studies conducted on Thai chili farms explicitly investigated the effect of GAP adoption on TE, and mixed conclusions were obtained. Krasachat [30,31] showed that farmers who employed GAP obtained higher TE than those who did not use GAP. In contrast, Krasachat and Yaisawarng [7] pointed out that there is no empirical evidence to conclude that GAP and non-GAP farms differ in terms of TE. Thus, there is uncertainty as to whether GAP adoption directly impacts the TE of Thai chili farms.

Overall, GAP adoption will likely increase farms' income, selling prices and chances to trade more considerable amounts. It also improves product quality, farm management, the health and safety of farmers, and environmental sustainability. However, it causes more investment in variable inputs and long-term structures, generates certification costs and the time needed for training and documentation and possibly increases production costs. Its effects on farms' productivity and TE are still indecisive.

3. Methods

3.1. Data

Thai government organizations actively stimulated GAP use for chili production in 2007, even though the GAP program was introduced in 2003. The pilot project was initiated in two districts in Chaiyaphoom Province in the northeastern region of Thailand. A research team visited the area, and several workshops on GAP standards were conducted using a participatory action research approach. These workshops taught farmers how to produce organic fertilizers, when and how to employ these 'homemade' fertilizers, and when and how to use microbial pesticides (e.g., Trichoderma, Beauveria Bassiana) to handle diseases [7].

Several farmers joined the program, while many others did not or selected not to use the GAP guidelines. Approximately 106 GAP farms and 101 non-GAP farms existed in the two districts in Chaiyaphoom Province and were covered by the pilot project in 2011. Under King Mongkut's Institute of Technology Ladkrabang Research Grant, 2562-0212017, a research team collected information about farms in the 2018 crop year. Farmers in the areas included in the pilot project were randomly selected and voluntarily interviewed using a structured questionnaire. One hundred surveys were completed, representing 48% of the total farm population in 2011. These 100 farms consisted of 60 GAP farms (60% of the GAP farm population) and 40 non-GAP farms (40% of the non-GAP farm population). The collected sample represents the farm population covered by the pilot project. Note that there is no formal statistical record for the total farm population included in the pilot project from recent years.

This study used the sample attained by the research team, as mentioned above. The initial sample comprised 100 small owner-operated chili farms, including 60 GAP farms and 40 non-GAP farms. Farms in both groups produced fresh chili, and the quantity was measured in kilograms (kgs). They all utilized four inputs: cultivated land (rai), labor (person-hours), capital (constant 2010 Thai baht (THB)), and materials (constant 2010 Thai baht (THB)). Following the approach used by Krasachat and Yaisawarng [7], the capital inputs included the costs incurred for the use of plant nurseries, tractors, water pumps, and other small tools. Material inputs comprised seeds, pesticides, herbicides, water irrigation, and other variable expenses, except the land, labor, and capital inputs described above. This study employed the Thailand Producer Price Index, retrieved from the Census and Economic Information Center (CEIC) [53], to modify the current value of capital and material inputs to constant THB to obtain physical units. This is similar to the real gross domestic product (GDP) concept, which is calculated as nominal GDP [7]. In sum, 61 and 39 farms grew chili using the rainy and dry season varieties. On average, the farmers were 55.53 years old, had 7.19 years of schooling, and had undertaken 2.91 training classes per crop per year. A total of 21% of their chili-cultivated areas had equal to, or more than, two rai. Note that the descriptive statistics of the initial sample are not reported to save space.

The last two variables included in this study were crop diversification and the ratio of total family labor to the area of chili cultivation. In general, farmers in the sample were growing chili using intercropping systems with other crops such as banana, rice, sugarcane, and cassava.

According to Wu et al. [54], many environmental variables have potential influencing factors that can be classified into two groups: natural factors, comprising soil type, groundwater depth, etc., and human activities, comprising cropping systems, irrigation, etc. Unfortunately, there was no availability of environmental variables for this study, such as weather, soil quality, rainfall, climate conditions, and irrigation. In addition, all farms were located in the same geographic region and had similar environments. However, this study views crop diversification as a related environmental variable.

In line with Mzyece and Ng'ombe [55], crop diversification was measured using the Simpson index of diversification (SID). It was calculated as $SID = 1 - \sum_{i=1}^{n} (A_i / \sum_{i=1}^{n} A_i)^2$, where A_i is the amount of land in rai allocated to the ith crop, and $\sum_{i=1}^{n} A_i$ is the total amount of land in rai cultivated by a farmer for all of their crops. Thus, $0 \geq$ SID ≥ 1, where 0 represents no diversification, and 1 represents complete diversification. In other words, higher values of the SID indicate more diversity in crops on a farm. This study showed that the chili farms in the sample had an average value of 0.16. This implies that the crop diversification of these farms was relatively low.

Chili is a labor-intensive crop [16], and farming households are generally very limited in the capital. Thus, family labor plays an essential role in chili production. Suppose the family's workforce can still complete farm work. In that case, there is no necessity to hire outside workers to save costs because family labor could be more productive and entail lower monitoring costs due to family members' higher motivation in their roles as residual claimants on farm profits [56,57]. According to Coelli et al. [58], accounting for the differences in labor quality is essential in measuring the labor input for a production process. Their suggestion was to classify workers according to some characteristics such as age, gender, and education levels, and then use them to construct an aggregated labor input variable. However, due to a lack of that information on farmers' family workers to account for the quality of different types of family labor, this study used the number of full-time equivalent workers to construct the variable of family labor involved in farming and divided by chili-cultivated area. The average amount of family labor involved in farming per chili-cultivated area in this sample was 2.39 person-days.

The initial sample was relatively small. However, it had a few advantages. First, the quality of the surveyed data was adequate because the information was collected by the team who are familiar with the chili-growing farmers and their farm locations and production characteristics. Unusual or inaccurate data were quickly noticed, and corrections were made in the field because of the research team's expertise. Second, all farmers who live in the project area were able to attend the GAP training workshops at no cost. They could decide whether to participate in a few or all of the technical training classes. After participating in these classes, assured farmers adopted the GAP standards. Farmers also had the choice to overlook the GAP classes they attended. Therefore, this dataset enabled the author to directly investigate the differences in TE between farms that applied the GAP standards and those that did not, without mixing up the impact of inefficient employment of resources and a lack of knowledge on how to appropriately utilize the resources under the GAP guidelines [7]. Third, in terms of geographic location, the sample was identical. As mentioned above, all farms were in a similar province, had the same soil quality, and were exposed to the same climate (rainfall, humidity, temperature, etc.). The soil quality and climate conditions impact chili production. Because of the homogeneity of the dataset, there was no necessity to employ proxy variables to eliminate sample diversity to make the efficiency analysis more precise [7].

Since GAP adoption is voluntary, there might have been a sample selection bias. A simple comparison of the TE scores between two groups, such as GAP and non-GAP farms, might produce findings with significant bias [59]. One way to correct the sample selectivity bias is to apply the matching procedure technique. However, a reasonably large sample is needed to analyze the propensity score model (PSM) [7]. This method was based on exogenous farm characteristics of a farmer's decision to adopt GAP standards. Its main target was to generate samples of GAP and non-GAP farms with the same exogenous characteristics.

Because of the limitation produced by the small farm number in this study sample, the PSM approach could not be used. This study used an 'indirect' procedure, introduced by Krasachat and Yaisawarng [7], to decrease the potential of observable sample selectivity bias. This method was used to obtain a control group similar to the group of farms with access to GAP technology. The procedure used comprised four steps. First, the original sample was categorized into four groups: Group 1 included non-GAP farms, Group 2 included GAP farms, Group 3 included farms that planted chili using dry-season varieties, and Group 4 included farms that grew the rainy-season type of chili.

As in Krasachat and Yaisawarng [7], the geographic location of farms in this study was not considered a potential factor for an observable sample selectivity bias due to the similarities of their geographic region and environments. Farmers' ages and cultivation experience, measured in years, were considered as alternatives.

Second, the average age and cultivation experience of farmers were independently computed for each group. Third, the group means were examined to determine whether the average age of non-GAP farmers was equal to that of GAP farmers using the non-parametric Wilcoxon two-sample and analysis of variance (ANOVA) tests. We specifically compared farmers' average age (or average experience) between Groups 1 and 2 and Groups 3 and 4, and we deleted potential outliers of each group if the null hypothesis was not accepted. Then, steps 2 and 3 were reiterated until the null hypothesis was not rejected. The procedure indicated that there was no selection bias in the initial sample.

Table 1 shows the estimated exogenous farm features in the finalized sample in the group and the test statistics of each null hypothesis. There was a similarity in the averaged age of non-GAP and GAP farmers. The alternative hypothesis indicates that an average age difference exists between the two respective groups. Our evidence suggests that the test did not reject the null hypothesis based on the Wilcoxon two-sample and ANOVA tests. This result indicates no difference in the averaged age between the two groups at the 5% significance level. Additionally, this study tested the difference in farmers' average experience between the two groups. Again, the results indicate no disparity in the averaged experience at the 5% level.

Similarly, the test statistics of each null hypothesis showed a similarity in the farmers' averaged age (or cultivation experience) between those working on farms producing the dry-season variety and those working on farms producing the rainy-season variety at the 5% level. Thus, the results indicate no difference in the averaged age (or experience). These results suggest that sample selection bias did not occur in the initial sample.

Table 1. Descriptive statistics of exogenous characteristics of farms by groups.

Variable	**Average**	**S.D.**	**Minimum**	**Maximum**
Group 1: Non-GAP farms (*n* = *40*)				
Age (years)	55.65	8.50	39	72
Cultivation experience (years)	13.30	9.65	1	42
Group 2: GAP farms (*n* = *60*)				
Age (years)	55.45	7.77	38	78
Cultivation experience (years)	15.18	10.18	1	40
Group 3: Farms using dry-season variety (*n* = *38*)				
Age (years)	55.21	6.85	42	73
Cultivation experience (years)	14.32	9.12	3	30
Group 4: Farms using rainy-season variety (*n* = *57*)				
Age (years)	57.47	8.54	38	78
Cultivation experience (years)	24.75	10.81	1	42

Hypothesis	ANOVA Test	Wilcoxon Two-Sample Test
H_0: No difference in averaged age between GAP and non-GAP farms	F-value =0.01 Prob > F =0.90	Z-value = 0.08 Pr > |Z| = 0.94
H_0: No difference in averaged years of experience between GAP and non-GAP farms	F-value =0.86 Prob > F = 0.36	Z-value = 0.89 Pr > |Z| = 0.38
H_0: No difference in averaged age between farms using dry-season variety and farms using rainy-season variety	F-value = 0.07 Prob > F = 0.79	Z-value = 0.14 Pr > |Z| =0.89
H_0: No difference in averaged years of experience between farms using dry-season variety and farms using rainy-season variety	F-value = 0.001 Prob > F = 0.98	Z-value = 0.31 Pr > |Z| =0.76

***, **, and * imply the 1%, 5%, and 10% significance levels, respectively.

There were a few missing values for the output, labor, and capital variables. Two non-GAP farms had missing values for the output variable, while another two non-GAP farms had missing values for the capital variable. In addition, one GAP farm had a missing labor variable value. In total, the author excluded 1 GAP farm and 4 non-GAP farms, resulting in 59 GAP farms and 36 non-GAP, with 38 farms using the dry-season variety and 57 farms using the rainy-season variety, for the analyses. Table 2 reports the descriptive statistics for all variables in the final sample.

Table 2. Descriptive statistics of good agricultural practices (GAP) and non-GAP farms (missing values excluded).

Variable	Group 1: Non-GAP Farms, *n* = 36					Group 2: GAP Farms, *n* = 59				
	Average	S.D. [1]	Min	Max	C.V. [2]	Average	S.D.	Min	Max	C.V.
Output (kgs)	2282.11	3879.06	15.00	18000.0	170.0	936.26	964.35	65.00	7941.0	103.0
Land (rai)	2.27	2.76	0.25	10.0	121.6	1.00	0.53	0.25	3.0	53.0
Labor (person-hours)	89.38	108.85	6.75	453.9	121.8	67.75	41.15	13.75	196.0	60.7
Capital (constant 2010 THB)	51.32	75.45	1.23	387.1	147.0	28.26	26.11	0.11	116.7	92.4
Materials (constant 2010 THB)	81.72	111.37	0.58	507.3	136.3	53.73	31.22	5.81	159.8	58.1
Good agricultural practices (GAP) (GAP adoption = 1; non-GAP adoption = 0)	0.00	0.00	0.00	0.0	-	1.00	0.00	1.00	1.0	0.0
Variety (rainy-season variety = 1; dry-season variety = 0)	0.83	0.38	0.00	1.0	45.8	0.46	0.50	0.00	1.0	108.7
Age (years)	55.39	8.09	39.00	72.0	14.6	55.36	7.80	38.00	78.0	14.1
Education (years of schooling)	6.56	2.14	0.00	14.0	32.6	7.48	2.52	6.00	16.0	33.7
Technical training classes (number of classes)	0.33	0.86	0.00	4.0	260.6	4.63	5.04	0.00	30.0	108.9
Cultivation experience (years)	13.25	10.09	1.00	42.0	76.2	15.39	10.14	1.00	40.0	65.9
Farm size (equal to or more than 2 rai of chili-cultivated area = 1; otherwise = 0)	0.36	0.49	0.00	1.0	136.1	0.10	0.30	0.00	1.0	300.0
Crop diversification (complete diversity = 1; completely uniform = 0)	0.15	0.14	0.01	0.5	93.3	0.17	0.13	0.00	0.48	76.5
Family labor involved in farming per area of chili cultivation (person-days/rai)	2.45	2.38	0.00	8.0	97.1	2.49	1.71	0.75	10.0	68.7

[1] and [2] denote the standard deviation and the coefficient of variation, respectively.

Table 2 shows that, on average, GAP farms had lower chili outputs and used less of all inputs than non-GAP farms in the 2018 crop year. In particular, the averaged farm size of non-GAP farms was 2.27 rai, around two times larger than that of GAP farms (1 rai). The difference in size (i.e., chili-cultivated land) between non-GAP and GAP farms may have contributed to this result. Therefore, this study examined the chili output to a unit of input (i.e., land, labor, capital, and materials) to explore this issue further.

When the average chili output to a unit of respective input was compared between GAP and non-GAP farms for the 2018 crop year, the data indicated that GAP farms received smaller yields per unit of all inputs used. In addition, non-GAP farms grew rainy-season chili in a higher proportion than GAP farms. In contrast, GAP farms possessed higher average values for farmer education and experience, crop diversification, family labor involved in farming, and training classes attended. However, GAP and non-GAP farmers were of similar ages.

3.2. Methodology and Empirical Model

3.2.1. Technical Efficiency Measurement

Technical efficiency analyses have developed significantly due to the presence of a highly competitive business environment that necessitates more rational use of resources [27]. Previous analyses on efficiency and productivity in the agricultural sector have applied two main approaches: parametric and non-parametric methods, with different variations (for more details, see [7,60,61]). Parametric analyses generally use the stochastic frontier analysis (SFA) approach, while non-parametric analyses involve the data envelopment analysis (DEA) approach [60]. SFA is defined by a set of explanatory variables, i.e., outputs, inputs, other possible explanatory variables, and two components: the random error and the inefficiency term. On the other hand, DEA calculates the ratio of the weighted sum of outputs to the weighted sum of inputs [62].

From a methodological standpoint, each technique has its own merits. The disadvantages and advantages of each method have been widely discussed (among others, [62–65]). Results from previous studies (among many others, [58,66]) indicate that the SFA approach has several primary advantages in terms of estimating the economic efficiency of a farm comprising two components: technical efficiency (TE) and allocative efficiency (AE). Coelli et al. [58] indicated that TE refers to the farm's ability to achieve the maximum output at given inputs, while AE quantifies the ability of the farm to employ inputs in optimal proportions at given input prices. Due to recent development in production and cost frontiers, productive efficiency, which indicates the farm's ability to produce the output at the lowest cost, has been measured [66]. In these efficiency estimations, the SFA approach deals with stochastic noise and allows statistical tests of hypotheses about the production structure and intensity of inefficiency.

Additionally, SFA allows simultaneous estimation of respondent farmers' TE and TE determinants [67]. However, the SFA approach's major disadvantage is that it needs the specifications of the technology and the inefficiency error term, which is restrictive in most cases [60,68]. It is required to make an assumption concerning a specific functional form of SFA studies a priori, and the wrong choice of production function may affect the empirical results [62].

Non-parametric approaches, such as DEA, involve the use of technical linear programing to measure the relative efficiency of a number of decision-making units (DMUs) or farms by identifying the optimal mix of inputs and outputs that are grouped based on their actual performance [69,70]. Due to their advantages, non-parametric efficiency analysis methods appeal to many researchers because of their unique ability to quantify the efficiency of multi-input and multi-output farms without imposing parametric restrictions on the underlying technology a priori [71,72]. However, non-parametric efficiency analysis methods also have at least three main shortcomings. First, these methods do not have a sound statistical foundation and are sensitive to outliers [71]. Second, as mentioned in the study of Murillo-Zamorano and Vega-Cervera [68], the non-parametric method estimator is based on an assumption of no noise. Therefore, any deviation from the frontier must contribute to inefficiency [63]. As a result, efficiency scores are contaminated by omitted variables, measurement errors, and other statistical noise sources [64,73]. Finally, non-parametric methods cannot estimate a model's parameters; hence, it is impossible to use them to test a hypothesis concerning a model's performance [60].

This study employed the SFA method because we believe that data noise is a significant concern because of the potential risks associated with agricultural production, commonly from natural conditions such as climate and disease [74–76]. In addition to the advantages of SFA mentioned above, DEA forms a frontier by building a piecewise linear surface over the top of the sample data. If there is data noise associated with a few frontier points, this will not only result in the frontier shifting out and exaggerating the mean level of TE but also alter the shape of the estimated frontier [58].

SFA was introduced by Aigner et al. [77] as an efficient analytical framework. It is one of several methods used to estimate distance functions [78]. Distance functions are increasingly gaining interest as alternative production technologies, with increasing numbers of empirical applications being published in the efficiency and productivity literature [79]. Rungsuriyawiboon and O'Donnell [80] mentioned two types of distance functions that have obtained substantial attention in the literature. An input distance function defines the maximum proportional reduction in the input vector possible without altering the output vector. In contrast, an output distance function depicts the degree to which a firm can increase its output vector given an input vector.

According to Coelli et al. [58], Coelli [81], Coelli et al. [82], and Li and Sicular [83], there are a few exceptional advantages when applying the input distance function. It does not necessitate the inclusion of price information, but it can offer a robust estimation if there are systematic deviations from cost-minimizing behaviors. Additionally, it can avoid the simultaneous equation bias problem when firms are cost minimizers. Moreover, as Atkinson and Primont [84] indicated, the strong relationship between the cost function and input distance function is consistent with duality theory, suggesting that the input distance function has a profound economic explanation. Finally, input distance functions are likely to be employed instead of output distance functions when firms have less control over outputs than inputs [58]. Due to these advantages, this study used the stochastic input distance function approach.

3.2.2. Empirical Model

The input distance function was first proposed by Shephard [85]. It expresses the extent to which the input vector may be proportionately decreased while the output vector is constant. We assumed that cross-sectional data on I farms could be retrieved and defined the input distance function over M outputs and N inputs as follows [58]:

$$d_i^I = d^I(X_{1i,}, X_{2i,}, \ldots X_{Ni,}, Y_{1i,}, Y_{2i,}, \ldots Y_{Mi,}) \tag{1}$$

where X_{ni} is the nth input of farm i; Y_{mi} is the mth output of farm i; and ≥ 1 is the maximum quantity by which the input vector can be radially reduced without altering the output vector. Coelli et al. [58], among many others, pointed out that the function $d_i^I(.)$ is linearly homogeneous, non-decreasing and concave in inputs, and non-increasing and quasi-concave in outputs.

Coelli et al. [58] revealed that, in the first step, a functional form of $d_i^I(.)$ must be selected for the econometric estimation of an input distance function. The distance functional form should ideally be easy to calculate and flexible and permit the imposition of homogeneity in inputs [86,87]. The translog functional form has been applied in many existing distance function studies (e.g., [86–90]). This is because it can fulfill these three requirements. However, the Cobb–Douglas form meets the criteria of being easy to calculate and allowing homogeneity to be imposed, but it is not flexible because of the restrictive elasticity of its substitution and scale properties [86]. In this study, a translog form was applied. In accordance with Honma and Hu [90], for the case with one output and four inputs, the log form of the translog input distance function was specified as

$$ln\ d_i^I = \beta_0 + \varnothing ln\ Y_i + \sum_{n=1}^{4} \beta_n ln\ X_{ni} + 1/2 \sum_{n=1}^{4} \sum_{k=1}^{4} \beta_{nk} ln\ X_{ni} ln\ X_{ki} + 1/2 \sum_{n=1}^{4} \beta_{yn} ln\ Y_i ln\ X_{ni} + 1/2\ \beta_{yy} ln\ Y_i ln\ Y_i + v_i, \tag{2}$$

where v_i is a random variable included to account for approximation errors and other sources of statistical noise (see [58,91] for details). According to Coelli and Perelman [86], Irz and Thirtle [87], Lovell et al. [92], and Singbo and Larue [93], linear homogeneity in the inputs suggests that the parameters in Equation (2) must be restricted as follows:

$$\sum_{n=1}^{4} \beta_n = 1; \sum_{k=1}^{4} \beta_{nk} = 0\,; \sum_{n=1}^{4} \beta_{yn} = 0; \tag{3}$$

Additionally, the symmetry property can be imposed by restricting $\beta_{nk} = \beta_{kn}$ $(n, k = 1, \ldots, 4)$.

As indicated by Coelli and Perelman [86], a convenient approach for imposing the homogeneity constraint upon Equation (2) is to follow the method suggested by Lovell et al. [92]. Notice that homogeneity implies that

$$d^I(\varphi X, Y) = \varphi d^I(X, Y) \text{ for any } \varphi > 0, \tag{4}$$

where X is assumed to be a vector of dimension 4. One of the inputs was arbitrarily chosen. In this case, X_2 and $\varphi = 1/X_2$ was set. Thus,

$$d^I(X/X_2, Y) = d^I(X, Y)/X_2. \tag{5}$$

The input distance function, Equation (2), was rewritten to enable its econometric estimation. Hence, the stochastic input distance function of the Thai chili farms in this study was specified as

$$-\,ln\, X_{2i} = \beta_0 + \varnothing ln\, Y_i + \sum_{n=1}^{3} \beta_n ln\, x_{ni} + 1/2 \sum_{n=1}^{3}\sum_{k=1}^{3} \beta_{nk} ln\, x_{ni} ln\, x_{ki} + 1/2 \sum_{n=1}^{3} \beta_{yn} ln\, Y_i ln\, x_{ni} + 1/2\, \beta_{yy} ln\, Y_i ln\, Y_i + v_i - \mu_i, \tag{6}$$

where $\mu_i \equiv ln\, d_i^I$, which is a non-negative variable associated with technical inefficiency, and $x_{ni} = X_{ni}/X_{2i}$. Thus, Equation (6) resulted in a model in the form of a stochastic frontier model. The maximum likelihood technique was applied to estimate the parameters of the model [58]. Y and X represent the variables reported in Table 2. βs and $\varnothing$ are parameters to be estimated. A random noise term, v_i, was assumed to be distributed as $N(0, \sigma_v^2)$. μ_i is a farm-specific inefficiency term that was presumed to be satisfied by truncation (at zero) of $N\left(\mu_i, \sigma_\mu^2\right)$ [58,94,95]. However, the estimated parameters of Equation (6) would have the opposite signs to those used for a standard input requirement function, as indicated by Morrison-Paul and Nehring [96]. In addition, the radial input-oriented measure of TE is

$$TE_i = \frac{1}{d_i^I} = exp(-\mu_i). \tag{7}$$

Therefore, firm-specific TE can be estimated (see [58] for details).

Several methods were summarized in Madau [40] and Coelli et al. [58] to explore TE determinants further. However, Battese and Coelli [97] pointed out that farm-specific and environmental factors should be included directly when estimating the input distance function because they may directly impact efficiency. In this study, in accordance with Kumbhakar et al. [98] and Battese and Coelli [97], the stochastic input distance function (6) and the inefficiency model parameters of Equation (8) were estimated simultaneously to overcome this problem, considering that the effects of technical inefficiency are stochastic. In this case, μ_i was presumed to represent non-negative, random, independently distributed variables derived from the truncation at zero of the normal distribution with variance, σ^2, and mean, $z_i\delta$. A vector of farm-specific and environmental factors, z_i, was assumed to define technical inefficiency, as reported in Table 2, and δs was used to represent parameters to be estimated, as indicated by Wilson et al. [99]. In this study, the inefficiency effect model was specified as

$$\mu_i = \delta_0 + \sum_{p=1}^{8} \delta_p z_i \tag{8}$$

Recall that this study aimed to investigate the impact of GAP adoption on farms' TE. Unfortunately, we could not directly compare TE scores between GAP farmers and non-GAP farmers estimated from the methodology because these scores are relative to the specific frontier technology used by farm groups [100]. Battese et al. [101] introduced a two-stage approach for the meta-frontier analysis of the aggregate efficiency of a farm. This way, TE can be directly compared for GAP and non-GAP farmers. As described by Honma and Hu [90], Battese et al. [101], and Huang et al. [102], this approach comprises two stages. In the first stage, the stochastic input distance function, shown in Equation (6), is employed to estimate the TE relative to the group frontier for farm i (TE_i^G). In the second stage, as shown by Honma and Hu [90] for the case of an input distance function, the optimal level of labor input (X_2) should first be estimated by contracting the actual labor input, such that $X_{2i}^{adj} = X_{2i} \times TE_i^G$. Hence, the second-stage stochastic input distance function, Equation (6), is altered as follows:

$$-\ln X_{2i}^{adj} = \beta_0 + \varnothing \ln Y_i + \sum_{n=1}^{3} \beta_n \ln x_{ni} + 1/2 \sum_{n=1}^{3}\sum_{k=1}^{3} \beta_{nk} \ln x_{ni} \ln x_{ki} + 1/2 \sum_{n=1}^{3} \beta_{yn} \ln Y_i \ln x_{ni} + 1/2\, \beta_{yy} \ln Y_i \ln Y_i + v_i^* - \mu_i^*. \quad (9)$$

The technology gap ratio (TGR) to measure the distance of a group frontier and meta-frontier for farm i, (TGR_i), can be calculated as follows:

$$TGR_i = \exp(\mu_i^*). \quad (10)$$

According to the two stages described by Huang et al. [102], by employing only stochastic frontier analysis, one can attain

$$TE_i^* = TE_i^G \times TGR_i, \quad (11)$$

where TE_i^* is the meta-frontier TE score for farm i, TE_i^G is the group TE score for farm i, and TGR_i is the technology gap ratio score for farm i. Notice that the greater the TGR score, the smaller the technology gap. All TE_i^*, $TE_i^G and\ TGR_i$ scores are right-censored at 1 and left-censored at 0, which follows the typical definition of an efficiency score mentioned by Honma and Hu [90]. Additionally, Huang et al. [102] suggested that the stochastic frontier, Equation (6), and the inefficiency effect model, Equation (8), can be simultaneously estimated by following the method suggested by Battese and Coelli [97].

The methodology described above assumes that there are two different technological frontiers for GAP and non-GAP farms. The assumption of technological heterogeneity between the two techniques needed to be examined to fit the efficiency model better, as suggested by Madau [40]. Therefore, this study followed the approaches applied by Irz and Thirtle [87], Singbo and Larue [93], Sipiläinen [103], Bouchaddakh and Ben Jemaa [104], and Wree et al. [105]. The original Equation (6) included a dummy variable (i.e., GAP variable) to reflect the farming technique (GAP adoption = 1; non-GAP adoption = 0). Through this, the author could test the hypothesis of technological homogeneity between GAP and non-GAP chili-growing farms.

Similarly, the rainy-season and dry-season varieties might lie on different input distance function frontiers based on the above basis. For this reason, we added Equation (6) as another dummy variable (i.e., rainy-season variety = 1; dry-season variety = 0) to examine the hypothesis about the homogeneity between rainy-season and dry-season varieties used by chili farms. Hence, the empirical model of the stochastic input distance function of the Thai chili farms was

$$\begin{aligned} -\ln X_{2i}^{adj} &= \beta_0 + \varnothing \ln Y_i + \sum_{n=1}^{3} \beta_n \ln x_{ni} + 1/2 \sum_{n=1}^{3}\sum_{k=1}^{3} \beta_{nk} \ln x_{ni} \ln x_{ki} \\ &+1/2 \sum_{n=1}^{3} \beta_{yn} \ln Y_i \ln x_{ni} + 1/2\, \beta_{yy} \ln Y_i \ln Y_i + \theta_{gap} GAP + \theta_{\vartheta} variety + v_i - \mu_i. \end{aligned} \quad (12)$$

where θ_{gap} and θ_{ϑ} are two additional parameters to be estimated, compared to Equation (6). Recall that all chili farms produced one output (y) and used the same four inputs: land (x_1), labor (x_2), capital (x_3), and materials (x_4). All variables were assessed in logarithmic terms, except GAP and variety.

Several explanatory factors could be incorporated into the inefficiency model presented in Equation (8) [97]. As previously mentioned, seven selected characteristics of farmers and environmental factors were analyzed to assess their impacts on the TE of the farms. The farmers' ages (z_1) and ages squared (z_2) were defined in terms of years and years squared. These variables were employed to investigate the effects of differences in farmers' ages and their square values on the efficiency of chili farms. Several studies have examined the impacts of farmers' age on the TE of their farms (e.g., [26,66,106,107]), and the effects of farmers' age and age squared on the efficiency of their farms (e.g., [55,108]).

This study assessed the impacts of farmers' education (z_3) and experience (z_4), measured in terms of years of schooling and cultivation, respectively, on farm efficiency. Many previously conducted studies (for example, [26,109–112]) directly investigated the effects of education or experience or both on efficiency in the agricultural sector.

Technical training classes (z_5) were an essential way for farmers to learn about GAP technology and farming practices in this study sample. The classes were introduced to investigate their effects on TE. Previous studies (for example, [83,107,113]) also assessed the impacts of training classes on efficiency. A dummy variable presented as a proxy for farm size (z_6) was used to explore the impact of the difference in farm size on technical inefficiency in chili farms. This factor was assessed in previous studies [30,114]. Furthermore, existing studies explicitly discussed the impact of crop diversification (z_7) on TE (e.g., [37,55,88,115–117]). This study investigated its effect on the efficiency of chili farms.

Finally, the impact of the ratio of family labor to chili-cultivated land (z_8), representing the intensity of the use of family labor for chili growing, on the farms' TE was evaluated. Previous studies (i.e., [118,119]) used a similar variable to assess rice farms in Vietnam and India. The input and output variables, the variables selected to examine inefficiency effects, and the descriptive statistics of all the variables used in the sample are shown in Table 2.

4. Results and Discussion

4.1. Hypothesis Tests

Statistical tests were used to examine the suitability of the adopted methodology. The maximum likelihood estimation (MLE) method introduced by Battese and Coelli [97] was applied to concurrently estimate the parameters of the stochastic input distance function (Equation (12)) and the technical inefficiency effect model (Equation (10)) employing FRONTIER Version 4.1, a computer program, as described in Coelli [120]. Note that the parameter estimates are not reported due to space limitations.

The results of the hypothesis tests are reported in Table 3. Likelihood ratio (LR) tests were applied in all cases. In addition, the Wald test, an approximation of the LR test, was employed when the LR test could not be estimated (see [121,122] for more details). The first test was conducted to assess the null hypothesis (H_0: $\beta_{nk}; \beta_{yn}; \beta_{yy} = 0$) that the Cobb–Douglas form is an adequate depiction of the frontier input distance function against the alternative translog form specification. This hypothesis was applied to the whole sample, i.e., pooled GAP and non-GAP farms, and was rejected at the 1% significance level. This result indicates that the translog functional form is suitable for the Thai chili farms in the sample.

The second test assessed whether a significant level of technological homogeneity existed between GAP and conventional non-GAP farms (i.e., $H_0: \ \theta_{gap} = 0$). The estimated value of the LR statistic test for this null hypothesis was 9.05, which is significantly higher than the critical value of 6.63 at the 1% significance level. Thus, the null hypothesis was firmly rejected, confirming that the two groups' production technologies were heterogeneous. This supported the use of the meta-frontier method to estimate the farms' TE. Similarly, the third test examined whether there was a significant level of technological homogeneity between the farms producing rainy-season and dry-season chili varieties. The null hypothesis ($H_0: \ \theta_{\vartheta} = 0$) was not rejected at the 1% level. This implies that the different chili varieties used do not represent an essential factor for explaining the TE in the sample.

The test results suggest that a common frontier should be adopted for the two chili varieties, and the meta-frontier approach should be applied for GAP and non-GAP farms for the following analysis.

Table 3. Hypothesis tests for the parameters of the pooled model (*n* = 95).

Null Hypothesis	Model	Statistic Test	Critical Value [1]	Result
H_0: $\beta_{nk}; \beta_{yn}; \beta_{yy} = 0$	Translog vs. Cobb–Douglas	41.96	23.20	Rejected H_0
H_0: $\theta_{gap} = 0$	Technological homogeneity (GAP [2] adoption vs. non-GAP adoption)	9.05	6.63	Rejected H_0
H_0: $\theta_{\vartheta} = 0$	Technological homogeneity (rainy-season variety vs. dry-season variety)	0.53 [3]	6.63	Not rejected H_0

[1] denotes significance at the 1% level; [2] and [3] represent good agricultural practices and the Wald statistical test.

4.2. Meta-Frontier Approach Results

Table 4 reports the parameter estimates of group TE, TE^G, and the technology gap ratio, TGR, using the MLE, which was introduced by Battese and Coelli [97]. In the first step, TE^G and its determinants were simultaneously estimated employing Equations (6) and (8) for each group of farms separately based on the group frontier. The results are reported in columns 2 and 4. In the second step, the parameter estimates of TGR were estimated using Equation (9) based on the meta-frontier, and the results are shown in column 6. Almost half of the estimated TE^G and TGR parameters were statistically significant at the 10% level at least. This suggests that the goodness of fit of these estimates was suitable for describing the sample's chili farms.

Table 4. Maximum likelihood estimation results.

Variable	Group Technical Efficiency (TE^G)				Technology Gap Ratio (TGR)	
	Non-GAP Farms		GAP Farms			
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Stochastic frontier:						
Constant	−5.267 ***	1.227	−0.997	1.153	−0.206	0.775
ln(output)	0.669 **	0.241	0.121	0.482	0.172	0.139
ln(land)	−1.598 ***	0.541	0.106	0.719	0.362	0.304
ln(capital)	−0.812	0.474	0.637 ***	0.144	0.371 **	0.154
ln(materials)	0.101	0.371	−0.394	0.600	−0.107	0.217
ln(land)xln(land)	−0.315 ***	0.093	−0.038	0.158	−0.120 ***	0.044
ln(capital)xln(capital)	−0.106 ***	0.029	0.014	0.017	0.014	0.010
ln(materials)xln(materials)	−0.074	0.086	0.077	0.131	0.071 *	0.039
ln(land)xln(capital)	−0.037	0.090	0.226 ***	0.053	0.082 **	0.041
ln(land)xln(materials)	0.134	0.121	−0.103	0.230	0.003	0.065
ln(capital)xln(materials)	−0.228 **	0.081	−0.090	0.095	−0.040	0.039
ln(land)xln(output)	0.020	0.052	0.060	0.083	−0.091***	0.031
ln(capital)xln(output)	0.080 **	0.035	0.048	0.083	−0.004	0.022
ln(materials)xln(output)	0.024	0.039	0.029	0.094	0.045	0.028
ln(output)xln(output)	−0.070 ***	0.010	−0.003	0.012	−0.065 ***	0.008
Inefficiency model:						
Constant	1.544	1.550	2.350 **	0.986		
age	−0.033	0.056	−0.057	0.034		
age^2	0.0004	0.0005	0.0004	0.0003		
education	0.015	0.015	0.024 **	0.010		
training class	−0.116 *	0.059	0.010 *	0.005		
experience	0.003	0.004	0.010 ***	0.003		
farm size	0.216 **	0.124	0.204 ***	0.021		
crop diversification	−0.525	0.406	0.820 ***	0.244		
family labor/chili-cultivated area	−0.218 ***	0.038	−0.141 ***	0.025		
$\sigma_s^2 = \sigma_\mu^2 + \sigma_v^2$	0.015 ***	0.003	0.023 ***	0.003	0.075 ***	0.021
$\gamma = \sigma_\mu^2 / \sigma_s^2$	0.601 **	0.244	0.999 ***	0.016	0.920 ***	0.101
Log-likelihood	25.957		28.098		35.096	
No. of farms	36		59		95	

***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

In the stochastic frontier analysis, the variance ratio parameter, γ, was used to indicate the relative contribution of μ to the error components. This parameter has a value between 0 and 1. A value close to zero would mean that the variance in the error components is totally due to random noise. In contrast, a value close to one would indicate that most of the variance stems from technical inefficiency. Table 4 shows that the values of γ for the TE^G of GAP farms and TGR models were large and statistically significant at the 1% level, suggesting that the variance in their error components could be almost totally described by the effects of inefficiency. For non-GAP farms, the value was not that large, but it was significant at the 5% level. These results suggest that the technical inefficiency effects on chili production in the sample were substantial.

Table 5 also shows several tests that were conducted on the TE^G and TGR models to ensure the quality of the empirical results. The first test (H_0:) aimed to explore whether the translog form was suitable for the TE^G and TGR models or whether the Cobb–Douglas form was more suitable. The results indicate that the translog form is the preferred specification for both the TE^G and TGR models.

Second, the null hypothesis (H_0: $\gamma = \delta_0 = \ldots = \delta_8 = 0$) is related to the inefficiency effect model. In this study, it was used to explore whether inefficiency effects are absent in Thai chili farms. In other words, it was used to determine whether the chili farms were operating on a technically efficient frontier and that the technical inefficiency effects were zero. The results show that the null hypotheses for Thai GAP and non-GAP farms were firmly rejected at the 1% significance level, implying that inefficiency effects occur in the chili farms. Third, the test (H_0: $\delta_1 = \ldots = \delta_8 = 0$) was used to determine whether farm-specific and environmental variables included in the inefficiency effect model do not influence the level of TE in both GAP and non-GAP chili farms. Once again, these null hypotheses were rejected at the 1% level, suggesting that the collective impact of the variables on the technical inefficiency model was statistically significant. In other words, if taken as a whole, the selected farm-specific and environmental variables were descriptive of the efficiency in both farm groups.

Table 5. Hypothesis tests for parameters of the meta-frontier analysis.

Null Hypothesis	Model	Statistic Test	Critical Value [1]	Result
	Good agricultural practice (GAP) farms (*n* = *59*)			
H_0: $\beta_{nk}; \beta_{yn}; \beta_{yy} = 0$	Translog vs. Cobb–Doulglas	30.79	23.20	Rejected H_0
H_0: $\gamma = \delta_0 = \ldots = \delta_8 = 0$	No inefficiency effects	74.91	23.20	Rejected H_0
H_0: $\delta_1 = \ldots = \delta_8 = 0$	No farm-specific factors	70.77	20.09	Rejected H_0
	Non-GAP farms (*n* = *36*)			
H_0: $\beta_{nk}; \beta_{yn}; \beta_{yy} = 0$	Translog vs. Cobb–Doulglas	57.12	23.20	Rejected H_0
H_0: $\gamma = \delta_0 = \ldots = \delta_8 = 0$	No inefficiency effects	47.62	23.20	Rejected H_0
H_0: $\delta_1 = \ldots = \delta_8 = 0$	No farm-specific factors	44.30	20.09	Rejected H_0
	Technology gap ratio (TGR) (*n* = *95*)			
H_0: $\beta_{nk}; \beta_{yn}; \beta_{yy} = 0$	Translog vs. Cobb–Douglas	75.62	23.20	Rejected H_0

[1] denotes significance at the 1% level.

In the final step, in accordance with Coelli et al. [58] and Coelli [120], the TE_i^G and TGR_i efficiency scores of the *i*th farm were calculated using Equations (7) and (10). Hence, the meta-frontier efficiency scores, TE_i^*, of the *i*th farm were retrieved using Equation (11). Table 6 provides the descriptive statistics for the TE_i^G, TGR_i, and TE_i^* scores by farm groups.

Recall that the primary aim of this study was to assess the impact of GAP adoption on the TE of the farms. The average TE_i^* score for the GAP farms was 0.383, which is lower than that of the non-GAP farms (0.399). Based on the Wilcoxon two-sample and ANOVA tests, the results reveal no statistically significant difference between the average scores of the two farm groups. However, when comparing TGR efficiencies, the average score of the GAP farms (0.861) was found to be higher than that of the non-GAP farms (0.769). Again, based on the above tests (at the 1% significance level), the results confirm the existence of a difference in TGR scores between the two farm types. This study concludes that GAP adoption positively affects TE in Thai chili farms. This conclusion is consistent with that of previous studies conducted by Krasachat [30,31] for Thai chili farms, Taraka et al. [28] for Thai rice farms, De Silva and Rathnayaka [29] for Sri Lankan tea smallholders, and Charamba and Thomas [33] for maize production in Namibia. However, this result contrasts with that of Thang and Dung [32], and Krasachat and Yaisawarng [7], who did not find an effect of GAP adoption on TE in Vietnamese grape and apple farms and Thai chili farms.

Table 6. Meta-frontier distance function technical efficiency results.

	Average	S.D. [1]	Min	Max
Good agricultural practice (GAP) farms				
Group technical efficiency (TE^G)	0.442	0.172	0.139	0.991
Technology gap ratio (TGR)	0.861	0.062	0.717	0.967
Meta-frontier efficiency (TE *)	0.383	0.158	0.117	0.889
Non-GAP farms				
Group technical efficiency (TE^G)	0.513	0.232	0.154	0.988
Technology gap ratio (TGR)	0.769	0.147	0.453	0.970
Meta-frontier efficiency (TE *)	0.399	0.214	0.118	0.913
Hypothesis	ANOVA Test		Wilcoxon Two-Sample Test	
H_0: No difference in the averaged meta-frontier technical efficiency (TE *) between GAP farms and non-GAP farms	F-value = 0.182 Prob > F = 0.671		Z-value = −0.061 Pr > ∣Z∣ = 0.951	
H_0: No difference in the averaged technology gap ratio (TGR) between GAP farms and non-GAP farms	F-value = 17.884 *** Prob > F = <0.001		Z-value = −2.631 *** Pr > ∣Z∣ = 0.009	

[1] represents the standard deviation. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.3. Determinants of Meta Efficiency

Based on the previous 'indirect' procedure results, this study found no differences between GAP and non-GAP farms for farm-specific and environmental variables. Through this, we can directly compare TE scores between the two farm groups because of the absence of sample selection bias, as described earlier. The results indicate a difference in TE between the two groups, implying that this difference was solely derived from the GAP adoption, not the above variables. However, it is noteworthy that group efficiency scores (TE^G) across farms in each group, as shown in Table 6, are comparable because they were evaluated against the same frontier. Given the relative difference in efficiency levels among those farms within each group of GAP and non-GAP farms, it was worthwhile further investigating why some firms can obtain comparatively high levels of efficiency. In contrast, others are technically less efficient [99]. Variation in the TE among farms in each group may result from farm-specific and environmental factors that effectively impact producers' ability to use the existing technology.

Table 4 shows the parameter estimates for the inefficiency effect models. Note that each farm-specific or environmental variable with a positive (negative) coefficient indicates an increase (a decrease) in the inefficiency score. However, following common practices, interpretation was carried out in terms of TE rather than inefficiency.

The empirical results suggest four important findings. First, the estimated coefficients of the ratio of family labor to chili-cultivated land have a negative value. They are statistically significant at the 1% level for both GAP and non-GAP farms. This means that GAP and non-GAP farmers can achieve higher TE levels if they intensively use family labor for chili production. This is because chili is a labor-intensive crop that requires the engagement of family labor in farm activities. Thus, the more intensive the labor employment in chili-growing land, the higher the TE of chili production. Additionally, as indicated by Masterson [114], family labor requires less advice and monitoring and is more inspired than hired labor and thus should be more efficient. This result is similar to that of Khai and Yabe [118] and Mithiya et al. [119].

Second, the estimated coefficient of farm size was significantly positive for both GAP and non-GAP farms, implying that a larger chili farm will likely have a lower TE than a smaller one. In this study, a farm with less than two rai of the chili-cultivated area was found to have greater efficiency than a farm with equal to, or more than, two rai of chili-cultivated land. This is because of the advantages of small farms employing family labor or labor-intensive processes [123] and those of producers with smaller farms engaged in more intensive land use who, thus, thoroughly care for their land [114]. This finding is similar to the empirical results from previous studies (e.g., [30,59,114]). In contrast, Krasachat [31] pointed out that a relationship between farm size and TE does not exist in Thai chili farms, while Jirarud and Suwanmaneepong [112] and Srisompun and Boontang [124] reported that larger Thai cassava and rice farms obtain greater TE. Therefore, mixed results exist for the relationship between farm size and TE.

Third, this study found mixed results concerning the relationship between the technical training variable and TE between the two farmer types. Training classes were defined as short courses, generally related to chili production and GAP issues, attended by farmers. The estimated coefficient for the training classes was found to be significantly negative for non-GAP farmers, suggesting that the training classes aiming to encourage non-GAP farmers to introduce GAP led to improved TE. This result is similar to that of Li and Sicular [83], Jara-Rojas et al. [107], and Cao et al. [113], who indicated a positive relationship between training and TE. However, the estimated coefficient of the training courses was found to be positive for GAP farmers. This implies that GAP farmers did not benefit from the training courses in terms of a boost in TE after a decade of GAP development in the sample areas. Therefore, training courses may need to be modified and developed more effectively, especially for GAP farms.

Fourth, the education variable showed a negative and significant relationship with TE in GAP farms. This finding implies that the more education farmers have, the smaller the TE, because the farmers persist with traditional production methods, despite the dispersal of modern agricultural technology such as high-yield variety seeds and irrigation [112,125]. Farmers insisted on using those techniques because they provided for their needs when adapting to changing social and economic conditions [125]. In addition, the proportion of the Thai agricultural workforce over 60 years of age has been two times higher in recent years, and the farm workforce has a higher median age than other industries [126]. As found in this study sample, older farmers usually have less motivation to improve their farms, are less likely to accept new knowledge and more efficient techniques, are less attempting in farm investment, and are less productive than younger farmers [127]. Younger farmers with better education choose to operate their farms with higher multifunctional farming using innovative mixed or organic production systems. They are likely to apply more sophisticated techniques [128]. However, in Thailand, older farmers tend to play an essential role in farm production due to their high traditional knowledge and experience in conventional farming techniques [126].

Based on the characteristics of farm types introduced by Schipane [129] and Toulmin and Guèye [130], Thai farms can be divided into two main groups: family and commercial. Family farms are operated and owned by a family, and their priority objectives are self-consumption in the farm households and selling some chili to the markets. These farms, on average, are relatively small (for example, 0.24 hectares in the sample) but have high diversification to reduce risk exposure. Commercial farms are mostly relatively large-scale operations. They produce mainly for sale or employ their produce as an ingredient in the food processing industry, use little or no family labor, and are controlled and owned by a company. Toulmin and Guèye [130] reported that, in West Africa, family farms could not deal with price, climate, and risk challenges. Still, they could maintain some extent of autonomy and flexibility that helped them handle difficult circumstances and adjust to emerging economic opportunities.

In contrast, commercial farms receive government support for privileged access to inputs and credit. In the case of Thailand, farms generally encounter relatively similar situations to those faced by farms in West Africa. However, comparing well-educated modern farmers and traditional farmers, well-educated modern farmers use modern equipment and technology-intensive agriculture methods. In contrast, traditional farmers apply conventional and age-old farming tools. Chuenchooklin et al. [131] reported that a young modern melon farmer earned a higher net income than a conventional farmer in Central Thailand.

Hyuha et al. [132] indicated that education is supposed to improve labor quality, but its impact depends on the environment. Schultz [133] confirmed that the effect of education is higher in rapidly changing technological or economic environments because the changes create an incentive to reallocate the resources going into farm production, while education positively influences the rate of resource reallocation. However, the chili farmers in the sample operated using traditional methods, slowly altering environments and lessening the influence of education.

In this study, the result agrees with that of Onumah and Acquah [110], Anang et al. [111], and Jirarud and Suwanmaneepong [112], who estimated the TE of fish farms in Ghana and rice farms in northern Ghana and Thailand. In contrast, Khai and Yabe [118], Asante et al. [134], and Ali et al. [135] found that educated rice farmers in Ghana, Vietnam, and Pakistan achieved higher levels of TE, while Taraka et al. [28] and Srisompun and Boontang [124] did not find any effect of education on TE for Thai rice and cassava farms. Therefore, the mixed effects of years of schooling on TE in the literature are due to differences in the crops or regions studied.

Fifth, surprisingly, this study reveals that the experienced GAP farmers achieved lower levels of TE. This may be because most experienced farmers may prefer to depend solely on their knowledge and may not be likely to pursue advice services from the extension office. This may result in inefficiency in comparison with their inexperienced counterparts, who may be more eager to use extension services, as pointed out by Asravor et al. [26]. This finding is similar to that of Asravor et al. [26] and Onumah et al. [109].

Sixth, this study found a significantly positive estimated coefficient of crop diversification (0.820) for GAP chili farms only, as shown in Table 4. Note that a higher Simpson index of diversification (SID) implies greater crop diversification. This finding indicates that greater diversity in crops on a GAP farm leads to greater inefficiency or lower TE. This may be because farmers would have more difficulty allocating farm resources, since they are growing many crops concurrently. In addition, farmers who differentiate their crops tend to have small and fragmented lands. Thus, the use of mechanization in their farms is impeded, as indicated by Nguyen [117]. This finding agrees with that of previous studies (e.g., [55,136]), while it contradicts the findings of other studies (e.g., [37,88,115–117]), confirming that crop diversity significantly improves TE.

Finally, there is no evidence that farmers' age and age squared influence the TE of chili farms. This finding agrees with the results of Mzyece and Ng'ombe [55] for smallholder farmers in Zambia. In contrast to Tenaye [108], the results indicate that older farmers have more efficiency than younger farmers in smallholder agriculture in Ethiopia.

5. Conclusions

This study applied a stochastic meta-frontier input distance function approach to measuring farm-specific TE and its determinants for GAP and non-GAP farms. This study assessed 2018 farm-level survey data from Thai chili farms using a single estimation technique involving the MLE method. An 'indirect' procedure was used to decrease the potential observable sample selectivity bias. The hypothesis tests indicated the existence of a difference in production technologies between GAP and non-GAP farms. However, no difference in the technologies was found between farms growing rainy-season and dry-season varieties. This confirms that the meta-frontier approach is an appropriate way to analyze the impacts of GAP adoption and farm-specific factors on TE in Thai chili farms.

The results indicate that producers who apply GAP achieve higher levels of TE than those who do not. It is possible to increase efficiency levels for both GAP and non-GAP farmers. Producers who use family labor intensively and have smaller farms are likely to obtain higher levels of TE. In contrast, GAP farmers with higher levels of education, cultivation experience, and crop diversification tend to have lower levels of TE than their counterparts. In addition, non-GAP farmers who attend training courses appear to attain higher levels of TE, whereas GAP farmers have lower levels of TE. Finally, there is no confirmation that farmers' age and age squared affect the TE of chili farms.

The findings confirm the advantages of adopting GAP technology, using family labor intensively, operating on small farms, and providing training classes (for non-GAP farms) for Thai chili farms. However, the results suggest that there are disadvantages for GAP farmers with higher levels of education, experience, and crop diversity. Therefore, the Thai government and private agencies should promote GAP adoption by chili farms. Through this, farmers could improve their productive efficiency, health, income, and access to the safe agricultural products market. In addition, as mentioned earlier, clean technologies, such as GAP, could have positive effects on the environment [6]. Thus, GAP implementation should positively impact sustainable chili production in Thailand over the long term.

To help chili farmers improve their TE further, the government and private agencies should encourage them to produce products more efficiently by utilizing family labor intensively and growing chili in small plots (i.e., less than two rai for this sample). This not only assists farmers by saving them the costs of hired labor, as mentioned earlier [57], but also allows them to manage chili fields more intensively. In addition, government policies should focus on investing in an increase in farmers' knowledge about new technology applications and expenditure management: for example, a reduction in farm input through short training courses or extension services. These actions also need to be reformed and developed more effectively and conducted separately for GAP and non-GAP farms. Moreover, guidelines on short-term training to increase GAP farmers' knowledge and inform farmers about the disadvantages of crop diversity on TE to improve TE in chili farms in Thailand should be developed.

Because this study was conducted under a pilot project, it had to be operated with modest time and resources, which limits the study's sample size and scope. This study's empirical results could be strengthened by supporting evidence from further operational considerations, including the need to increase the sample size by extending the study areas and data collection to other regions where GAP are promoted. Through this, the sample size would be more prominent, environmental issues could be collected to explore their effects on TE, and the matching procedure technique to correct the sample selection bias could be applied. In addition, information on farmers' family workers must be included in the data collection to account for the quality of different types of family labor.

Funding: The KMITL Business School (former Faculty of Administration and Management), King Mongkut's Institute of Technology Ladkrabang, grant number 2562-0212017.

Institutional Review Board Statement: This study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethics Committee of King Mongkut's Institute of Technology Ladkrabang (EC-KMITL_64_042).

Informed Consent Statement: All subjects gave their informed consent for inclusion before they participated in this study.

Data Availability Statement: Restrictions apply to the availability of these data. Data were obtained from the KMITL Business School, grant number 2562-0212017, and are available from the corresponding author with the permission of the KMITL Business School.

Acknowledgments: This research was commenced when Suthathip Yaisawarng spent her sabbatical leave at King Mongkut's Institute of Technology Ladkrabang, Thailand. The author appreciates the comments, encouragement, and assistance given by Suthathip Yaisawarng during the data collection and preparation period. The author acknowledges the funding support. It would not have been feasible to complete this project without this support.

Conflicts of Interest: The author declares no conflict of interest.

References

1. Malorgio, G.; Felice, A. Chapter 9. Trade and logistics: The fruit and vegetables industry. In *MediTERRA 2014 (English): Logistics and Agro-Food Trade. A Challenge for the Mediterranean*; Dans, C.L., Ed.; Presses de Sciences Po.: Paris, France, 2014; pp. 149–171. [CrossRef]
2. Krause, H.; Lippe, R.S.; Grote, U. Adoption and income effects of public GAP standards: Evidence from the horticultural sector in Thailand. *Horticulturae* **2016**, *2*, 18. [CrossRef]
3. Gorodnichenko, Y.; Svejnar, J.; Terrell, K. Globalization and innovation in emerging markets. *Am. Econ. J.-Mcroecon.* **2010**, *2*, 194–226. Available online: https://www.jstor.org/stable/25760301 (accessed on 20 October 2022). [CrossRef]
4. Wongprawmas, R.; Canavari, M.; Waisarayutt, C. A multi-stakeholder perspective on the adoption of good agricultural practices in the Thai fresh produce industry. *Brit. Food J.* **2015**, *117*, 2234–2249. [CrossRef]
5. Hobbs, J.E. *Incentives for the Adoption of Good Agricultural Practices (GAPs)*; Background Paper for the FAO Expert Consultation on a Good Agricultural Practice Approach: Rome, Italy, 2003. Available online: http://www.fao.org/3/ag854e/ag854e00.pdf (accessed on 20 October 2022).
6. Aldieri, L.; Makkonen, T.; Vinci, C.P. Environmental knowledge spillovers and productivity: A patent analysis for large international firms in the energy, water, and land resources fields. *Resour. Policy* **2020**, *69*, 101877. [CrossRef]
7. Krasachat, W.; Yaisawarng, S. Directional distance function technical efficiency of chili production in Thailand. *Sustainability* **2021**, *13*, 741. [CrossRef]
8. Henson, S.; Humphrey, J. Understanding the complexities of private standards in global agri-food chains as they impact developing countries. *J. Dev. Stud.* **2010**, *46*, 1628–1646. [CrossRef] [PubMed]
9. Subervie, J.; Vagneron, I. Can Fresh Produce Farmers Benefit from Global Gap Certification? In *The Case of Lychee Producers in Madagascar*; Paper presented to the Conference of International Association of Agricultural Economists: Foz do Iguacu, Brazil, 2012. [CrossRef]
10. Oya, C.; Schaefer, F.; Skalidou, D.; McCosker, C.; Langer, L. Effects of certification schemes for agricultural production on socio-economic outcomes in low- and middle-income countries: A systematic review. *Campbell Syst. Rev.* **2017**, *13*, 1–346. [CrossRef]
11. Fiankor, D.-D.D.; Flachsbarth, I.; Masood, A.; Brümmer, B. Does GlobalGAP certification promote agrifood exports? *Eur. Rev. Agric. Econ.* **2020**, *47*, 247–272. [CrossRef]
12. Amekawa, Y.; Bumrungsri, S.; Wayo, K.; Gebre, G.G.; Hongsibsong, S. Pesticide use under public good agricultural practices standard: A comparative study in Thailand. *Agriculture* **2022**, *12*, 606. [CrossRef]
13. Salakpetch, S. Quality management system: Good agricultural practices (GAP) for on-farm production in Thailand. In *Good Agricultural Practice (GAP) in Asia and Oceania. Proceedings International Seminar on Technology Development for Good Agricultural Practice in Asia and Oceania*; Hu, S., Bejosano-Gloria, G., Eds.; Food and Fertilizer Technology Center: Tsukuba, Japan, 2005; pp. 44–53. Available online: https://www.fftc.org.tw/en/publications/detail/728 (accessed on 25 October 2022).
14. Laosutsan, P.; Shivakoti, G.P.; Soni, P. Factors influencing the adoption of good agricultural practices and export decision of Thailand's vegetable farmers. *Int. J. Commons* **2019**, *13*, 867–880. [CrossRef]
15. Athipanyakul, T.; Pak-Uthai, W. Determinants of good agricultural practices (GAP) adoption in the chili production system in Northeastern Thailand: A case of participatory approach. *Int. J. Environ. Rural Dev.* **2012**, *3*, 175–180. Available online: http://iserd.net/ijerd32/32175.pdf (accessed on 19 October 2022).
16. FAO. The Vegetable Sector in Thailand—A Review. In *Regional Office for Asia and Pacific*; RAP Publication: Bangkok, Thailand, 1999. Available online: http://www.fao.org/3/ac145e/AC145E00.htm#for (accessed on 20 October 2022).
17. Department of Agriculture. *Chili Production Situation*; Horticulture Research Institute: Bangkok, Thailand, 2020. Available online: https://www.doa.go.th/hort/?page_id=19041 (accessed on 20 October 2022).
18. Mustafa, U.; Ali, M.; Satapornvorasak, T.; Dissataporn, O.; Thailand, A.M. (Eds.) *Food Chain Analysis: Setting Research Priorities in Asia*; The World Vegetable Center, GTZ: Shanhua, Taiwan, 2006; pp. 197–245. Available online: https://worldveg.tind.io/record/13713/ (accessed on 25 October 2022).
19. Ooraikul, S.; Siriwong, W.; Siripattanakul, S.; Chotpantarat, S.; Robson, M. Risk assessment of organophosphate pesticides for chili consumption from chili farm area, Ubon Ratchathani Province, Thailand. *J. Health Res.* **2011**, *25*, 141–146. Available online: https://he01.tci-thaijo.org/index.php/jhealthres/article/view/81160 (accessed on 25 October 2022).
20. Wanwimolruk, S.; Phopin, K.; Boonpangrak, S.; Prachayasittikul, V. Food safety in Thailand 4: Comparison of pesticide residues found in three commonly consumed vegetables purchased from local markets and supermarkets in Thailand. *PeerJ* **2016**, *4*, e2432. [CrossRef] [PubMed]
21. Poapongsakorn, N.; Ruhs, M.; Tangjitwisuth, S. Problems and outlook of agriculture in Thailand. *TDRI Q. Rev.* **1998**, *13*, 3–14. Available online: https://tdri.or.th/2012/12/tdri-quarterly-review-june-1998/ (accessed on 25 October 2022).

22. Nicolopoulou-Stamati, P.; Maipas, S.; Kotampasi, C.; Stamatis, P.; Hens, L. Chemical pesticides and human health: The urgent need for a new concept in agriculture. *Front. Public Health* **2016**, *4*, 148. [CrossRef] [PubMed]
23. Hughes, D.; Thongkum, W.; Tudpor, K.; Turnbull, N.; Yukalang, N.; Sychareun, V.; Vo, T.V.; Win, L.L.; Watkins, A.; Jordan, S. Pesticides use and health impacts on farmers in Thailand, Vietnam, and Lao PDR: Protocol for a survey of knowledge, behaviours and blood acetylcholinesterase concentrations. *PLoS ONE* **2021**, *16*, e0258134. [CrossRef] [PubMed]
24. Schreinemachers, P.; Schad, I.; Tipraqsa, P.; Williams, P.M.; Neef, A.; Riwthong, S.; Sangchan, W.; Grovermann, C. Can public GAP standards reduce agricultural pesticide use? The case of fruit and vegetable farming in northern Thailand. *Agric. Hum. Values* **2012**, *29*, 519–529. [CrossRef]
25. Aktar, W.; Sengupta, D.; Chowdhury, A. Impact of pesticides use in agriculture: Their benefits and hazards. *Interdisc Toxicol.* **2009**, *2*, 1–12. [CrossRef] [PubMed]
26. Asravor, J.; Onumah, E.E.; Osei-Asare, Y.B. Efficiency of chili pepper production in the Volta Region of Ghana. *J. Agric. Ext. Rural Dev.* **2016**, *8*, 99–110. [CrossRef]
27. López-Penabad, M.-C.; Maside-Sanfiz, J.M.; Torrelles Manent, J.; Iglesias-Casa, A. Application of the DEA double bootstrap to analyze efficiency in Galician Sheltered Workshops. *Sustainability* **2020**, *12*, 6625. [CrossRef]
28. Taraka, K.; Latif, I.A.; Shamsudin, M.N.; Sidique, S.B.A. Estimation of technical efficiency for rice farms in central Thailand using stochastic frontier approach. *Asian J. Agric. Dev.* **2012**, *9*, 1–11. [CrossRef]
29. De Silva, T.B.Y.A.; Rathnayaka, R.M.S.D. Impact of Good Agricultural Practices on Technical Efficiency of Tea Small Holders. In Proceedings of the Research Symposium on Value Addition for Sustainable Development, Uva Wellassa University of Sri Lanka, Badulla, Sri Lanka, 11–12 December 2014. Available online: http://www.uwu.ac.lk/wp-content/uploads/Pro-TEA.pdf (accessed on 20 October 2022).
30. Krasachat, W. Directional Input Distance Function Technical Efficiency of Chili Production in Thailand: Parametric Approach. In Proceedings of the 28th International Scientific Conference on Economic and Social Development, Paris, France, 19–20 April 2018; Omazic, M.A., Roska, V., Grobelna, A., Eds.; Varazdin Development and Entrepreneurship Agency: Varazdin, Croatia; Faculty of Management University of Warsaw: Warsaw, Poland; University North: Koprivnica, Croatia, 2018; pp. 464–471.
31. Krasachat, W. Technical inefficiency of chili farms in Thailand: A parametric approach. *Test. Eng. Manag.* **2020**, *83*, 30415–30421.
32. Thang, D.Q.; Dung, D.V. The efficiency of development investment in agricultural production applying good agricultural practices (Gap) standard of household—Case study of grapes and apple in Ninh Thuan province, Vietnam. *J. Bus. Manag. Econ. Res.* **2019**, *3*, 8–16. [CrossRef]
33. Charamba, V.; Thomas, B. Estimation of farm level technical efficiency for small scale irrigation farmers of Etunda and Olushandja irrigation schemes of North-Central Namibia: A stochastic frontier approach. *J. Dev. Agric. Econ.* 2022, *in press*.
34. FAO. *Development of a Framework for Good Agricultural Practices*; Committee on Agriculture, Seventeenth Session Food and Agriculture Organization: Rome, Italy, 2003. Available online: http://www.fao.org/3/y8704e/y8704e.htm (accessed on 20 October 2022).
35. Ministry of Agriculture and Cooperatives. *Good Agricultural Practices for Peppers. Royal Gaz*; Volume 122 Special Section 117D; Office of the Prime Minister: Bangkok, Thailand, 2005. Available online: https://www.acfs.go.th/standard/download/eng/GAP_peppers.pdf (accessed on 25 October 2022).
36. Villano, R.; Bravo-Ureta, B.; Solís, D.; Fleming, E. Modern rice technologies and productivity in the Philippines: Disentangling technology from managerial gaps. *J. Agric. Econ.* **2015**, *66*, 129–154. [CrossRef]
37. Ahmadzai, H. *Crop Diversification and Technical Efficiency in Afghanistan: Stochastic Frontier Analysis*; CREDIT Research Paper No. 17/04; The University of Nottingham, Centre for Research in Economic Development and International Trade (CREDIT): Nottingham, UK, 2017. Available online: http://hdl.handle.net/10419/162749 (accessed on 19 October 2022).
38. Phetcharat, C.; Chalermphol, J.; Siphumin, P.; Khempet, S. The determinants of farmers' cropping systems adoption: A case of the upland farmers in Northern Thailand. *Appl. Econ. J.* **2017**, *24*, 52–62. Available online: https://so01.tci-thaijo.org/index.php/AEJ/article/view/115018 (accessed on 25 October 2022).
39. Rosa-Schleich, J.; Loos, J.; Mußhoff, O.; Tscharntke, T. Ecological-economic trade-offs of Diversified Farming Systems—A review. *Ecol. Econ.* **2019**, *160*, 251–263. [CrossRef]
40. Madau, F.A. Technical efficiency in organic and conventional farming: Evidence from Italian cereal farms. *Agric. Econ. Rev.* **2007**, *8*, 5–22. [CrossRef]
41. Acknowledge Management Institution. *Thailand 4.0: Thriving in the 21st Century through Security, Prosperity & Sustainability*; Thailand Research Fund: Bangkok, Thailand, 2017. Available online: https://thaiembdc.org/2016/11/21/thailand-4-0-thriving-in-the-21st-century-through-security-prosperity-sustainablility/ (accessed on 19 October 2022).
42. Dörr, A.; Grote, U. The role of certification in the Brazilian fruit sector. *Rev. Econ. Contemp.* **2009**, *13*, 539–571. [CrossRef]
43. Purnamasari, F.; Waluyati, L.R.; Masyhuri, M. The effect of good agriculture practices (GAP) on soybean productivity with Cobb-Douglas production function analysis in Kulon Progo Regency. *Agro Ekonomi* **2017**, *28*, 220–236. [CrossRef]
44. Bayramoglu, Z.; Gundogmus, E.; Tatlidil, F.F. The impact of EurepGAP requirements on farm income from greenhouse tomatoes in Turkey. *Afr. J. Agric. Res.* **2010**, *5*, 348–355. Available online: https://academicjournals.org/journal/AJAR/article-stat/C81866C27521 (accessed on 19 October 2022).
45. Bairagi, S.; Mishra, A.K.; Giri, A. Good agricultural practices, farm performance, and input usage by smallholders: Empirical evidence from Nepal. *Agribusiness* **2019**, *35*, 471–491. [CrossRef]

46. Lazaro, V.; Rajendran, S.; Afari-Sefa, V.; Kazuzuru, B. Analysis of good agricultural practices in an integrated maize-based farming system. *Int. J. Veg. Sci.* **2017**, *23*, 598–604. [CrossRef]
47. Asfaw, S.; Mithöfer, D.; Waibel, H. What impact are EU supermarket standards having on developing countries' export of high-value horticultural products? Evidence from Kenya. *J. Int. Food Agribus. Mark.* **2010**, *22*, 252–276. [CrossRef]
48. Tran, H.B.C.; Le, T.Q.A. Impact of VietGAP Vegetable Production on the Health of Farmers Thua Thien Hue Province, Vietnam. In *EEPSEA Research Report No. 2015-RR19*; Economy and Environment Program in Southeast Asia (EEPSEA): Laguna, Philippines, 2015. Available online: https://eepseapartners.org/impact-of-vietgap-vegetable-production-on-the-health-of-farmers-in-thua-thien-hue-province-vietnam/ (accessed on 25 October 2022).
49. Thanh Truc, N.T.; Thuc, L.V. Impacts of adopting specialized agricultural programs relying on "good practice"-Empirical evidence from fruit growers in Vietnam. *Open Agric.* **2022**, *7*, 39–49. [CrossRef]
50. Lippe, R.S.; Grote, U. Costs and Benefits of GAP Standards Adoption in Thai Horticulture. In *Aktuelle Forschung in der Gartenbauökonomie, Proceedings of the 1st Symposium für Ökonomie im Gartenbau, Göttingen, Germany, 27 November 2013*; Dirksmeyer, W., Theuvsen, L., Kayser, M., Eds.; Johann Heinrich von Thünen-Institut: Braunschweig, Germany, 2015; pp. 205–214. Available online: https://literatur.thuenen.de/digbib_extern/dn062217.pdf (accessed on 20 October 2022).
51. Pongvinyoo, P.; Yamao, M.; Hosono, K. Cost efficiency of Thai national GAP (QGAP) and mangosteen farmers' understanding in Chanthaburi Province. *Am. J. Rural Dev.* **2015**, *3*, 15–23. [CrossRef]
52. Lippe, R.S.; Grote, U. Determinants affecting adoption of GLOBALG.A.P. standards: A choice experiment in Thai horticulture. *Agribusiness* **2017**, *33*, 242–256. [CrossRef]
53. CEIC. Available online: https://www.ceicdata.com/en/thailand/producer-price-index-2010100-classification-of-production-by-activities-cpa/producer-price-index (accessed on 20 October 2022).
54. Wu, Z.; Liu, Y.; Li, G.; Han, Y.; Li, X.; Chen, Y. Influences of environmental variables and their interactions on Chinese farmland soil organic carbon density and its dynamics. *Land* **2022**, *11*, 208. [CrossRef]
55. Mzyece, A.; Ng'ombe, J.N. Does crop diversification involve a trade-off between technical efficiency and income stability for rural farmers? Evidence from Zambia. *Agronomy* **2020**, *10*, 1875. [CrossRef]
56. Kostov, P.; Davidova, S.; Bailey, A. Effect of family labour on output of farms in selected EU Member States: A non-parametric quantile regression approach. *Eur. Rev. Agric. Econ.* **2018**, *45*, 367–395. [CrossRef]
57. Saidah, Z.; Harianto; Hartoyo, S.; Asmarantaka, R.W. Change on production and income of red chili farmers. *IOP Conf. Ser.: Earth Environ. Sci.* **2020**, *466*, 012003. [CrossRef]
58. Coelli, T.J.; Rao, D.S.P.; O'Donnell, C.J.; Battese, G.E. *An Introduction to Efficiency and Productivity Analysis*, 2nd ed.; Springer: New York, NY, USA, 2005. [CrossRef]
59. Morais, G.A.S.; Silva, F.F.; Freitas, C.O.d.; Braga, M.J. Irrigation, technical efficiency, and farm Size: The case of Brazil. *Sustainability* **2021**, *13*, 1132. [CrossRef]
60. Ajibefun, I.A. An evaluation of parametric and non-parametric methods of technical efficiency measurement: Application to small scale food crop production in Nigeria. *J. Agri. Soc. Sci.* **2008**, *4*, 95–100. Available online: http://www.fspublishers.org/published_papers/70167_..pdf (accessed on 19 October 2022).
61. Jarzębowski, S. Parametric and non-parametric efficiency measurement—The comparison of results. *Quant. Methods Econ.* **2013**, *14*, 170–179. Available online: http://qme.sggw.pl/pdf/MIBE_T14_z1.pdf (accessed on 20 October 2022).
62. Asmare, E.; Begashaw, A. Review on parametric and nonparametric methods of efficiency analysis. *Open Acc. Biostat. Bioinform.* **2018**, *2*, 1–7. Available online: https://crimsonpublishers.com/oabb/fulltext/OABB.000534.php (accessed on 19 October 2022).
63. Huang, T.H.; Wang, M.H. Comparison of economic efficiency estimation methods: Parametric and non-parametric techniques. *Manch. Sch.* **2002**, *70*, 682–709. [CrossRef]
64. Porcelli, F. Measurement of technical efficiency. A brief survey on parametric and non-parametric techniques. *Univ. Warwick* **2009**, *11*, 1–27. Available online: https://scholar.google.co.th/citation?user=r3aedaaaaj&hl=en&oi=sra (accessed on 25 October 2022).
65. Silva, E.; Mendes, A.B.; Santos, J. Efficiency measures in the agricultural Sector: The beginning. In *Efficiency Measures in the Agricultural Sector*; Mendes, A.L.D.G., Soares da Silva, E., Azevedo Santos, J., Eds.; Springer: Dordrecht, The Netherlands, 2013. [CrossRef]
66. Anyanwu, S.O.; Kalio, A.E.; Olatunji, O.; Akonye, L. A stochastic frontier production function approach to technical efficiency among cassava farmers in Rivers State, Nigeria. *Asian J. Agric. Ext. Economics Sociol.* **2014**, *3*, 746–755. [CrossRef]
67. Battese, G.E.; Corra, G.S. Estimation of a production frontier model with application to the pastoral zone of Eastern Australia. *Aust. J. Agr. Econ.* **1977**, *21*, 169–179. [CrossRef]
68. Murillo-Zamorano, L.R.; Vega-Cervera, J.A. The use of parametric and non-parametric frontier methods to measure the productive efficiency in the industrial sector: A comparative study. *Int. J. Prod. Econ.* **2001**, *69*, 265–275. [CrossRef]
69. Alrafadi, K.M.S.; Yusuf, M.; Hisham, B. Measuring efficiency in banks: A brief survey on non-parametric technique (data envelopment analysis). *Int. J. Bus. Econ. Mang.* **2016**, *3*, 52–68. [CrossRef]
70. Roman, M.; Gotiu, L. Non-parametric methods applied in the efficiency analysis of European structural funding in Romania. *J. Appl. Quant. Methods* **2017**, *18*, 1–23. Available online: https://mpra.ub.uni-muenchen.de/80548/ (accessed on 25 October 2022).
71. Musa, H.A.; Lemma, Z.; Endrias, G. Measuring technical, economic and allocative efficiency of maize production in subsistence farming: Evidence from the central rift valley of Ethiopia. *Appl. Stud. Agribusiness Comm.* **2015**, *9*, 63–73. [CrossRef]
72. Aldamak, A.; Zolfaghari, S. Review of efficiency ranking methods in data envelopment analysis. *Measurement* **2017**, *106*, 161–172. [CrossRef]

73. Zamanian, G.R.; Shahabinejad, V.; Yaghoubi, M. Application of DEA and SFA on the measurement of agricultural technical efficiency in MENA countries. *Int. J. Appl. Oper. Res.* **2013**, *3*, 43–51. Available online: https://ijorlu.liau.ac.ir/article-1-227-en.pdf (accessed on 25 October 2022).
74. Coelli, T.J. Recent developments in frontier modelling and efficiency measurement. *Aust. J. Agric. Res. Econ.* **1995**, *39*, 219–245. [CrossRef]
75. Lema, T.Z.; Tessema, S.A.; Abebe, F.A. Analysis of Technical Efficiency of Rice Production in Fogera District of Ethiopia: A Stochastic Frontier Approach. 2016. Available online: https://mpra.ub.uni-muenchen.de/77774/ (accessed on 20 October 2022).
76. Kea, S.; Li, H.; Pich, L. Technical efficiency and its determinants of rice production in Cambodia. *Economies* **2016**, *4*, 22. [CrossRef]
77. Aigner, D.; Lovell, C.A.K.; Schmidt, P. Formulation and estimation of stochastic frontier production function models. *J. Econometrics* **1977**, *6*, 21–37. [CrossRef]
78. Cuesta, R.A.; Zofío, J.L. Hyperbolic efficiency and parametric distance functions: With application to Spanish savings banks. *J. Prod. Anal.* **2005**, *24*, 31–48. [CrossRef]
79. Abdul-Majid, M.; Saal, D.S.; Battisti, G. The Efficiency and Productivity of Malaysian Banks: An Output Distance Function Approach. In *Aston Business School Research Papers No. RP0815*; Aston University: Birmingham, UK, 2008. Available online: https://research.aston.ac.uk/en/publications/the-efficiency-and-productivity-of-malaysian-banks-an-output-dist (accessed on 19 October 2022).
80. Rungsuriyawiboon, S.; O'Donnell, C. Curvature-Constrained Estimates of Technical Efficiency and Returns to Scale for U.S. In *Electric Utilities, Centre for Efficiency and Productivity Analysis Working Paper Series, No. 07/2004*; University of Queensland: Brisbane, Australia, 2004. Available online: http://www.uq.edu.au/economics/cepa/docs/WP/WP072004.pdf (accessed on 25 October 2022).
81. Coelli, T.J. On the Econometric Estimation of the Distance Function Representation of a Production Technology. In *CORE Discussion Papers*; Universite Catholique de Louvain: Ottignies-Louvain-la-Neuve, Belgium, 2000. Available online: http://hdl.handle.net/2078.1/4131 (accessed on 20 October 2022).
82. Coelli, T.; Singh, S.; Fleming, E. *An Input Distance Function Approach to the Measurement of Technical and Allocative Efficiency: With Application to Indian Dairy Processing Plants*; Working paper; School of Economics, University of New England: Armidale, NSW, Australia, 2003; Available online: https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=esam2003&paper_id=105 (accessed on 20 October 2022).
83. Li, M.; Sicular, T. Aging of the labor force and technical efficiency in crop production: Evidence from Liaoning Province, China. *China Agric. Econ. Rev.* **2013**, *5*, 342–359. [CrossRef]
84. Atkinson, S.E.; Primont, D. Stochastic estimation of firm technology, inefficiency, and productivity growth using shadow cost and distance functions. *J. Econometrics* **2002**, *108*, 203–225. [CrossRef]
85. Shephard, R.W. *Theory of Cost and Production Functions*; Princeton University Press: Princeton, NJ, USA, 1970.
86. Coelli, T.J.; Perelman, S. Technical efficiency of European railways: A distance function approach. *Appl. Econ.* **2000**, *32*, 1967–1976. [CrossRef]
87. Irz, X.; Thirtle, C. Dual technological development in Botswana agriculture: A stochastic input distance function approach. *J. Agric. Econ.* **2004**, *55*, 455–478. [CrossRef]
88. Coelli, T.J.; Fleming, E. Diversification economies and specialisation efficiencies in a mixed food and coffee smallholder farming system in Papua New Guinea. *Agr. Econ.* **2004**, *31*, 229–239. [CrossRef]
89. Rasmussen, S. Scale efficiency in Danish agriculture: An input distance–function approach. *Eur. Rev. Agric. Econ.* **2010**, *37*, 335–367. [CrossRef]
90. Honma, S.; Hu, J.-L. A meta-stochastic frontier analysis for energy efficiency of regions in Japan. *J. Econ. Struct.* **2018**, *7*, 1–16. [CrossRef]
91. Zhou, P.; Ang, B.W.; Zhou, D.Q. Measuring economy-wide energy efficiency performance: A parametric frontier approach. *Appl. Energy* **2012**, *90*, 196–200. [CrossRef]
92. Lovell, C.A.K.; Travers, P.; Richardson, S.; Wood, L. Resources and functionings: A new view of inequality in Australia. In *Models and Measurement of Welfare and Inequality*; Eichhorn, W., Ed.; Springer-Verlag: Berlin, Germany, 1994; pp. 787–807. [CrossRef]
93. Singbo, A.; Larue, B. Scale Economies and Technical Efficiency of Quebec Dairy Farms. In *Working Paper 2014-7, Center for Research on the Economics of the Environment, Agri-Food, Transports and Energy (CREATE)*; Social Science Research Network (SSRN): Rochester, NY, USA, 2014. [CrossRef]
94. Battese, G.E.; Coelli, T.J. Frontier production function, technical efficiency and panel data: With application to paddy farmers in India. *J. Prod. Anal.* **1992**, *3*, 153–169. [CrossRef]
95. Greene, W.H. The Econometric approach to efficiency analysis. In *The Measurement of Productive Efficiency: Techniques and Applications*; Fried, H.O., Lovell, C.A.K., Schmidt, S.S., Eds.; Oxford University Press: New York, NY, USA, 1993.
96. Morrison Paul, C.J.; Nehring, R. Product diversification, production systems, and economic performance in U.S. agricultural production. *J. Econometrics* **2005**, *126*, 525–548. [CrossRef]
97. Battese, G.E.; Coelli, T.J. A Model of technical inefficiency effects in a stochastic frontier production function for panel data. *Empir. Econ.* **1995**, *20*, 325–332. [CrossRef]
98. Kumbhakar, S.C.; Ghosh, S.; McGuckin, J.T. A generalized production frontier approach for estimating determinants of inefficiency in US dairy farms. *J. Bus. Econ. Stat.* **1991**, *9*, 279–286. [CrossRef]
99. Wilson, P.; Hadley, D.; Ramsden, S.; Kaltsas, I. Measuring and explaining efficiency in UK potato production. *J. Agric. Econ.* **1998**, *49*, 294–305. [CrossRef]

100. Gonzalez-Flores, M.; Bravo-Ureta, B.; Solıs, D.; Winters, P. The impact of high value markets on smallholder efficiency in the Ecuadorean Sierra: A stochastic production frontier approach correcting for selectivity bias. *Food Policy* **2014**, *44*, 237–247. [CrossRef]
101. Battese, G.E.; Rao, D.P.; O'Donnell, C.J. A Metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *J. Prod. Anal.* **2004**, *21*, 91–103. [CrossRef]
102. Huang, C.J.; Huang, T.H.; Liu, N.H. A new approach to estimating the metafrontier production function based on a stochastic frontier framework. *J. Prod. Anal.* **2014**, *42*, 241–254. [CrossRef]
103. Sipiläinen, T. Sources of productivity growth on Finnish dairy farms—Application of an input distance function. *Acta Agric. Scand. A Food Econ.* **2007**, *4*, 65–76. [CrossRef]
104. Bouchaddakh, Z.; Ben Jemaa, M.M. Risk Sharing Vs Risk Bearing and Shifting: Evidence from Conventional and Islamic Banks of MENA Region Using Metafrontier Directional Distance Functions. In *Working Paper 1042, Economic Research Forum*; Economic Research Forum (ERF): Giza, Egypt, 2016; Available online: http://bit.ly/2bDYHWl (accessed on 19 October 2022).
105. Wree, P.; Sauer, J.; Wimmer, S. Economic evaluation of yield-increasing wheat seeds using a distance function approach. *Agric. Resour. Econ. Rev.* **2018**, *47*, 610–633. [CrossRef]
106. Mohammed, B.; Ahmed, B.; Abdulsalam, Z. Technical efficiency of chilli pepper production in Kaduna State, Nigeria. *J. Exp. Agric. Int.* **2015**, *9*, 1–9. [CrossRef]
107. Jara-Rojas, R.; Bravo-Ureta, B.E.; Solís, D.; Arriagada, D.M. Technical efficiency and marketing channels among small-scale farmers: Evidence for raspberry production in Chile. *Int. Food Agribus. Manag. Rev.* **2017**, *21*, 351–364. [CrossRef]
108. Tenaye, A. Technical efficiency of smallholder agriculture in developing countries: The case of Ethiopia. *Economies* **2020**, *8*, 34. [CrossRef]
109. Onumah, E.E.; Brümmer, B.; Hörstgen-Schwark, G. Productivity of the hired and family labour and determinants of technical inefficiency in Ghana's fish farms. *Agric. Econ.–Czech* **2010**, *56*, 79–88. [CrossRef]
110. Onumah, E.E.; Acquah, H.d. A stochastic production investigation of fish farms in Ghana. *Agris On-Line Pap. Econ. Inform.* **2011**, *3*, 55–65. [CrossRef]
111. Anang, B.T.; Bäckman, S.T.; Sipiläinen, T.A. Technical efficiency and its determinants in smallholder rice production in Northern Ghana. *J. Dev. Areas* **2016**, *50*, 311–328. [CrossRef]
112. Jirarud, S.; Suwanmaneepong, S. Technical efficiency of rice farmers under the large agricultural plot scheme in Khlong Khuean District, Chachoengsao Province, Thailand. *World Rev. Entrep. Manag. Sustain. Dev.* **2020**, *16*, 228–240. [CrossRef]
113. Cao, T.M.; Thongrak, S.; Kiatpathomchai, S. Technical efficiency in rice production of the farmers in cooperatives: A study in Kien Giang Province, Mekong Delta, Vietnam. *Int. J. Econ. Res.* **2017**, *14*, 689–704.
114. Masterson, T. *Productivity, Technical Efficiency, and Farm Size in Paraguayan Agriculture*; Working Paper No. 490; The Levy Economics Institute: New York, NY, USA, 2007. Available online: http://www.levyinstitute.org/pubs/wp_490.pdf (accessed on 25 October 2022).
115. Manjunatha, A.V.; Anikc, A.R.; Speelman, S.; Nuppenau, E.A. Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India. *Land Use Policy* **2013**, *31*, 397–405. [CrossRef]
116. Ogundari, K. Crop diversification and technical efficiency in food crop production: A study of peasant farmers in Nigeria. *Int. J. Soc. Econ.* **2013**, *40*, 267–287. [CrossRef]
117. Nguyen, H. *Crop Diversification, Economic Performance and Household Behaviour Evidence from Vietnam*; MPRA Paper No. 59090; Social Science Research Network (SSRN): Rochester, NY, USA, 2014. [CrossRef]
118. Khai, H.V.; Yabe, M. Technical efficiency analysis of rice production in Vietnam. *J. ISSAAS* **2011**, *17*, 135–146. Available online: https://agris.fao.org/agris-search/search.do?recordID=PH2013000242 (accessed on 20 October 2022).
119. Mithiya, D.; Bandyopadhyay, S.; Mandal, K. Measuring technical efficiency and returns to scale in Indian agriculture using panel data: A case study of west Bengal. *Appl. Econ. Fin.* **2019**, *6*, 1–14. [CrossRef]
120. Coelli, T.J. A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation. In *Centre for Efficiency and Productivity Analysis (CEPA) Working Paper 96/07*; University of New England: Armidale, Australia, 1996. Available online: https://economics.uq.edu.au/cepa/software (accessed on 20 October 2022).
121. Agresti, A. *Categorical Data Analysis*; John Wiley and Sons: New York, NY, USA, 1990.
122. Glen, S. Wald Test: Definition, Examples, Running the Test. Available online: https://www.statisticshowto.com/wald-test/ (accessed on 20 October 2022).
123. Fan, S.; Chan-Kang, C. Is small beautiful? farm size, productivity, and poverty in Asian agriculture. *Agr. Econ.* **2005**, *32*, 135–146. [CrossRef]
124. Srisompun, O.; Boontang, S. Production efficiency and its determinants of cassava farm in Maha Sarakham, Thailand. *J. ISSAAS* **2020**, *26*, 73–85. Available online: http://issaasphil.org/wp-content/uploads/2020/06/7.-Srisompun-and-Boontang-2020-Cassava-technical-efficiency-FINAL.pdf (accessed on 20 October 2022).
125. Srimongkol, K.; Marten, G.G. Traditional agriculture in northern Thailand. In *Traditional Agriculture in Southeast Asia: A Human Ecology Perspective*; Marten, G.G., Ed.; Westview Press: Boulder, Colorado, 1986. Available online: http://gerrymarten.com/traditional-agriculture/pdfs/Traditional-Agriculture-chapter-04.pdf (accessed on 25 October 2022).
126. Gorman, M. Older Women, Older Farmers—The Hidden Face of Agriculture. Available online: https://www.helpage.org/silo/files/older-women-older-farmers-the-hidden-face-of-agriculture.pdf (accessed on 20 October 2022).
127. Jansuwan, P.; Zander, K.K. Getting young People to Farm: How effective is Thailand's young smart farmer programme? *Sustainability* **2021**, *13*, 11611. [CrossRef]

128. Jansuwan, P.; Zander, K.K. Multifunctional farming as successful pathway for the next generation of Thai farmers. *PLoS One* **2022**, *17*, e0267351. [CrossRef] [PubMed]
129. Schipane, S. A Guide to Types of Farms. Available online: https://hellohomestead.com/a-guide-to-types-of-farms (accessed on 25 October 2022).
130. Toulmin, C.; Guèye, B. Is there a future for family farming in west Africa? *IDS Bulletin* **2005**, *36*, 23–29. [CrossRef]
131. Chuenchooklin, S.; Pangnakorn, U.; Chaowakul, M.; Soonthornnondha, P. Comparative Study of Traditional and Smart-farm Irrigation Systems for Melon Farms in Chai Nat Province, Thailand. 2019. Available online: https://www.icid.org/9imic2019_papers/9th_imic_st1_paper(20).pdf (accessed on 20 October 2022).
132. Hyuha, T.S.; Bashaasha, B.; Nkonya, E.; Kraybill, D. Analysis of profit efficiency in rice production in eastern and northern Uganda. *Afr. Crop Sci. J.* **2007**, *15*, 243–253. Available online: http://www.ajol.info/index.php/acsj/article/view/54465/42983 (accessed on 20 October 2022).
133. Schultz, T.W. The value of the ability to deal with disequilibrium. *J. Econ. Lit.* **1975**, *13*, 827–846. Available online: http://www.jstor.org/stable/2722032 (accessed on 25 October 2022).
134. Asante, B.O.; Wiredu, A.N.; Martey, E.; Sarpong, D.B.; Mensah-Bonsu, A. NERICA adoption and impacts on technical efficiency of rice producing households in Ghana: Implications for research and development. *J. Exp. Agric. Int.* **2014**, *4*, 244–262. [CrossRef]
135. Ali, S.; Murtaza; Ahmad, W.; Bibi, N.; Khan, A.; Khan, J. Does education and farming experience affect technical efficiency of rice crop growers? Evidence from Khyber Pakhtunkhwa, Pakistan. *Sarhad J. Agric.* **2022**, *38*, 1147–1159. [CrossRef]
136. Llewelyn, R.V.; Williams, J.R. Nonparametric analysis of technical, pure technical, and scale efficiencies for food crop production in East Java, Indonesia. *Agric. Econ.* **1996**, *15*, 113–126. [CrossRef]