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Evaluation of Environmental Efficiency of Edible Canna Production in Vietnam

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Abstract: Increasing yield while minimizing environmental pollution in agricultural production is nowadays the primary concern in agriculture-based countries, including Vietnam. This study aims to assess the environmental efficiency and technical efficiency, as well as to determine the factors influencing efficiency of edible canna farms in Backan province, by using the stochastic frontier analysis and truncated regression, respectively. Data were collected from a face-to-face interview of 346 farmers in 2017/2018 production year. The findings revealed that the average environmental efficiency score was low, of 0.57 and 0.58 for Nari and Babe districts, respectively; while the technical efficiency was found to be higher than the environmental efficiency with 0.74 for Nari district and 0.72 for Babe district. In addition, the results of the inefficient effects and truncated regression model indicated that education, extension contact, and experience individually had a significant and positive effect on efficiency scores. Hence, the government should designate policies focused on the extension system to provide training and facilitate technology transfer for farmers.

Keywords: environmental efficiency; edible canna farm; technical efficiency; stochastic frontier analysis; truncated regression model; Vietnam

1. Introduction

Edible canna (*Canna edulis* Ker) is considered to be one of the food crops that plays an important role in the agriculture of Vietnam as well as many countries in the world. It belongs to the genus *Canna* (Cannceae), which is widely planted in the tropical regions or subtropical highlands, including South America, Thailand, China, and Vietnam [1,2]. The acreage grown by edible canna was reported to be 200,000 to 300,000 ha all over the world with the average productivity of 30 tons per ha [3]. In Vietnam, edible canna is found in both mountainous and delta areas and is the most popularly grown in the northern mountainous regions. The cultivated areas of edible canna in Vietnam were reported to be from 20,000 to 30,000 ha [4,5]. With a population of approximately 319,000, Backan is known as one of the poorest mountainous provinces of Vietnam with a poverty rate of 15.8% in 2016 [6]. In addition, the majority of the population of Backan province are minor ethnic people with three main groups, namely Tay, Dao, and Kinh. Edible canna production is considered as an important means of livelihood for these minor ethnic people in Backan province as well as other provinces in the North of Vietnam, especially the minor ethnic people who live and cultivate in the highlands area such as Tay and Dao [7]. Therefore, the development of edible canna production in a sustainable manner plays a vital role in meeting domestic demands, creating income opportunities, and more importantly, contributing to poverty reduction for the local community.

However, the edible canna production in Backan province has been facing many challenges recently. First, the edible canna production is mainly based on experience and traditional cultivation technique in upland fields. As a consequence, the quality of produce is poor and fresh tuber yield is unstable as well. Second, it is difficult to introduce canna products to new markets, i.e., the demand is low and stagnant, which results in the low and unstable domestic prices. Third, the production scale is small due to the lack of productive resources such as capital, labor, fertilizer, machine, etc. Moreover, the farm households are economically poor with low education level, which barricades them from accessing better and more advanced technique as well as being granted for credits.

From the challenges stated above, the question is whether edible canna production in Backan can bring economic and environmental benefits to farmers? What solutions can be applied to address these problems? In addition, the assessment of environmental efficiency has become an important measure in agricultural production. However, the research on environmental efficiency in agriculture is limited in Vietnam, and the recent studies regarding edible canna mainly focused on analyzing physiological characteristics, molecular structure, and quality of starch from it [8,9].

Recently, many researchers employed stochastic frontier analysis (SFA) to estimate the technical and environmental efficiency the efficiency in various agricultural crop production, e.g., rice production in Bangladesh [10], Nepal [11], and Vietnam [12,13]; tea production [14]; and vegetable production in Turkey [15]. SFA is considered as a popular methodology in agricultural studies because of its advantages compared to non-parametric data envelopment analysis (DEA). One of the advantages of SFA is that it can show the reason for deviations in production function such as measurement error and random effects, which leads to the inefficiency [16,17]. Given the commitment to sustainable development arising from the pro-environmentalism, assessing environmental efficiency in agricultural production has become an urgent issue and concerned by many countries around the world. Therefore, there were emerging number of studies that were conducted to investigate the environmental efficiency for a wide range of agricultural production either at the farm or national level (for example, Reinhard et al. [18] investigated the environmental efficiency level of dairy farms in the Netherlands by incorporating the detrimental variables into the analysis; Zhang and Xue [19] applied SFA to analyze environmental efficiency in vegetable production in China; Kouser and Mushtaq [20] assessed the environmental efficiency of rice farms in Pakistan; and Vo Hong et al. [21] evaluated and compared the environmental efficiency level for both the ecological and the normal rice farms in Vietnam). Furthermore, at the local level, Trang et al. [22] employed SFA approach to evaluate technical and environmental efficiency of farms transforming from sugarcane to shrimp cultivation in the Mekong delta region of Vietnam. The results showed that average technical efficiency was higher than environmental efficiency after changing the aim of land usage in this region. In addition, several studies have accessed and compared the technical and environmental efficiency across countries, e.g., Le et al. [23] showed the difference in technical and environmental efficiency level in agricultural production of nine countries in the East Asia during the period from 2002 to 2010, and Makutėnienė and Baležentis [24] evaluated and compared the technical and environmental efficiency in agricultural production of European countries. These studies indicated that environmental efficiency was less than technical efficiency in all countries. Authors gave evidences to show the negative effects of agricultural production on the natural environment.

This study aims to analyze both the technical and environmental efficiency of edible canna farms in Backan province of Vietnam, and in the hope to improve the livelihood of local community by adopting sustainable production of edible canna. To the authors' knowledge, studies analyzing the technical and environmental efficiency of edible canna production in Vietnam have not been explored. As such, the present study would fill up the gap in the literature.

Following the introduction, the methodology is presented, including the study area and sampling design, theoretical models, and data source. Results are then given and interpreted accordingly. Finally, the conclusions and policy implications are addressed.

2. Methodology

2.1. Study Area and Sampling Design

This study was conducted in Backan province because this region accounts for the largest edible canna production of Vietnam with more than 63,000 tons in 2017 [25]. Backan province borders Caobang province to the North, Thainguyen province to the South, Langson province to the East and Tuyenquang to the West. Backan province consists of seven districts, Pacnam, Nari, Babe, Nganson, Bachthong, Chodon, Chomoi, and one city. Given the geographical advantages, Backan province holds many opportunities to produce, process, and consume the edible canna products.

In this study, a multi-stage procedure was applied for sampling design. At first, two districts of Backan province were chosen, namely Nari and Babe due to the fact that the majority of farmers in this region grows edible canna. Then, eight communes, i.e., Conminh, Cule, Kimlu, Quangphong, Dongxa, Yenduong, Phucloc, and Khangninh, were chosen based upon the acreage and yield of edible canna production. After removing invalid samples, which include incomplete questionnaire and farms that did not use chemical fertilizer, the dataset consisting of 346 farms was used for analyses.

2.2. Theoretical and Empirical Analysis Model

2.2.1. Empirical Analysis Model for Estimating Technical Efficiency and Determinants

There are two popular methods to measure efficiency that include parametric SFA and DEA. According to Coelli [26], SFA related to the use of economic methods while DEA pays more attention to the use of linear programming. In some cases, both methods achieve highly correlated results [27]. However, the results of DEA approach are very sensitive due to the lack of examining the effect of random variables on technical efficiency [28]. Hence, in the present research, SFA was applied to estimate environmental and technical efficiency of edible canna farms because it is likely to be more suitable with agricultural studies, as the data are often influenced by natural factors [29].

The stochastic frontier production function is described as follows:

$$Y_i = f(X_i,\ Z_i,\ \beta)\ \exp\ (v_i -\ u_i) \tag{1}$$

where X_i and Z_i denote the vector of normal and detrimental inputs, which the farmer uses to produce the output Y_i, and β is a vector of an unknown parameter to be estimated. The statistical distributions for u_i and v_i are assumed distribution. v_i is independent and identically distributed to normal random variables with mean zero and constant variance as N (0, $\sigma_v{}^2$) that describes exogenous factors beyond the control of growers such as the impact of weather, climate change, luck, etc. The term u_i is one-sided of independent and identically distributed-i.i.d. random variables ($u_i \geq 0$ and $u_i \sim N^+ (0, \sigma_u{}^2)$) [20,21]. The equation is used to compute the variance parameters of the model as follows:

$$\sigma_s{}^2 = \sigma_v{}^2 + \sigma_u{}^2; \gamma = \frac{\sigma_u{}^2}{\sigma_v{}^2 +\ \sigma_u{}^2} = \frac{\sigma_u{}^2}{\sigma_s{}^2} \tag{2}$$

where $\sigma_s{}^2$ is the variance parameter, γ is applied to test the existence of random variables affecting on technical inefficiency of firms. The γ value ranges from 0 to 1. If $\gamma = 0$, there is no evidence to show the existence of technical inefficiency. In contrast, the γ value close to 1 indicates that there is an existence of technical inefficiency in edible canna production [21,30].

In this research, SFA was used to measure both technical and environmental efficiency of edible canna farms. First, the output-oriented technical efficiency (TE) of i-th edible canna farm was computed by Equation (3) as follows:

$$TE_i = \frac{Y_i}{f(X_i,\ Z_i, \beta)\ \exp\ (v_i)} = \exp\ (-u_i) \tag{3}$$

where TE_i denotes technical efficiency score of i-th farm. Therefore, $0 \leq \exp(-u_i) \leq 1$, and $u_i \geq 0$.

Second, to estimate environmental efficiency, the translog production function designed by Vo Hong et al. [21] and Reinhard et al. [18] was adopted in this study. Zhang and Xue [19] argued that the translog production function is more appropriate than the simple Cobb–Douglas function to estimate environmental efficiency because it allows one to add new variables, which represent the detrimental inputs to the environment in the production. The translog function form is expressed as Equation (4):

$$\begin{aligned} \text{Ln } Y_i = \ & \beta_0 + \beta_1 \text{Ln}X_1 + \beta_2 \text{Ln}X_2 + \beta_3 \text{Ln}Z_1 + \beta_4 \text{Ln}Z_2 + \tfrac{1}{2}\beta_{11}(\text{Ln}X_1)^2 \\ & + \tfrac{1}{2}\beta_{22}(\text{Ln}X_2)^2 + \tfrac{1}{2}\beta_{33}(\text{Ln}Z_1)^2 + \tfrac{1}{2}\beta_{44}(\text{Ln}Z_2)^2 + \beta_{12}\text{Ln}X_1\text{Ln}X_2 \\ & + \beta_{13}\text{Ln}X_1\text{Ln}Z_1 + \beta_{14}\text{Ln}X_1\text{Ln}Z_2 + \beta_{23}\text{Ln}X_2\text{Ln}Z_1 + \beta_{24}\text{Ln}X_2\text{Ln}Z_2 \\ & + \beta_{34}\text{Ln}Z_1\text{Ln}Z_2 + v_i - u_i \end{aligned} \quad (4)$$

where Ln represents the natural logarithm, Y_i denotes the output quantity of edible canna farm (Kg/acre), and X_1 and X_2 are normal inputs including seed input (Kg/acre) and labor cost of the farm (1000 VND/acre). Z_1 is the quantity of nitrogen fertilizer (Kg/acre) and Z_2 denotes the quantity of phosphorus fertilizer (Kg/acre). When Z_1 and Z_2 are overused, this would cause adverse impacts on the environment, or it is referred to as producers using it inefficiently.

Technical Inefficiency Effects Model

To identify factors affecting the inefficiency level of farms, many studies adopt a two-step procedure model to show the relationship between inefficiency level and socioeconomic variables. However, using a two-step procedure has still caused many problems due to its biased estimation in the first step. Biased estimations of applying a two-step procedure in measuring inefficiency and assessing its determinants were also pointed out by Wang and Schmidt [31] and Kumbhakar et al. [32]. Hence, in this study, the one-stage estimation procedure is applied to take into account the parameters of the translog production function and determinants of technical inefficiency in edible canna production. According to Battese and Broca [33], the model of technical inefficient effects is expressed as follows:

$$\begin{aligned} U_i = \ & \delta_0 + \delta_1 \text{Age} + \delta_2 \text{Education} + \delta_3 \text{Experience} + \delta_4 \text{Dis tan ce} + \delta_5 \text{Typehousehold} \\ & + \delta_6 \text{CreditAccess} + \delta_7 \text{FamilySize} + \delta_8 \text{ExtensionContact} + W_i \end{aligned} \quad (5)$$

where U_i represents the technical inefficiency of edible canna farms. $\delta_0, \delta_1 \ldots \delta_8$ are vectors of the estimated parameters. W_i denotes the random error ($W_i \sim N^+ (0, \sigma_w{}^2)$).

2.2.2. Empirical Analysis Model for Measuring the Environmental Efficiency and Determinants

As mentioned by Reinhard et al. [18], environmental efficiency (EE) is the ability of farms to reduce the use of detrimental inputs without changing the output quantity and conventional inputs. Vo Hong et al. [21] stated that EE is known as a part of TE because EE shows the ability of farms in reducing all bad inputs while TE is considered as the ability of farms in reducing both normal and detrimental inputs to optimal levels without changing the output. Hence, the mathematical equation of EE is expressed as:

$$EE = \min\{\varnothing : f(X, \varnothing Z) \geq Y\} \leq 1 \quad (6)$$

where $f(X,\varnothing Z)$ is the new form of frontier production with X normal input and Z detrimental input, which are used to produce the output Y. To measure environmental efficiency score, Reinhard et al. [34] suggested that setting the Equation (4) with $u_i = 0$ and changing all detrimental inputs Z_1 and Z_2 by $\varnothing Z_1$ and $\varnothing Z_2$, respectively, to make a new form of the translog production function. In the new equation, EE score is the ∅ value. As the results, the new translog function model was described as follows:

$$\begin{aligned}\mathrm{Ln}\,Y_i = {}& \beta_0 + \beta_1 \mathrm{Ln}X_1 + \beta_2 \mathrm{Ln}X_2 + \beta_3 \mathrm{Ln}\varnothing Z_1 + \beta_4 \mathrm{Ln}\varnothing Z_2 + \tfrac{1}{2}\beta_{11}(\mathrm{Ln}X_1)^2 + \tfrac{1}{2}\beta_{22}(\mathrm{Ln}X_2)^2 \\ &+ \tfrac{1}{2}\beta_{33}(\mathrm{Ln}\varnothing Z_1)^2 + \tfrac{1}{2}\beta_{44}(\mathrm{Ln}\varnothing Z_2)^2 + \beta_{12}\mathrm{Ln}X_1\mathrm{Ln}X_2 + \beta_{13}\mathrm{Ln}X_1\mathrm{Ln}\varnothing Z_1 + \beta_{14}\mathrm{Ln}X_1\mathrm{Ln}\varnothing Z_2 \\ &+ \beta_{23}\mathrm{Ln}X_2\mathrm{Ln}\varnothing Z_1 + \beta_{24}\mathrm{Ln}X_2\mathrm{Ln}\varnothing Z_2 + \beta_{34}\mathrm{Ln}\varnothing Z_1\mathrm{Ln}\varnothing Z_2 + v_i\end{aligned} \tag{7}$$

According to the statement of the previous studies, a farm is considered as fully environmental efficient when it farm can reduce all bad inputs to an optimal level while holding the normal inputs and the quantity of output constant [21]. Therefore, the output of Equation (4) is equal to that in Equation (7). It can be expressed as Equation (8):

$$\begin{aligned}&\beta_3(\mathrm{Ln}\varnothing Z_1 - \mathrm{Ln}Z_1) + \beta_4(\mathrm{Ln}\varnothing Z_2 - \mathrm{Ln}Z_2) + \tfrac{1}{2}\beta_{33}(\mathrm{Ln}\varnothing Z_1\mathrm{Ln}\varnothing Z_1 - \mathrm{Ln}Z_1\mathrm{Ln}Z_1) \\ &+ \tfrac{1}{2}\beta_{44}(\mathrm{Ln}\varnothing Z_2\mathrm{Ln}\varnothing Z_2 - \mathrm{Ln}Z_2\mathrm{Ln}Z_2) + \beta_{13}\mathrm{Ln}X_1(\mathrm{Ln}\varnothing Z_1 - \mathrm{Ln}Z_1) \\ &+ \beta_{14}\mathrm{Ln}X_1(\mathrm{Ln}\varnothing Z_2 - \mathrm{Ln}Z_2) + \beta_{23}\mathrm{Ln}X_2(\mathrm{Ln}\varnothing Z_1 - \mathrm{Ln}Z_1) + \beta_{24}\mathrm{Ln}X_2(\mathrm{Ln}\varnothing Z_2 - \mathrm{Ln}Z_2) \\ &+ \beta_{34}(\mathrm{Ln}\varnothing Z_1\mathrm{Ln}\varnothing Z_2 - \mathrm{Ln}Z_1\mathrm{Ln}Z_2) + u_i = 0\end{aligned} \tag{8}$$

Due to $\mathrm{LnEE} = \mathrm{Ln}\varnothing = \mathrm{Ln}\left(\frac{\varnothing Z}{Z}\right)$, the Equation (8) could be represented as follow:

$$\left(\frac{1}{2}\beta_{33} + \frac{1}{2}\beta_{44} + \beta_{34}\right)\mathrm{Ln}^2\mathrm{EE} + \left[\begin{array}{l}\beta_3 + \beta_4 + \beta_{33}\mathrm{Ln}Z_1 + \beta_{44}\mathrm{Ln}Z_2 + \beta_{13}\mathrm{Ln}X_1 \\ + \beta_{14}\mathrm{Ln}X_1 + \beta_{23}\mathrm{Ln}X_2 \\ + \beta_{24}\mathrm{Ln}X_2 + \beta_{34}(\mathrm{Ln}Z_1 + \mathrm{Ln}Z_2)\end{array}\right]\mathrm{LnEE} + u_i = 0 \tag{9}$$

As can be seen from Equation (9), it is consistent with the formula as: $ax^2+bx+c = 0$. Therefore, Equation (9) can be expressed as:

$$a(\mathrm{LnEE})^2 + b\mathrm{LnEE} + u_i = 0. \tag{10}$$

Here, $a = \frac{1}{2}\beta_{33} + \frac{1}{2}\beta_{44} + \beta_{34}$, with $\forall a \neq 0$

$b = \beta_3 + \beta_4 + \beta_{33}\mathrm{Ln}Z_1 + \beta_{44}\mathrm{Ln}Z_2 + \beta_{13}\mathrm{Ln}X_1 + \beta_{14}\mathrm{Ln}X_1 + \beta_{23}\mathrm{Ln}X_2 + \beta_{24}\mathrm{Ln}X_2 + \beta_{34}(\mathrm{Ln}Z_1 + \mathrm{Ln}Z_2)$.

From Equation (10), LnEE will be estimated as Equation (11):

$$\mathrm{LnEE} = \frac{-b \pm \sqrt{b^2 - 4au_i}}{2a}. \tag{11}$$

Hence, $\mathrm{EE} = \exp\left(\frac{-b\pm\sqrt{b^2-4au_i}}{2a}\right)$.

According to the statement of Vo Hong et al. [21], Reinhard et al. [34], and Zhang and Xue [19], the value of $\mathrm{EE} = \exp\left(\frac{-b-\sqrt{b^2-4au_i}}{2a}\right)$ is rejected because this value is not suitable with the model when $u_i = 0$. Therefore, EE is computed by Equation (12) as:

$$\mathrm{EE} = \exp\left(\frac{-b + \sqrt{b^2 - 4au_i}}{2a}\right). \tag{12}$$

Or

$$\mathrm{EE} = \exp\left\{\begin{array}{l} -\left[\begin{array}{l}\beta_3 + \beta_4 + \beta_{33}\mathrm{Ln}Z_1 + \beta_{44}\mathrm{Ln}Z_2 + \beta_{13}\mathrm{Ln}X_1 + \beta_{14}\mathrm{Ln}X_1 + \beta_{23}\mathrm{Ln}X_2 \\ + \beta_{24}\mathrm{Ln}X_2 + \beta_{34}(\mathrm{Ln}Z_1 + \mathrm{Ln}Z_2)\end{array}\right] \\ + \left[\begin{array}{l}\left(\begin{array}{l}\beta_3 + \beta_4 + \beta_{33}\mathrm{Ln}Z_1 + \beta_{44}\mathrm{Ln}Z_2 + \beta_{13}\mathrm{Ln}X_1 + \beta_{14}\mathrm{Ln}X_1 + \beta_{23}\mathrm{Ln}X_2 \\ + \beta_{24}\mathrm{Ln}X_2 + \beta_{34}(\mathrm{Ln}Z_1 + \mathrm{Ln}Z_2)\end{array}\right)^2 \\ -4\left(\frac{1}{2}\beta_{33} + \frac{1}{2}\beta_{44} + \beta_{34}\right)u_i\end{array}\right]^{0.5}\end{array}\right\} / (\beta_{33} + \beta_{44} + 2\beta_{34}). \tag{13}$$

2.2.3. The Output Elasticity for Each Input

The output elasticity is defined as the percentage variation of the edible canna output quantity due to a change of 1% in using of all input variables [35]. In Cobb–Douglas, the output elasticity is the estimated parameters. However, in the case of the translog production function form in this study, the output elasticity is not consistent with the estimated parameters. Therefore, the output elasticity for each input in this research depends on the relationship between estimated parameters and input levels. It is computed by applying the Equation (14) as:

$$e_i = \frac{\partial Y}{\partial X_i}\frac{X_i}{Y} = \beta_i + \sum_{i=1}^{4} \beta_{ij} LnX_i \tag{14}$$

where i represents the number of input variables and j presents the number of explanatory variables. For example, the output elasticity of seed input (X_1) is can be calculated as:

$$e_1 = \beta_1 + \beta_{11}LnX_1 + \beta_{12}LnX_2 + \beta_{13}LnZ_1 + \beta_{14}LnZ_2.$$

Then, with other inputs, the output elasticity could be computed using the same formula.

2.2.4. Truncated Regression Model

The Tobit regression model refers to set of regression models in which the observed range of the dependent variable is censored in some way [36]. Several studies used this model as a tool for the second stage because the efficiency score of farms calculated in the first stage ranged from 0 to 1 and had censored distributions [37]. However, recent studies also showed that there exists an inadequacy in the result of the Tobit model due to the biased estimation [38]. Hence, the truncated regression model is a more appropriate choice to explain the relationship between environmental efficiency score and independent variables related to the socioeconomic characteristics of edible canna farms. The proposed model is expressed by Equation (15) as follows:

$$\begin{aligned} EE = {} & \beta_0 + \beta_1 Age + \beta_2 Education + \beta_3 Experience + \beta_4 Dis\tan ce + \beta_5 Typehousehold \\ & + \beta_6 CreditAccess + \beta_7 FamilySize + \beta_8 Extensioncontact + \varepsilon_i \end{aligned} \tag{15}$$

where EE denotes the environmental efficiency of farms, β_1, $\beta_{2\ldots}$ β_8 are unknown coefficients, which illustrate the correlation between the individual independent variables and EE. The independent variables, including age of farmer (years), the education level of farmers (years), the experiences of farmers (years), the distance of farm to local market (km), type of household (dummy), credit access of farms (dummy), the family size (numbers), and extension contact (dummy), respectively. The STATA software version 15.0 is used for the analysis. The bootstrapping technique is also applied to provide standard error for the estimated parameters in the truncated regression model.

2.3. Data Source and Characteristics of Data

The primary data were gathered from 346 edible canna farms using face-to-face interviews. The printout questionnaires were used to collect data during the harvesting period of 2017/2018. The structured questionnaire was designed with two sections. In the first section, questions related to socioeconomic variables of farmers were addressed, including name of household head, gender, age, ethnic group, education level, occupation of household's head, attended association, the distance from farm to the local market, type of household, the number of members in household, the information about agricultural land use, and the general information about accessing credit loan. The second section was designated to collect information related to production activities, the quantity of inputs, seed, labor, chemical fertilizer, and cultivated land; and amount of outputs, yield, and sale price. Two types of inputs were further classified, i.e., conventional inputs, seed, and labor cost; and detrimental inputs, nitrogen, and phosphorus, along with the output or yield (in kilogram per acre), were used in the analysis. Tables 1 and 2 show the descriptive statistics of variables in the two sections of the questionnaire, respectively.

Table 1. Descriptive statistics of socioeconomic variables of the sample.

Variables	Mean	Std. Deviation	Minimum	Maximum
Age (Years)	44.59	10.45	23.00	73.00
Education (Years)	6.07	3.51	0.00	18.00
Experience (Years)	6.20	3.88	1.00	23.00
Distance from farm to local market (Kilometers)	5.17	4.82	0.02	23.00
Type of household (1 = Poor, 0 = Others)	0.41	0.49	0.00	1.00
Credit access (1 = Yes, 0 = No)	0.73	0.44	0.00	1.00
Family size (Number)	4.78	1.42	2.00	10.00
Extension contact (1 = Yes, 0 = No)	0.45	0.50	0.00	1.00

Table 2. Descriptive statistics of production activity variables of the sample [1].

Variables	Nari District (n = 223)				Babe District (n = 123)			
	Mean	Min	Max	Std. Dev.	Mean	Min	Max	Std. Dev.
Output quantity $^{+}$ (Y)	1395.52	205.71	3240.00	636.26	971.50	180.00	3780.00	677.04
Conventional inputs								
Seed quantity $^{+}$ (X_1)	84.73	10.29	1080.00	76.57	60.84	12.00	288.00	43.98
Labor cost $^{++}$ (X_2)	2435.19	540.00	9216.00	1146.94	1622.74	204.48	8568.00	1260.34
Detrimental inputs								
Nitrogen quantity $^{+}$ (Z_1)	2.91	0.18	33.57	3.25	3.92	0.06	25.20	5.43
Phosphorus quantity $^{+}$ (Z_2)	5.08	0.36	29.52	4.10	4.39	0.12	37.80	6.46

[1]: The average values for 2017/2018 production year, $^{+}$: kg/acre (1 acre = 360 m^2); $^{++}$: in thousand VND/acre.

In the sample, on average, farmers had 6.07 years of education; 6.20 years of experience in edible canna production; 5.17 km of distance from their respective farm to the market; and with 4.78 persons in the household; 41% are considered poor; 73% have availed credit access; and 45% have contact with extension agencies. Usually, the longer distance from the farm to the market would adversely affect the quality of produce due to the damage and spoilage resulted from the handling and transportation. On the other hand, for the rest of socioeconomic variables, it would be expected to exert positive effects on the quality and yield of edible canna production. That is, more education, experience, credit access, bigger household size, and with more extension contacts, would either improve the knowledge and technique of production or allow one to procure more productive resources such that it would lead to be more productive.

Among 346 edible canna farms in the sample, 223 were located in Nari district while another 123 were in Babe district.

Table 2 shows that, on average, for the output or the yield of the edible canna, it was 1395.52 kg/acre in Nari district, which was significantly higher than that of Babe district, 971.50 kg/acre; for the inputs, the use of conventional inputs as a whole was also higher than that of Babe district; however, for the detrimental inputs, there was no such consistency between Nari district and Babe district. The mean quantity of seed was 84.73 kg/acre in Nari district, while it was 60.84 kg/acre in Babe district. In addition, the labor cost was high in both Nari and Babe districts with 2435.19 (1000 VND/acre) and 1622.74 (1000 VND/acre), respectively. In terms of detrimental inputs, the quantity of nitrogen fertilizer used in Nari district was lower than that in Babe district whilst the use of phosphorus was the opposite. It may be attributed to the differences in socioeconomic variables and geographical locations as well between these two districts.

3. Results and Discussion

3.1. Technical Efficiency of Edible Canna Farms and Determinants

This study employed the FRONTIER software version 4.1 [39] to estimate the translog production function using maximum likelihood method. The translog production function was adapted based on the result of the likelihood-ratio test. The likelihood test was used for testing the null hypothesis H_0: $\beta_{ij} = 0$. The likelihood ratio was computed as the Equation (16).

$$LR = -2\{\ln[L(H_0)] - \ln[L(H_1)]\} \quad (16)$$

where H_0 was assumed by the value of log likelihood for Cobb–Douglas and H_1 represented the alternative hypothesis and was assumed by the value of log likelihood for the translog model [29].

From Equation (16), the result of likelihood ratio test was calculated as LR = −2 [−213.727 − (−202.009)] = 23.436. This value exceeded the critical value of Chi-squared distribution for the degree of freedom of 10, 18.307, at significance level of 5% level. Therefore, the null hypothesis was rejected. It means that the translog frontier production function was approved to be an appropriate model for the data collected in this study as compared with the Cobb–Douglas production function, which is usually adopted in the literature. Furthermore, the present study used the results of maximum likelihood estimation (MLE) of regression to explain the data because the γ value was close to unity. As mentioned in the studies of Bezat [40], Kea et al. [41], and Taraka et al. [42], if $\gamma = 0$, the technical inefficiency was not present, suggesting that OLS was adequately representative of the data.

Table 3 shows the estimation results of translog production function by using MLE; the value of γ was 0.8376, indicating that 83.76% of the variation of output quantity resulted from the technical inefficiency of farms. In addition, the results of the inefficiency effects model revealed that out of eight exogenous variables used, only education had a significant negative impact on the technical inefficiency of edible canna farms at the 10% significant level. The negative coefficient of education indicated that farmers with more years of schooling tended to achieve higher technical efficiency, which might be attributed to better ability in managing, allocating capital sources, as well as applying science and technology in production. This finding is consistent with statements of Bozoğlu and Ceyhan [15], Khairo and Battese [43], and Yami et al. [44]. This result also indicated that agricultural policies focusing on technical training courses should be initiated to help farmers in improving the efficiency of edible canna production.

The estimated coefficients in the translog production function were further used to compute the output elasticity of four inputs addressed in this study. The results of the calculated output elasticities with respect to individual input factors were presented in Table 4. On average, the output elasticities of all inputs were positive. Given the estimated output elasticity of seed and labor cost were the highest (0.425 and 0.194, respectively), implying that if the seed and labor cost increase individually by 1%, the yield of canna will also grow by 0.425% and 0.194%, respectively. The output elasticity with respect to the nitrogen and phosphorus fertilizer were estimated to be 0.048 and 0.078 respectively, demonstrating that if nitrogen and phosphorus fertilizer individually increase by 1%, the yield will increase by 0.048% and 0.078%, respectively. In edible canna production, labor was required heavily during the harvest season, which usually lasts for a month. Consequently, the labor cost would have a direct as well as significant impact on the efficiency of edible canna production in Backan province.

Table 3. Maximum likelihood estimates for parameter of translog production function [2].

Variables	Coefficients	Std. Err.	t-Ratio
Constant (β_0)	−2.1912	3.3104	−0.6619
LnX_1 (β_1)	0.9092	0.5914	1.5373
LnX_2 (β_2)	1.5709 *	0.9537	1.6472
LnZ_1 (β_3)	0.0305	0.3260	0.0937
LnZ_2 (β_4)	0.2340	0.4610	0.5016
$(LnX_1)^2/2$ (β_{11})	−0.2080 *	0.1142	−1.8202
$(LnX_2)^2/2$ (β_{22})	−0.1976	0.1554	−1.2711
$(LnZ_1)^2/2$ (β_{33})	0.0033	0.0410	0.0818
$(LnZ_2)^2/2$ (β_{44})	−0.0366	0.0643	−0.5695
LnX_1 LnX_2 (β_{12})	0.0399	0.0991	0.4022
LnX_1 LnZ_1 (β_{13})	−0.0605	0.0543	−1.1131
LnX_1 LnZ_2 (β_{14})	0.1010	0.0737	1.3691
LnX_2 LnZ_1 (β_{23})	0.0362	0.0520	0.6952
LnX_2 LnZ_2 (β_{24})	−0.0707	0.0810	−0.8732
LnZ_1 LnZ_2 (β_{34})	−0.0048	0.0032	−0.1516
Inefficiency Effects Model			
Constant	1.3916 *	0.7270	1.9141
Age (Years)	−0.0070	0.0094	−0.7374
Education (Years)	−0.0796 *	0.0467	−1.7045
Experience (Years)	-0.1185	0.0917	−1.2927
Distance from farm to local market (Kilometers)	−0.0237	0.0267	−0.8870
Type of household (1 = Poor, 0 = Others)	0.2890	0.1841	1.5696
Credit access (1 = Yes, 0 = No)	−0.0014	0.1574	−0.0088
Family size (Number)	−0.0346	0.0666	−0.5188
Extension contact (1 = Yes, 0 = No)	−1.2854	0.8738	−1.4711
σ^2	0.5060 **	0.2105	2.4034
γ	0.8376 ***	0.0647	12.936
Log Likelihood	−174.4469		

[2]: *,**,*** indicates the significant at 10%, 5%, and 1%, respectively.

Table 4. The output elasticity with respect to input variables.

Variables	Mean	Maximum	Minimum	Std. Dev.
Seed	0.425	0.888	−0.218	0.131
Labor cost	0.194	0.700	−0.204	0.138
Nitrogen	0.048	0.146	−0.087	0.029
Phosphorus	0.078	0.346	−0.139	0.061

In short, the results revealed that it is recommended for the edible canna farms in Backan province as a whole to increase labor and seed quantities to boost the yield. In other words, the results suggested that the individual edible canna farmers should adjust and allocate input factors such as seed, labor, and fertilizer appropriately from overuses to improve efficiency in edible canna production, and in turn, farmers' incomes would increase; this could further contribute to reducing the poverty rate in Backan province because the local livelihood relies heavily on edible canna production.

By using the translog production function, the results of the technical efficiency of edible canna farms in Backan province are exhibited in Table 5. The findings revealed that the average technical efficiency of edible canna farms was low with 0.74 and 0.72 in Nari district and Babe district, respectively. In other words, canna farms in Nari district and Babe district could expand their output by 26% and 28%, respectively, without changing the current input levels.

Table 5. The distribution of technical efficiency (TE) levels of edible canna farms in Backan province.

TE Levels	Nari District (n = 223)		Babe District (n = 123)	
	Number of Farms	Percentage (%)	Number of Farms	Percentage (%)
≤0.40	13	5.58	7	5.69
0.41–0.50	12	5.15	8	6.50
0.51–0.60	12	5.15	11	8.94
0.61–0.70	25	10.73	24	19.51
0.71–0.80	43	18.45	23	18.70
0.81–0.90	102	43.78	40	32.52
≥0.90	16	6.87	10	8.13
Mean	0.74		0.72	
Min	0.20		0.24	
Max	0.94		0.95	
Std. Dev.	0.17		0.16	

3.2. Environmental Efficiency of Edible Canna Farms and Determinants

EE of edible canna farms was computed by employing Equation (13) and the results are presented in Table 6.

Table 6. The distribution of environmental efficiency of edible canna farms in Backan province.

EE Levels	Nari District (n = 223)		Babe District (n = 123)	
	Number of Farms	Percentage (%)	Number of Farms	Percentage (%)
≤0.30	32	14.35	15	12.20
0.31–0.40	12	5.38	10	8.13
0.41–0.50	23	10.31	20	16.26
0.51–0.60	36	16.14	14	11.38
0.61–0.70	52	23.32	24	19.51
0.71–0.80	52	23.32	25	20.33
≥0.80	16	7.17	15	12.20
Mean	0.57		0.58	
Min	0.03		0.10	
Max	0.89		0.92	
Std. Dev.	0.20		0.20	

The findings revealed that the average EE of canna farms was 0.57 and 0.58 in Nari district and Babe district, respectively. In other words, edible canna farms in Nari district and Babe district could have the potential to reduce 43% and 42%, respectively, of bad inputs usage without changing the current output and conventional input level. As shown in Tables 5 and 6, EE scores were found to be lower than TE scored in both districts, which is consistent with the findings of Bakhsh [45], Sheikh et al. [46], and Zhang and Xue [19].

Moreover, the percentage of farms with the EE below 0.50 in Babe district was 36.59% and higher than that in Nari district, 30.04%. This suggests that approximately 30–36% of canna farms in both districts have the potential reducing bad inputs by 50% without altering the output and conventional input levels. Lowering the use of bad inputs, on one hand, could be reflected directly and positively on the environment, while on the other hand, saves input cost, which could be indirectly transferred into farm incomes.

3.3. Factors Influencing on Environmental Efficiency of Edible Canna Farms in Backan Province

The results of truncated regression between the dependent variable, environmental efficiency score, and the independent variables, eight socioeconomic variables of farmers, are described in Table 7. The results revealed that education level, experience, distance, and extension contact positively affected

EE at the significance level of 1%; while age of household was also found to be positively related to EE at the 5% significance level. The positive coefficient of age indicated that the older farmers scored higher EE levels than the younger peers, which is consistent with the finding of Chiona et al. [35]. As expected, education was also shown to exert positive influence on EE levels of edible canna farms, i.e., with more years of schooling or more human capital, farmers are likely to be more productive and efficient because of better skills in planning farming activities, transferring technology, and accessing market information. This result is in agreement with Nargis and Lee [47], Linh [48], and Raheli et al. [49]. Therefore, a means to improve the efficiency level of edible canna farms in Backan province could focus on short-term training courses for farmers. In addition, the results also indicated that the efficiency of farms would increase if famers have a close connection with extension officers. In fact, agricultural extension services play a crucial role in training technology, improving income, and reducing poverty for locals in rural areas of Vietnam [50,51]. Moreover, the positive coefficient of the experience EE confirmed that farmers with more years in edible canna cultivation can achieve higher efficiency level compared to less experienced counterparts, which is in line with Hong and Yabe [14].

Table 7. Truncated regression estimates for factors influencing on EE of edible canna farms[3].

Variables	Coefficients	Bootstrap Std. Err.
Age (Years)	0.0023 **	0.0010
Education (Years)	0.0156 ***	0.0028
Experience (Years)	0.0155 ***	0.0027
Distance from farm to local market (Kilometers)	0.0056 ***	0.0020
Type of household (1 = Poor, 0 = Others)	−0.0496 **	0.0199
Credit access (1 = Yes, 0 = No)	−0.0040	0.0213
Family size (Number)	−0.0013	0.0054
Extension contact (1 = Yes, 0 = No)	0.1780 ***	0.1684
Constant	0.1946 **	0.0761

[3]: **,*** indicates statistical significance at 5% and 1%, respectively.

4. Conclusions and Policy Implications

In this study, a translog stochastic frontier production function was applied to estimate the technical and environmental efficiency of edible canna farms in Backan province in Vietnam. First, the likelihood test was used to show the appropriateness of the translog production function with the data used in this study. Second, the output elasticity with respect to each input variable was calculated using the estimated parameters from the translog production function. The findings revealed that the output elasticity of all inputs was positive, and that of seed and labor cost was found to be the highest and the second highest, suggesting that seed and labor cost should be increased to improve the yield of edible canna, rather than nitrogen and phosphorus fertilizer.

The technical efficiency of edible canna farms was computed by the translog production function. The average values of technical efficiency of edible canna farms in Nari and Babe district were 0.74 and 0.72, respectively. This result showed that there was a potential for farms to increase the output quantity by 26% and 28% for Nari district and Babe district, respectively, while holding the input factors constant. Moreover, the mean EE scores of farms in Backan province was shown to be lower compared to TE. The low EE scores point out that edible canna production has imposed a negative impact on the environment. Thus, farmers are recommended to reduce the usage of detrimental inputs to enhance the efficiency level and, in turn, to protect the natural environment.

In sum, the model of inefficient effects and truncated regression analysis were applied to determine the factors influencing TE and EE of edible canna farms in this study. The results indicated that education, experience, and extension contact positively affected the environmental efficiency of edible canna production in Backan province, whilst technical efficiency was only impacted by education level. In addition, the technical efficiency of the studied edible canna farms on average was found to be low; and environmental efficiency was even lower. Therefore, to tackle these problems, the government is urged to take the initiative to enact policies that address the provision of training courses as well as the establishment of a well-functioned reach-out extension system, which can deliver farmers the knowledge of using inputs properly and efficiently such that the yield can be improved while reducing environmental pollution. Furthermore, extension activities, e.g., sharing experience and demonstrating first-hand knowledge of environmental protection in cultivation, processing, and accessing to the output market, can be regularly held to help less experienced farmers to improve their efficiency.

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References

1. Imai, K. Edible canna: A prospective plant resource from South America. *Jpn. J. Crop. Sci.* **2008**, *2*, 46–53.
2. Zhang, J.; Wang, Z.-W. Soluble dietary fiber from *Canna edulis* Ker by-product and its physicochemical properties. *Carbohydr. Polym.* **2013**, *92*, 289–296. [CrossRef] [PubMed]
3. Hue, N.T.N.; Loc, T.D. *Root Tubers Plant and Intensive Farming Techniques*; Social Labor Publishing House: Hanoi, Vietnam, 2005; pp. 7–27.
4. Hung, P.V.; Morita, N. Physicochemical properties and enzymatic digestibility of starch from edible canna (*Canna edulis*) grown in Vietnam. *Carbohydr. Polym.* **2005**, *61*, 314–321. [CrossRef]
5. Hermann, M.; Quynh, N.; Peters, D. Reappraisal of edible canna as a high-value starch crop in Vietnam. *CIP Program Rep.* **1997**, *98*, 415–424.
6. General Statistics Office (GSO). *Result of the Vietnam Household Living Standard Survey 2016*; General Statistics Office: Ha Noi, Vietnam, 2016; pp. 20–22.
7. Trædal, L.T.; Vedeld, P. Cultivating forests: The role of forest land in household livelihood adaptive strategies in the Backan province of Northern Vietnam. *Land Use Policy* **2018**, *73*, 249–258. [CrossRef]
8. Thitipraphunkul, K.; Uttapap, D.; Piyachomkwan, K.; Takeda, Y. A comparative study of edible canna (*Canna edulis*) starch from different cultivars. Part II. Molecular structure of amylose and amylopectin. *Carbohydr. Polym.* **2003**, *54*, 489–498. [CrossRef]
9. Wandee, Y.; Uttapap, D.; Puncha-arnon, S.; Puttanlek, C.; Rungsardthong, V.; Wetprasit, N. Quality assessment of noodles made from blends of rice flour and canna starch. *Food Chem.* **2015**, *179*, 85–93. [CrossRef] [PubMed]
10. Rahman, K.; Mia, M.; Bhuiyan, M. A stochastic frontier approach to model technical efficiency of rice farmers in Bangladesh: An empirical analysis. *Agriculturists* **2012**, *10*, 9–19. [CrossRef]
11. Piya, S.; Kiminami, A.; Yagi, H. Comparing the technical efficiency of rice farms in urban and rural areas: A case study from Nepal. *Trends Agric. Econ.* **2012**, *5*, 48–60. [CrossRef]
12. Hien, N.T.M.; Kawaguchi, T.; Suzuki, N. A study on technical efficiency of rice production in the Mekong Delta, Vietnam by stochastic frontier analysis. *J. Fac. Agric.* **2003**, *48*, 325–357.
13. Khai, H.V.; Yabe, M. Technical efficiency analysis of rice production in Vietnam. *J. ISSAAS* **2011**, *17*, 135–146.
14. Hong, N.B.; Yabe, M. Resource use efficiency of tea production in Vietnam: Using translog SFA model. *J. Agric. Sci.* **2015**, *7*, 160–172. [CrossRef]
15. Bozoğlu, M.; Ceyhan, V. Measuring the technical efficiency and exploring the inefficiency determinants of vegetable farms in Samsun province, Turkey. *Agric. Syst.* **2007**, *94*, 649–656. [CrossRef]
16. Bezat, A. Comparison of the deterministic and stochastic approaches for estimating technical efficiency on the example of non-parametric DEA and parametric SFA methods. *Metod. Ilościowe Bad. Ekon.* **2009**, *10*, 20–29.
17. Chen, C.-F. Applying the stochastic frontier approach to measure hotel managerial efficiency in Taiwan. *Tour. Manag.* **2007**, *28*, 696–702. [CrossRef]

18. Reinhard, S.; Lovell, C.K.; Thijssen, G.J. Environmental efficiency with multiple environmentally detrimental variables; estimated with SFA and DEA. *Eur. J. Oper. Res.* **2000**, *121*, 287–303. [CrossRef]
19. Zhang, T.; Xue, B.D. Environmental efficiency analysis of China's vegetable production. *Biomed. Environ. Sci.* **2005**, *18*, 21–30. [PubMed]
20. Kouser, S.; Mushtaq, K. Environmental efficiency analysis of basmati rice production in Punjab, Pakistan: Implications for sustainable agricultural development. *Pak. Dev. Rev.* **2010**, *49*, 57–72.
21. Vo Hong, T.; Yabe, M.; Trang, N.T.; Khai, H.V. Environmental efficiency of ecologically engineered rice production in the Mekong Delta of Vietnam. *J. Fac. Agric. Kyushu Univ.* **2015**, *60*, 493–500.
22. Trang, N.; Khai, H.; Tu, H.; Hong, N. Environmental efficiency of transformed farming systems: A case study of change from sugarcane to shrimp in the Vietnamese Mekong Delta. *For. Res. Eng. Int. J.* **2018**, *2*, 54–60.
23. Le, T.L.; Lee, P.-P.; Peng, K.C.; Chung, R.H. Evaluation of total factor productivity and environmental efficiency of agriculture in nine East Asian countries. *Agric. Econ.* **2019**, *65*, 249–258.
24. Makutėnienė, D.; Baležentis, T. The trends of technical, environmental and resource efficiency across agricultural sectors of European countries. *Manag. Theor. Stud. Rural Bus. Infrastruct. Dev.* **2015**, *37*, 241–251. [CrossRef]
25. BDARD. *Report about Production and Processing of Edible Canna of Backan Province in 2017 and Plan for 2018*; Backan Department of Agriculture and Rural Development: Backan, Vietnam, 2017.
26. Coelli, T.J.; Rao, D.S.P.; O'Donnell, C.J.; Battese, G.E. *An Introduction to Efficiency and Productivity Analysis*; Springer Science & Business Media: New York, NY, USA, 1998; pp. 184–198.
27. Toma, P.; Miglietta, P.P.; Zurlini, G.; Valente, D.; Petrosillo, I. A non-parametric bootstrap-data envelopment analysis approach for environmental policy planning and management of agricultural efficiency in EU countries. *Ecol. Indic.* **2017**, *83*, 132–143. [CrossRef]
28. Vu, H.D. Technical efficiency of FDI firms in the Vietnamese manufacturing sector. *Rev. Econ. Perspect.* **2016**, *16*, 205–230. [CrossRef]
29. Coelli, T.J.; Rao, D.S.P.; O'Donnell, C.J.; Battese, G.E. *An Introduction to Efficiency and Productivity Analysis*; Springer Science & Business Media: New York, NY, USA, 2005; pp. 241–261.
30. Trong, P.H.; Napasintuwong, O. Profit inefficiency among hybrid rice farmers in Central Vietnam. *Agric. Agric. Sci. Procedia* **2015**, *5*, 89–95. [CrossRef]
31. Wang, H.-J.; Schmidt, P. One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *J. Product. Anal.* **2002**, *18*, 129–144. [CrossRef]
32. Kumbhakar, S.C.; Wang, H.-J.; Horncastle, A.P. *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*; Cambridge University Press: Cambridge, UK, 2015; pp. 71–72.
33. Battese, G.E.; Broca, S.S. Functional forms of stochastic frontier production functions and models for technical inefficiency effects: A comparative study for wheat farmers in Pakistan. *J. Product. Anal.* **1997**, *8*, 395–414. [CrossRef]
34. Reinhard, S.; Lovell, C.K.; Thijssen, G. Analysis of environmental efficiency variation. *Am. J. Agric. Econ.* **2002**, *84*, 1054–1065. [CrossRef]
35. Chiona, S.; Kalinda, T.; Tembo, G. Stochastic frontier analysis of the technical efficiency of smallholder maize farmers in Central province, Zambia. *J. Agric. Sci.* **2014**, *6*, 108–118. [CrossRef]
36. Tobin, J. Estimation of relationships for limited dependent variables. *Econometrica* **1958**, *26*, 24–36. [CrossRef]
37. Sağlam, Ü. A two-stage data envelopment analysis model for efficiency assessments of 39 state's wind power in the United States. *Energy Convers. Manag.* **2017**, *146*, 52–67. [CrossRef]
38. Dlamini, S.I.; Huang, W.-C. A double hurdle estimation of sales decisions by smallholder beef cattle farmers in Eswatini. *Sustainability* **2019**, *11*, 5185. [CrossRef]
39. Coelli, T.J. *A Guide to Frontier Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation*; CEPA Working Papers; University of New England: Armidale, Australia, 1996; pp. 1–33.
40. Bezat, A. Estimation of technical efficiency by application of the SFA method for panel data. *Zesz. Nauk. Szkoły Głównej Gospod. Wiej. Warszawie Probl. Rol. Światowego* **2011**, *11*, 5–13.
41. Kea, S.; Li, H.; Pich, L. Technical efficiency analysis of Cambodian households rice production. *Glob. J. Human. Soc. Sci. Res.* **2016**, *16*, 32–44.
42. 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.

43. Khairo, S.; Battese, G. A study of technical inefficiencies of maize farmers within and outside the new agricultural extension program in the Harari region of Ethiopia. *S. Afr. J. Agric. Ext.* **2005**, *34*, 136–150.
44. Yami, M.; Solomon, T.; Begna, B.; Fufa, F.; Alemu, T.; Alemu, D. Source of technical inefficiency of smallholder wheat farmers in selected waterlogged areas of Ethiopia: A translog production function approach. *Afr. J. Agric. Res.* **2013**, *8*, 3930–3940.
45. Bakhsh, K. Environmental and technical efficiency analysis in bitter gourd production. *Pak. J. Agri. Sci.* **2012**, *49*, 583–588.
46. Sheikh, T.A.; Hasseeb, A.; Kouser, S. Environmental efficiency in vegetable production in Pakistan's Punjab: Implications for sustainable agriculture. *Pak. J. Appl. Econ.* **2012**, *22*, 77–99.
47. Nargis, F.; Lee, S. Efficiency analysis of boro rice production in North-Central region of Bangladesh. *J. Anim. Plant Sci.* **2013**, *23*, 527–533.
48. Linh, T.L.; Lee, P.P.; Ke-Chung, P.; Rebecca, H.C. Factors influencing technical efficiency of rice farms in Dongthap province, Vietnam: An application of two-stage DEA. *Am. Eurasian J. Agric. Environ. Sci.* **2017**, *17*, 245–249.
49. Raheli, H.; Rezaei, R.M.; Jadidi, M.R.; Mobtaker, H.G. A two-stage DEA model to evaluate sustainability and energy efficiency of tomato production. *Inf. Process. Agric.* **2017**, *4*, 342–350. [CrossRef]
50. De, N.; Uchiyama, T.; Ohara, K. Vietnam agricultural extension: Its roles, problems and opportunities. *Bull. Fac. Bioresour. Mie Univ.* **2005**, *32*, 79–94.
51. Hoang, L.A.; Castella, J.-C.; Novosad, P. Social networks and information access: Implications for agricultural extension in a rice farming community in Northern Vietnam. *Agric. Hum. Values* **2006**, *23*, 513–527. [CrossRef]