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Research article

Efficiency measurement of edible canna production in Vietnam

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Abstract: Edible canna cultivation was considered as one of the potential means to create job, contribute to increase income and reduce poverty for local communities in developing countries such as Vietnam. The study objective was to analyze the efficiency of edible canna production in Vietnam and subsequently to determine the factors affecting its inefficiency. The data envelopment analysis (DEA) was first applied to measure technical, scale, allocative and economic efficiency. The Tobit model was then applied to investigate what factors affecting the inefficiency scores of edible canna production in Vietnam. The data of 346 farmers gathered by face-to-face interviews was used to analyze in this study. The findings unveiled that mean pure technical efficiency (PTE) was highest (0.752), followed by scale efficiency (0.681), overall technical efficiency (0.513) and economic efficiency (0.258). Tobit regression analysis revealed that age, education and extension contact individually had a significantly negative impact on inefficient scores of farms, indicating that government should provide public investment policies tailoring in training, developing well-functioned extension systems as well as enhancing education level to improve the productivity of edible canna production in Vietnam efficiently.

Keywords: data envelopment analysis (DEA); edible canna farms; efficiency; Tobit model; Vietnam

1. Introduction

Edible canna production plays a crucial role in the rural economy of Vietnam and many developing countries in the world, and is widely cultivated in tropical and subtropical regions of South America, Thailand, China, and Vietnam [1,2]. The global edible canna acreage was approximately 200,000–300,000 ha with 30 tons of the mean productivity per ha [3]. In Vietnam, the edible canna is popularly grown in the northern mountainous regions, nevertheless it is also found in the delta areas. Current statistics indicate that edible canna was produced with the acreage of 20,000 to 30,000 ha in Vietnam [4,5]. Edible canna is an important crop in Backan, where it is pivotal to the livelihoods of the generally poor population. Backan is the poorest mountainous province of Vietnam with a population of about 319,000 and 15.8% of the total population is the poverty in 2016 [6]. In addition, with a natural area of 485,996 ha and around 85% of it is being mountains and hills, therefore forest land plays a vital role in the economic growth for Backan province. As such it is difficult to cultivate the main staple food of Vietnam, rice, in Backan, because of the geographical limitations given by ruggedness and steepness scattered around low lying valleys. Therefore, apart from rice production, edible canna is considered as a strategic crop to ensure local food security attributed to its high productivity and adaptability to the land condition of the region. According to the survey conducted by the local government of Backan province in 2017, the cultivated area of edible canna was 907 ha with an average yield of 70 tons/ha [7]. Moreover, edible canna cultivation is also common in northern highlands of Vietnam, especially for the Tay and Dao minor ethnic people. In essence, people in Backan province largely depend on edible canna for their household consumption and income generation [8]. Therefore, sustainable development in the production of edible canna is an imperative hunger-and-poverty reduction strategy for the people of these local communities.

Important as it may be, yet edible canna production in Backan province suffers from several challenges, out of which low unstable yields and quality are the paramount. It is produced under traditional farming systems on upland fields with low production resources and over-dependence on experience, thus resulting in inefficiency in the production. This in turn limits its potential in improving the livelihoods of the farming community. Moreover, the prevailing high illiteracy among the population propagates poverty, which successively barricades technological advancement as well as prompts poor management in resource adoption and allocation, especially for grants and farm credits. Low education further undermines the battle against environmental deterioration which leads to lower economic efficiency among edible canna farms in Backan province.

Hence, the big problem is whether production of edible canna crop in Backan is technically and economically efficient to award maximum benefits without deteriorating the future perspective of the environment? The measurement of technical, scale, allocative and economic efficiency is far-reaching in addressing sources of inefficiency in the production process, i.e., ameliorating production without increasing the input base. It is a strategy widely applied to intensify production for poor farming households that usually do not have sufficient funds to solicit more inputs. However, in Vietnam, the studies on the efficiency of edible canna are limited and primarily concerned about analyzing botanical characteristics, molecular component, and starch quality of edible canna [9–12]. In this regard, this study explores production efficiency of edible canna in Vietnam to fill the existing gap in the literature.

Studies on efficiency were based on theories that stated by Coelli et al. [13], Cooper et al. [14], and Farrell [15]. The efficiency of a farm includes three main components, namely, technical efficiency (TE), allocative efficiency (AE) and economic efficiency (EE) [15]. DEA is one of the non-parametric methods that considered to be a popular technique in measuring efficiency because of its advantages compared to stochastic frontier analysis (SFA) methodology, i.e., a production function form was not required in DEA; and the DEA approach can be employed to analyze the cases with multiple outputs and inputs while SFA approach is more appropriate with a single output [16]. Recently, DEA approach has been adopted to analyze the efficiency on various crops such as vegetable [17–20], tomato [21,22], maize [23–25] and rice [26–28]. Moreover, Toma et al. [29] applied DEA approach to estimate the efficiency of agricultural production in European countries for the period from 1993 to 2013; Gatimbu et al. [30] employed DEA method to measure environmental efficiency of tea production in Kenya; Coluccia et al. [31] used DEA approach to access the eco-efficiency in agricultural production in Italy; and and Li et al. [32] showed the solution to solve the unbalance problem by using DEA to evaluate cross-efficiency. In fact, the economic results and production yield must be balanced with the environmental damage generated by agricultural activities [33]. In addition, compared to the SFA, the DEA does not show the factors of the efficiency in the initial stage. Thus, the Tobit regression model is usually proposed to be used in the second stage because efficiency scores are ranged from 0 to 1 [24,34–37].

The aim of this research was to evaluate the efficiency level of edible canna farms and then to describe the sources of inefficiency. The findings paramount in assisting farmers by decreasing the usage of inputs while keeping output quantities intact such that the efficiency could be improved. On the other hand, the results could serve as references for policymakers to establish policy measures aiming at enhancing the performance of edible canna production in the Northern region of Vietnam.

2. Materials and methods

2.1. Data source and sampling method

Two districts, Nari and Babe, of Backan province were chosen as the study sites due to the fact that they account for the most acreage in growing edible canna (81.92% of total area) [7]. Eight communes with larger production area of edible canna within these two districts were then chosen to conduct the survey for this study (Figure 1). A total number of 385 farms were chosen randomly among edible canna farms in eight communes, 346 valid questionnaires were collected, resulting in a response rate of 89.9%.

The data were collected during the crop year 2017/18 through survey using face-to-face interviews. The structured questionnaire with two sections was designed to collect data. In the first section, a set of questions pertaining to farmer's socioeconomic situation were addressed, including age, education, experience, distance to the local market, kind of households, credit access, family size, and the number of extension contact. The second section attempted to collect data about production activities, i.e., inputs such as seed, chemical fertilizer, labor, and planted land; and output or the edible canna yield.

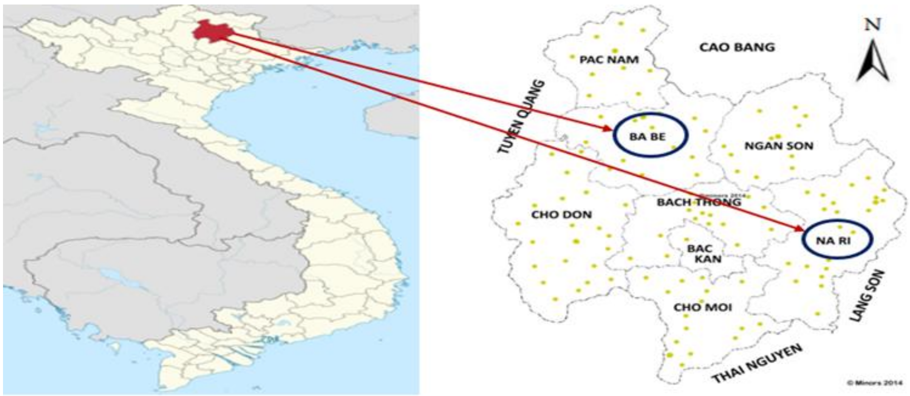

Figure.1. The map of study area [8,38].

2.2. Data analysis method

This study applied the two-stage DEA methodology to measure efficiency score for edible canna farms and then to determine factors influencing inefficiency of farms. In the initial step, the input-oriented DEA under constant returns to scale (CRS) and variable returns to scale (VRS) were applied to estimate efficiency levels of farms. In the second stage, socioeconomic variables were used to explain the correlation in measuring inefficiencies by adopting the Tobit model. The data obtained from the questionnaires were coded, edited and analyzed by using SPSS version 22, DEAP version 2.1, and STATA version 15.

2.3. Empirical models

The DEA evaluates the performance of Decision-making units (DMUs) in which several inputs are converted into multiple outputs [39,40]. In this study, DMU refers to each individual edible canna farm. According to Coelli et al. [13], the method is commonly used in the measurement of efficiency scores since it does not specify the production function, nor does not require to specification of a distributional form of the inefficiency term.

The DEA can be specified as an input-oriented or an output-oriented model. The former is achieved by minimizing the input levels without reducing the output quantities, while the latter can be done by increasing the quantity of output without adding the inputs. The characteristics of DMU_s determine the selection of the appropriate approach [41]. The current study used the input-oriented method to analyze given the situation that there is only one output with several inputs [13,37].

2.4. The empirical formula for measuring technical efficiency

The CRS model designed by Charnes et al. [42] was used to calculate the technical efficiency score of farms. This model expressed as follow:

$$
\begin{aligned}
&TE_{CRS} = Min_{\theta_{i\lambda}} \theta, \\
&Subject\ to \quad Y\lambda - y \geq 0 \\
&\qquad\qquad\quad X\lambda - \theta_i X_i \leq 0 \\
&\qquad\qquad\quad \lambda \geq 0
\end{aligned}
\tag{1}
$$

where Y and X denote output and input vectors, respectively, θ_i denotes the technical efficiency score of the i-*th* farm under CRS, and λ is a N × 1 vector of constant. The θ value ranges from 0 to 1. For any farm, if θ = 1, indicating that the farm is on the production frontier and is totally technically efficient under the assumption of CRS. On the other hand, if θ < 1, it means that the farm stands below the frontier and is considered technically inefficient [15].

2.5. The empirical model for estimating pure technical and scale efficiency

According to Banker et al. [43], the expansion of the CRS-DEA captures the variable returns to scale (VRS) situations by incorporating the convexity constraint N1'λ = 1 to equation (1). Under VRS DEA model, the pure technical efficiency (PTE) and SE of edible canna farms were calculated. The VRS linear programming was expressed by Eq (2) as follow:

$$
\begin{aligned}
&TE_{VRS}(PTE) = Min_{\theta_{i\lambda}} \theta, \\
&Subject\ to \quad Y\lambda - y_i \geq 0, \\
&\qquad\qquad\quad X\lambda - \theta_i X_i \leq 0 \\
&\qquad\qquad\quad N1'\lambda = 1;\ \lambda \geq 0
\end{aligned}
\tag{2}
$$

where θ presents the PTE of edible canna households, and N1'λ illustrates a convexity constraint to ensure that an inefficient edible canna farm was only benchmarked against farms of a similar-size farm [13,44].

Moreover, SE denotes quantitative information of scale characteristics. It is also used to indicate the association between the optimal farm size and the level of efficiency. In this study, the SE of edible canna farms was simply computed by a ratio of TE_{CRS} to TE_{VRS}, as indicated by Eq (3):

$$
SE = \frac{TE_{CRS}}{TE_{VRS}} \tag{3}
$$

If SE = 1, indicating the farm scale efficiency or CRS. In contrast, SE < 1 reflects that the farm is scale-wise inefficient, either the farmer is operating their production at increasing (IRS) or decreasing returns to scale (DRS) [40,44].

2.6. The economic and allocative efficiency model

Based on Coelli et al. [13], the cost-minimization DEA model under CRS was applied for measuring farm economic efficiency in this study. The linear programming to estimate economic efficiency was illustrated by Eq (4) below:

$$\begin{aligned} &Min^{*}_{x_i\lambda} w_i x_i^{*}, \\ &Subject\ to \quad Y\lambda - y_i \geq 0, \\ &\qquad\qquad\quad X\lambda - x_i^{*} \leq 0, \\ &\qquad\qquad\quad \lambda \geq 0 \end{aligned} \tag{4}$$

where w_i is price of input for the i^{th} farm, x_i^* is the vector of cost-minimizing of input quantities for the i-th farm, and y_i is the output levels. Hence, EE can be computed by dividing minimum cost with observed cost as the following equation:

$$EE = \frac{w_i x_i^{*}}{w_i x_i} \tag{5}$$

From the results of EE and TE under CRS, the value of AE can be further computed as a ratio of economic efficiency to technical efficiency.

$$AE = \frac{EE}{TE_{CRS}} \tag{6}$$

2.7. The Tobit regression model

In the second stage involved the separate regression of TE, AE and EE scores on a vector of socio-economic characteristics independent variables to identify the sources of inefficiency. Tobit regression model was considered most appropriate for the second stage compared to other methods since the efficiency scores range between 0 and 1 [45]. Socioeconomic variables related to farmer/farm, i.e., age, education, experience, market distance, kind of household, farm credit, household size and extension visit, were used as explanatory variables in the Tobit regression model to compute the correlation between inefficiency level and the socioeconomics characteristics of farm. The model is illustrated as formula (7):

$$\begin{aligned} &\theta^{*} = \beta Z_i + \varepsilon_i,\ i = 1, 2, ...N \\ &\theta_i = \theta^{*}\ if\ \theta^{*} > 0, \\ &\theta_i = 0\ if\ \theta^{*} \leq 0 \end{aligned} \tag{7}$$

where β is a value of unidentified coefficients which illustrates the interaction between the vector of independent variables (Z_i), θ^* is the latent variable; and ε_i represents the error term, $\varepsilon_i \sim N(0, \sigma^2)$. θ_i denotes the inefficiency scores of the i^{th} farm which was estimated in the first stage, including overall technical, scale, allocative and economic inefficiency scores.

3. Results and discussion

3.1. Descriptive statistics

Table 1 shows the descriptive statistics of variables used in the study. All the individual production variables were found to have a large range. The average per acre yield of edible canna was 1244.79 kg ranged from 180.00 kg to 3780.00 kg. It is reasonable to believe that farmers would use various combination of inputs depend on their experiences, financial ability and scale of production. Consequently, it would lead to vast difference among farms for each individual inputs as indicated by wide range in Table 1. The average labor per acre by both family and hired labors was 14.04 man-days with a range from 1.2 to 61.20 man-days, implying that edible canna production tended to be highly labor intensive. The mean quantity of seed was 76.24 kg per acre with a wide range from 10.29 to 1080.00 kg. It was followed by chemical fertilizer with a per acre mean value of 41.36 kg ranged from 1.20 to 306 kg.

Table 1. Descriptive statistic of production and socioeconomic variables of edible canna farms.

	Unit	Mean	Std. Dev.	Min.	Max.
Production Variables					
Output					
Edible canna yield	Kg/acre	1244.79	681.10	180.00	3780.00
Inputs					
Seed	Kg/acre	76.24	67.73	10.29	1080.00
Chemical fertilizer	Kg/acre	41.36	39.79	1.20	306.00
Labor	Man-days/acre	14.04	8.07	1.28	61.20
Land	Acre	9.04	10.78	0.83	83.33
Seed price	1000 VND/kg	2.61	0.76	1.00	5.00
Chemical fertilizer price	1000 VND/kg	6.14	0.71	2.67	8.20
Labor price	1000 VND/man-day	152.63	12.05	100.00	200.00
Land rent price	1000 VND/m^2	10.19	0.39	10.00	11.00
Socioeconomic Variables					
Age (Z1)	Years	44.59	10.45	23.00	73.00
Education (Z2)	Years	6.07	3.51	0.00	18.00
Experiences (Z3)	Years	6.20	3.88	1.00	23.00
Market distance (Z4)	Km	5.17	4.82	0.02	23.00
Household's group (Z5)	Dummy	0.41	0.49	0.00	1.00
Farm credit (Z6)	Dummy	0.73	0.44	0.00	1.00
Household size (Z7)	Members	4.78	1.42	2.00	10.00
Extension visit (Z8)	Dummy	0.45	0.50	0.00	1.00

Note: 1 acre = 360 m^2 = 0.036 ha.

Similarly, household size also varied significantly as well, ranging from 0.83 to 83.33 acres, with mean size of 9.04 acres per farm. For the socioeconomic variables, other than three dummy variables, i.e., type of household, farm credit, and extension visit; the rest individual socioeconomic variables were also varied considerably with a wide range. An average farmer was 44.59 years old with about 6.0 formal years of schooling and 6.0 years of experience working in canna cultivation. Typically, the market distance was 5.17 km; and the average household size was 4.78 persons. In addition, 41% of the sampled households were considered poor; 73% and 45% of farmers respectively had access to credits and extension services.

3.2. The distribution of efficiency scores

This study applied DEAP 2.1 program [46] to estimate the efficiency of edible canna farms. Table 2 presents the efficiency scores and their distribution. The results exposed that the mean pure efficiency (or TE_{VRS}) was the highest of 0.752, followed by SE, overall technical efficiency (or TE_{CRS}), AE and EE of 0.681, 0.513, 0.509 and 0.258, respectively. In other words, the overall technical efficiency and economic performance in edible canna production can be improved by reducing 48.70% of inputs which would be equivalent to 74.20% reduction in input cost without adversely affecting the output quantity of edible canna. The number of farms of efficiency scores more than 0.9 was the highest in pure efficiency and scale efficiency with 72 (or 20.81%) and 71 (or 20.52%), respectively; while it was 5 (or 1.45%) for allocative efficiency, and 1 (or 0.29%) for economic efficiency.

Table 2. The frequency of efficiency scores distribution of edible canna farms in Backan province.

Efficiency scores	TE_{CRS}		TE_{VRS} (PTE)		SE		AE		EE	
	No. of farms	%	No. of farms	%	No. of farms	%	No. of farms	%	No. of farms	%
Less than 0.5	181.00	52.31	20.00	5.78	83.00	23.99	166.00	47.98	327.00	94.51
0.5–0.59	54.00	15.61	44.00	12.72	39.00	11.27	102.00	29.48	16.00	4.62
0.6–0.69	41.00	11.85	71.00	20.52	45.00	13.01	48.00	13.87	2.00	0.58
0.7–0.79	32.00	9.25	81.00	23.41	50.00	14.45	20.00	5.78	0.00	0.00
0.8–0.89	22.00	6.36	58.00	16.76	58.00	16.76	5.00	1.45	0.00	0.00
0.9 or more	16.00	4.62	72.00	20.81	71.00	20.52	5.00	1.45	1.00	0.29
Total	346.00	100.00	346.00	100.00	346.00	100.00	346.00	100.00	346.00	100.00
Mean	0.513		0.752		0.681		0.509		0.258	
Min	0.092		0.354		0.149		0.093		0.028	
Max	1.000		1.000		1.000		1.000		1.000	

Table 3 illustrated the mean values of efficiency score for two districts investigated in this study, i.e., Nari and Babe. Overall, the average values of TE_{CRS}, TE_{VRS}, SE, AE and EE of edible canna production in Babe were higher than those of Nari district, yet only the latter three efficiency scores are shown statistically different between these two districts. This might be attributed to the difference in input use between the two districts. Moreover, the characteristic of the cultivated land of farms in Babe district was better than Nari district. Hence, the produced output quantity per acre of edible canna farms in Babe was also higher. The results revealed that the highest efficiency score was TE_{VRS} in both district with 0.814, and 0.779 in Babe and Nari, respectively. Given the estimated scores of SE, it indicated that the scale efficiency of canna production in Nari and Babe can be further improved by 29.6% and 27.5% respectively by adjusting the size of operation. However, the estimated scores for economic efficiency were low in both districts, which might be addressed to the unbalance use and allocation of the inputs (Table 3).

The differences in returns to scale of edible canna production for two studied districts are unveiled in Table 4. In Nari district, out of the 223 farms, 92.38% of total farms were being operated under IRS, 5.80% were CRS, and the remaining 1.79% were DRS. Comparatively the percentage of farms operating under IRS was lower in Babe (83.06%), yet it was higher for CRS. Moreover, the proportion of farms operating at IRS in both districts were high, indicating that farmers could improve their efficiency in edible canna cultivation by increasing their scale. As such, it can be concluded that the farm operation scale was one of the factors influencing the performance of edible canna production.

Table 3. Comparison efficiency scores of farms in Backan province by region.

District	Efficiency scores				
	TE_{CRS}	TE_{VRS}	SE	AE	EE
Nari	0.550	0.779	0.704	0.488	0.270
Babe	0.590	0.814	0.725	0.728	0.422
t-value	-1.578^{ns}	-0.833^{ns}	-1.979^{**}	-14.393^{***}	-8.607^{***}

Note: Significance levels ** $p < 0.05$ and *** $p < 0.01$.

Table 4. Summary of returns to scale of edible canna farms.

Characteristics	Nari district		Babe district	
	No. of farms	Percentage (%)	No. of farms	Percentage (%)
Increasing returns to scale (IRS)	206	92.38	103	88.06
Decreasing returns to scale (DRS)	4	1.79	4	3.23
Constant returns to scale	13	5.80	16	12.90
Total	223	100	123	100

3.3. Factors influence on the efficiency of edible canna farms

The findings of Tobit model are presented in Table 5. The findings indicated that three variables affected overall technical inefficiency of the edible canna farms, i.e., age, education level, and extension contact. Age was found to have a significantly negative impact on both technical inefficiency and scale inefficiency. In other words, old farmers were more technically and scale-wise efficient than the young counterparts, which is in line with the finding by Chiona et al. [47].

The results revealed that education had a negative and significant effect on technical and economic inefficiency ($p < 0.05$). These results confirmed that education plays an important role in efficiency improvement as pointed out by several previous studies such as Raheli et al. [37], Linh [48] and Khan and Ali [49]. According to Nargis and Lee [50], farmers with more schooling years were most likely to obtain better efficiency due to better knowledge in planning farms and applying high technology in production. It is believed that good education can facilitate quality learning, therefore government policies should strive to tackle the prevailing illiteracy in the rural areas by encouraging people to attain more education, which would in turn enhance efficiency in edible canna production.

Household size was found to have a positive and significant impact on the technical inefficiency, signifying that a bigger family tends to achieve less technical efficiency than the small household ones. This reason may be due to almost large households in Backan province were poor and they have fewer opportunities in access to high farming tools. Therefore, using the labor input of large edible canna farms was not efficient Long and Yabe [51]. However, in term of allocative inefficiency of edible canna farms, the size of the household had a negative effect, signifying that a bigger family can achieve higher allocative efficiency. This might be due to the valuable role of family labor in allocating resources in edible canna production in the study sites. This finding is harmony with the statement by Mailena et al. [52].

Table 5. Factors influencing inefficiency scores of edible canna farms.

Variables	TE		SE		AE		EE	
	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Age	-0.0024^{**}	0.040	-0.0031^{**}	0.018	0.0006	0.442	−0.0010	0.134
Education level	-0.0092^{**}	0.018	−0.0065	0.130	0.0025	0.353	-0.0046^{**}	0.049
Experiences	−0.0047	0.104	−0.0013	0.690	0.0018	0.372	−0.0010	0.573
Market distance	0.0032	0.259	−0.0007	0.820	-0.0041^{**}	0.033	0.0001	0.938
Type of household	0.0100	0.658	−0.0119	0.636	0.0063	0.684	0.0144	0.291
Farm credit	0.0088	0.725	0.0077	0.781	0.0048	0.778	0.0093	0.535
Household size	0.0158^{**}	0.042	−0.0012	0.892	-0.0115^{**}	0.032	0.0034	0.461
Extension visit	-0.1175^{***}	0.000	-0.1218^{***}	0.000	−0.0150	0.337	-0.0674^{***}	0.000
Constant	0.6267^{***}	0.000	0.5618^{***}	0.000	0.5147^{***}	0.000	0.8232^{***}	0.000
Log likelihood	47.096		10.324		192.864		236.888	

Note: Significance levels ** $p < 0.05$ and *** $p < 0.01$.

In addition, it was revealed that extension visit had a significantly negative effect on technical, scale and economic inefficiency of edible canna farms (Table 5), illustrating that the efficiency level of farms increase when producer had more contacts with extension agency, which is similar with the results by Ali et al. [44], Nargis and Lee [50] and Shrestha et al. [20]. Ali et al. [44] stated that the inefficiency level of farms would decline when the producer had a close relationship with extension staffs; and Nargis and Lee [50] found that the support from extension agencies had a significantly positive impact on the technical efficiency of rice farms in Bangladesh. Therefore, government institutions and extension agencies should design and provide training courses in demand, e.g., technical know-how, management skills and marketing knowledge, to farmers with the aims to improve edible canna production efficiency in Vietnam.

Surprisingly, in this study, the distance from farm to local market was found to be significantly negative on allocative inefficiency at a significance level of 5%, which is in contrast to the finding of most previous studies [53–55]. Usually, it would be expected that higher transportation cost is involved when the farm is located further away from the market [44]. This may be attributed to that owners of those distant farms aware the fact that it would cost them more in terms of transportation; therefore, they would use inputs more carefully and thus attain higher allocative efficiency.

4. Conclusions

The two-stage method was employed to measure the efficiency of edible canna production in Vietnam. The results showed that all the estimated efficiency scores (TE, PTE, SE, AE and EE) were generally low, meaning that the edible canna production in Backan province was inefficient. In addition, the edible canna farms located Babe district showed higher efficiency in the aspects of scale, allocation, and economics as compared to Nari district. In the second stage, Tobit regression analysis methodology was applied to explore the factors affecting the inefficiency level of edible canna farms.

The findings implied that age, education and extension visit individually had a significantly negative impact on inefficiency levels of edible canna farms.

Based on the synthesis of findings, it is recommended that the government should address public investment policy on fortifying extension system by emphasize training to teach farmers on how to use inputs efficiently as well as assist them to adopt high technologies to enhance yield. In addition, government needs to encourage edible canna farmers to attain more education which could facilitate the learning process and in turn to improve the production efficiency. The public policies should be directed to support the growth of the edible canna production due to the fact that it accounts for the most economic activities and is the major income generator in the study sites.

This study provided meaningful information about the efficiency of edible canna production in Vietnam. Regarding the limitation of this study, given that it is the first study addressed on the efficiency analysis of edible canna production; and the findings mainly focused on evaluating the efficiency as well as its determinants, which only revealed the situation of one side of edible canna production in the Northern regions of Vietnam. Obviously, there are other problems related to edible canna production such as high input price, low selling price of edible canna, and under-developed consumer market of edible canna products. Therefore, future studies might focus on the value chain analysis of sustainable production of edible canna which could consolidate linkages in production, processing, and consumption.

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Conflict of interest

Authors declare no conflict of interest.

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