Kurdish Studies
Apr 2023
Volume: 11, No: 2, pp. 3315-3325
ISSN: 2051-4883 (Print) | ISSN 2051-4891 (Online)
www.KurdishStudies.net

Received: May 2023 Accepted: June 2023
DOI: https://doi.org/10.58262/ks.v11i2.240

Allocative Efficiency of Chu-Mango Farms in Dong Thap, Vietnam

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Abstract

The purpose of this research was to examine the allocative efficiency of Chu mango cultivation in Dong Thap, Vietnam. Stochastic frontier analysis was used to estimate farm-level efficiency ratings, and maximum likelihood estimation methods were used to determine parameter coefficients. A well-structured questionnaire was used to collect data for 684 observating samples. The study's findings indicated that the mean allocative efficiency was 0.639, 0.693, and 0.840 in seasons 1, 2, and 3, respectively. The most efficient farmer of mangoes would have recommended a gain in allocative efficiency of 77,79%, 83.59%, and 24.85%, whereas the least efficient one would have saved 33,74% in season 1, 25.37% in season 2, and 15.71% in season 3. The cost of fertiliser, pesticide, wrapping bags, hired labour, and family labour are the major factors affecting Chu mango output. In terms of socioeconomic variables, family size increases allocative efficiency in season 2, whereas age and farming experience reduce allocative efficiency in season 2. Allocative efficiency in the second season is positively correlated with credit availability and education, but negatively correlated with age and agricultural experience. The study recommends prioritising credit programmes for Chu mango growers via the Agriculture and Rural Developmenr Bank Sytstem. In Dong Thap, Vietnam, connecting small-scale Chu mango growers to micro-finance institutions for loans and incorporating them into sustainable training and extension programmes will boost production efficiency.

Keywords: *Allocative efficiency, Sustainable production, Dong Thap*

1 Introduction

Over 50% of tropical fruit production is made up of mango. Approximately 160 varieties of mangoes are grown in over 90 countries, yet only 3.6% is exported. This fruit can't be imported or exported for very long since it's perishable and difficult to transport. Major mango varieties include Pakistan and India. In 2017, India's 2.3 million hectares produced 18.4 million tonnes of mangoes, accounting for 40% of global production. Tommy Atkins, Kent, Haden, and Keitt export mangoes are firmer and more suited for extended journeys. These mangoes are grown in South America. Green mangoes from Atalfo and Amelie are available in international markets (FAO, 2019).

In Asia region, mango production in China and Thailand was 4.8 and 3.8 million tonnes. Mangoes were also grown in Indonesia, Mexico, Pakistan, and Egypt (1.39 million tons). Vietnam produced mangoes 14th worldwide. In 2019, Vietnam produced 900,000 tonnes of mango over

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87,000 hectares, ranking 8th in Asia after India, China, and Thailand. Thailand, Indonesia, Philippines, and Vietnam are among Asia's top 10 mango producers. Thailand exports mangoes second after Mexico. The Mekong Delta (MD) is Vietnam's tropical fruit hub. It provided the most mangoes in 2019 with 48,200 hectares (46.3% of total national farming area) and 511,800 tonnes (62.8% of national production volume). Dong Thap, An Giang, Vinh Long, and Tien Giang have the most mangoes in both production area and volume (GSO, 2020).

Dong Thap was the most mangoes in the Mekong Delta (MD) with 11,500 ha and 130,000 tonnes in 2019. This represented 24% of MD mango producing area and 25.4% of fresh mango output volume. Mango output grew by 8.0% and 9.2% from 2016 to 2019. Chu-mango (45%), Hoaloc-mango (21%), Green Tuong-mango (18%), and others (16%) were Dong Thap's principal mangoes (GSO, 2020). This MD region produces mangoes, notably Chu-mangoes.

The mango business in Dong Thap is less efficiency due to rising input costs and small-scale farming. Thus, managerial strategies, input costs, and high-yielding cultivars may lower production costs. Nowadays, they begin emphasising on production efficiency for farming sustainability. Economic efficiency comes from technological and allocative efficiency (Ume et al., 2020). This research emphasises allocative efficiency. Okoye et al. (2015) defined allocative efficiency as managing limited resources and technological know-how to maximise economic advantage. Furthermore, Ubokudom et al. (2021) defined allocative efficiency as the ratio of the farmer's technically maximum production to the optimal output. In the present research, constraint allocative efficiency implies producers allocate a set capital expenditure to specific inputs during the Chu mango growing season. Growers aim to optimise production at a given cash investment. Management methods promote allocative efficiency, where marginal production of each input equals the ratio of input and output prices. The research estimated Chu mango grower allocative efficiency and affecting variables to control input cost (fertiliser, insecticides, and herbicides) towards sustainable production.

2 Methodology

2.1 Sampling technique

An investigation that was carried out in two areas of the province of Dong Thap during the 2021farming season provided the information. Cao Lanh district and Cao Lanh city are the two districts in investigation. It takes up 60.9% and 64.5% of Dong Thap's total production area and volume, respectively (GSO, 2020). A simple random sampling procedure was employed to choose 684 respondents overall (300, 300, and 84 observations for seasons 1, 2, and 3, respectively). Information was collected on factors like the size of the business, the amount of loans advanced for mango production, the way the farmers invested the capital for mango production, the wage rate for hired labors, and the quantity and cost of inputs like fertiliser, insecticides, and herbicides.

2.2 Empirical model

Aigner, et al. (1977) and Meeuseen (1977) created the stochastic frontier model for production unit analysis based on Farrell (1957). Coelli (1995) recommended stochastic frontier for farm-level data analysis when measurement errors and climatic conditions may be substantial impacts. The research used the stochastic frontier model. A farm's general stochastic production model is presented as follws:

$$Y_i = f(x_i, \beta)\exp(v_i - u_i) \quad [1]$$

Where Yi is the ith farmer's output, x_i is a vector of farm inputs, and β is a vector of parameters to be estimated. The v_i measures the random variation in output due to factors outside the farm's control is assumed to be identically and independently distributed as N(0, σ_v^2), independent of u_i, which has a half normal non-negative distribution. The non-negative technical inefficiency effects u_i are farmer-controlled and assumed to be independently distributed with mean u_i and σ^2 variance. Maximum likelihood estimates equation [1] coefficients. The model's variance σ^2 is calculated by adding the variances of random errors σ_v^2 and inefficiency effects σ_u^2 ($\sigma^2 = \sigma_v^2 + \sigma_u^2$).

The gamma γ, the ratio of the inefficiency impact variance to total variance, measures the overall deviation of output from the frontier due to the technical inefficiency $\gamma = \sigma_u^2 / \sigma^2$. The value of the γ is between 0 and 1 (Battese and Corra, 1997). The cost function composite error term is changed from $\varepsilon_i = v_i - u_i$ to $\varepsilon_i = u_i + v_i$. The cost function is the production function transformed and is defined:

$$C_i = f(Y^*, P_i, \alpha_i)\exp(u_i + v_i) \quad [2]$$

Where Ci is the minimum input cost of the ith farm associated with the observed output Y*, Pi is the vector of input prices, and α is a vector of parameters. v_i is a random variable assumed to be N(0, σ_v^2) and independent of u_i. The farm's cost inefficiency is attributed to non-negative variables N(0, σ_u^2). It determines the firm's operating margin. Individual grower allocative efficiency is minimum cost/observed cost:

$$AE = \frac{C_i^*}{C_i} = \frac{f(Y^*, P_i, \alpha_i)\exp(u_i + v_i)}{f(Y^*, P_i, \alpha_i)\exp(v_i)} = \exp(u_i) \quad [3]$$

Where: AE: Allocative efficiency; Ci*: Minimum potential farm cost; Ci: Observed farm cost. The value of allocative efficiency ranges between 0 and 1. A farm is allocative efficient if $C^* = C$ and inefficient if $C^* > C$. The formula calculated individual farm-level allocative inefficiency as follows:

$$u_i = \delta Z_i + w_i \quad [4]$$

Where: Zi is a vector of explanatory factors describing farmer allocation inefficiency. The w_i is an unobserved random variable and δ is a vector of parameters to estimate

Cobb-Douglas production function or the Transcendental logarithmic

This research investigated three basic hypotheses. (i) The translog model is suitable, (ii) there is no production and cost inefficiency impact, (ii) and external variables are not responsible for the inefficiency term (ui). Hypothesis test results determine Cobb-Douglas or Translog production function. Asymptotically, this test statistic is a chi-square random variable with a degree of freedom equal to the number of restrictions. The generalised likelihood ratio test statistic stated as evaluated the three hypotheses (Coelli 1995).

$$LR(\lambda) = \frac{-2\ln L(H_0)}{L(H_1)} = -2\{\ln[L(H_0] - \ln[L(H_1)]\} \quad [5]$$

The probability functions of null and alternative hypotheses, H0 and H1, are L(H0) and L(H1). LR greater than the critical threshold rejects H0 (Taymaz and Saarci, 1997). If H0 is true, the LR has a mixed chi-quare distribution asymptotic distribution, $\frac{1}{2}$ X^2_0 + $\frac{1}{2}$ X^2_1 (Coelli, 1995). SFA tests two basic hypotheses to validate method application:

Stochastic frontier model functional form (Cobb-Doughlas or Translog)

H0 = *0 Cobb-Douglas form fits data.*

H1 > *0 Cobb-Douglas form cannot reflect data.*

Empirical model of the stochastic and cost functions

The allocative efficiency of Chu mango growers in the study site was determined using a multiple regression model based on the stochastic frontier cost function with Cobb-Douglas functional form:

$$\ln Y_i = \beta o + \beta 1 \ln X1 + \beta 2 \ln X2 + \beta 3 \ln X3 + \beta 4 \ln X4 + \beta 5 \ln X5 + \beta 6 \ln X6 + \varepsilon_i \quad [6]$$

The translog production function is also defined as:

$$\ln Yi = \beta o + \beta 1 lnX1 + \beta 2 lnX2 + \beta 3 lnX3 + \beta 4 lnX4 + \beta 5 lnX5 + 0.5\beta 6(lnX1)^2 + 0.5\beta 7 ln(lnX2)^2 + 0.5\beta 8 ln(lnX3)^2 + 0.5\beta 9 ln(lnX4)^2 + 0.5\beta 10 ln(lnX5)^2 + \beta 11 lnX1lnX2 + \beta 12 lnX1lnX3 + \beta 13 lnX1lnX4 + \beta 14\ lnX1lnX5 + \beta 15 lnX2lnX3 + \beta 16 lnX2lnX4 + \beta 17 lnX2lnX5 + \beta 18 lnX3lnX4 + \beta 19 lnX3lnX5 + \beta 20 lnX4lnX5 + \varepsilon_i \quad [7]$$

Where:

Ln = Natural logarithm
Yi = the value of product computed for i-th farmer (vnd)
X1 = fertiliser cost (vnd);
X2 = pesticide cost (vnd);
X3 = wrapping bag cost (vnd);
X4 = energy cost (vnd);
X5 = hired labor cost (vnd);
X6 = faminly cost (vnd);

ε_i = error
β_0 = constant
$\beta_{1\ldots20}$, and β_k are parameters to be estimated, represents statistical disturbance term and
u_i = represents cost inefficiency effects of i-th farmer.
Equation of variables determining allocative inefficiency as follows:

$$\boldsymbol{u_i = \delta_0 + \sum_{r=1}^{10} \delta_r Z_r + w_r} \quad [8]$$

Where:
u_i = represents profit inefficiency effects of i-th farmer
α_0 and α_r = Parameters to be estimated,

w_r = An unobserved random variable
Z_r = Variables explaining inefficiency effects, r =1,2,3..., n, k is truncated random variable.
Z_1 = Agro-input wholesaler payment (crop ending =1, payment immediately =0),
Z_2 = Credit access (access =1, no access = 0)
Z_3 = Farming experience (year)
Z_4 = Farmer`s age (year)
Z5 = Level of education (years spent in acquiring formal education)
Z_6 = Plant density (plants/ha)

Maximizing the likelihood function on FRONTIER 4.1 generated estimates for all cost function and inefficiency model parameters.

3 Results and Discussion

Table 1 shows that the Generalised Likelihood Ratio test was used to determine the best functional form for the data and the impact of socio-economic determinants in cost inefficiency. Cobb-Douglas form was the optimal functional form for season 2 data since $\boldsymbol{\lambda 2}$ = 10.32 was lower than critical value (32.67) at 5% significance. In season 1 and 3, the null hypothesis was rejected because lambda values $\boldsymbol{\lambda 1}$ =38.56, $\boldsymbol{\lambda 3}$ =65.24 were more than critical value (32.67) at 5% significance. The stochastic frontier model of seasons 1 and 3 implies that translog model findings suit the data well.

Table 1: Results of Hypotheses Test

Seasons	Null Hypotheses	Log likelihood (H_0)	Log likelihood (H_1)	Test statistic (λ)	Degree of Freedom	Critical value (5%)	Decision
1	HàmCobb-Douglas	-51,15	-31,87	38,56	21	32,67	Translog
2	HàmCobb-Douglas	-175,87	-169,71	12,32	21	32,67	Cobb-Douglas
3	Hàm Cobb-Douglas	-18,02	14,60	65,24	21	32,67	Translog

* * Critical values with asterisk are taken from Kodde and Palm (1986). For these variables the statistic λ is distributed following a mixed χ2 distribution.

Table 2 shows the anticipated parameters and statistical test results from the maximum likelihood estimates (MLE) of the Cobb-Douglas and Translog based on stochastic frontier cost function for mango growers in southern Vietnam. The sigma squares ($\sigma 2$) of 0.09902 in season 1, 1.31466 in season 2, and 0.00189 in season 3 were disparity from zero, indicating a satisfactory model fit and proper distributional assumptions. Gamma values $\gamma 1$=0.9361 in season 1 (at 1% probability), $\gamma 2$=0.9518 in seasons (at 1% probability), $\gamma 3$=0.4476 (at 10% probability) were high and significant. Variables explained almost 93.61%, 95.18%, and 44.76% of allocative efficiency in seasons 1, 2, and 3, respectively, and the remaining 6.39%, 4.82%, and 55.24% in seasons 1, 2, and 3, respectively are due to random error.

Table 2: Maximum Likelihood Estimates of the stochastic frontier odels of cost function

Varianle	Season 1		Season 2		Season 3	
	Coef	SE	Coef	SE	Coef	SE
[Dependent Variable: Product value (vnd)]						
Constant	-32,829	48,316	14,865***	0,712	-6,623**	2,883
(X_1) Ln fertiliser cost (vnd)	2,566	2,225	0,026**	0,013	-0,020*	0,015
(X_2) Ln pesticide cost (vnd)	-4,266**	2,743	0,031	0,036	0,318***	0,106
(X_3) Ln wrapping bag cost (vnd)	-1,205	1,702	0,114***	0,032	0,798***	0,197
(X_4) Ln energy cost (vnd)	0,335	1,603	-0,015	0,022	0,029	0,177
(X_5) Ln hired labor cost (vnd)	2,894	2,717	0,085***	0,020	-0,405*	0,274
(X_6) Ln family labor cost (vnd)	5,921***	2,369	0,020	0,019	1,338***	0,189
½ *Ln $(X1)^2$	0,021	0,038			-0,071	0,227
½ *Ln $(X2)^2$	-0,007	0,048			0,005***	0,001
½ *Ln $(X3)^2$	0,028**	0,016			0,025***	0,001
½ *Ln $(X4)^2$	-0,004	0,020			0,072***	0,006
½ *Ln $(X5)^2$	-0,050	0,062			0,015***	0,006
½ *Ln $(X6)^2$	-0,023	0,023			0,009***	0,001
Ln (X1)*Ln (X2)	0,026	0,055			-0,004	0,004
Ln (X1)*Ln (X3)	-0,001	0,049			0,002	0,004
Ln (X1)*Ln (X4)	-0,012	0,043			-0,028***	0,007
Ln (X1)*Ln (X5)	-0,086	0,098			0,005	0,008
Ln (X1)*Ln (X6)	-0,117**	0,053			0,002**	0,001
Ln (X2)*Ln (X3)	0,012	0,056			-0,004	0,005
Ln (X2)*Ln (X4)	0,007	0,038			-0,055***	0,007
Ln (X2)*Ln (X5)	0,210**	0,119			0,009	0,015
Ln (X2)*Ln (X6)	0,022	0,051			-0,033***	0,013
Ln (X3)*Ln (X4)	0,003	0,035			0,008	0,011
Ln (X3)*Ln (X5)	-0,004	0,060			-0,005	0,010
Ln (X3)*Ln (X6)	0,021	0,044			-0,058***	0,006
Ln (X4) *Ln (X5)	0,019	0,061			0,015	0,014
Ln (X4) *Ln (X6)	-0,028	0,032			0,001	0,006
Ln (X5) *Ln (X6)	-0,221***	0,093			-0,008	0,008
Variance Parameters						
Sigma square (σ2)	0,09902		1,31466		0,00189	
Gamma (γ)	0.93618***		0.95183***		0.44764*	
Log-likelihood function	-31,879		-175,8747		146,049	
Observations (N)	300		300		84	

Source: Field Survey Data, 2022

* Significant at 10% level, ** significant at 5% level, *** significant at 1% level

The computed model showed that the fertiliser cost coefficient was positive and statistically significant at 5% in season 2. In season 2, a 10% fertiliser cost increase resulted in 0.26% income rise for mango producers. The pesticide cost variable had a negative impact on mango growers' productivity in season 1 and a positive effect on their income in season 3 at the conventional significance levels. In seasons 2 and 3, the wrapping bag cost increased Chu mango farmer revenue at 1% significance level. Mango growers' income will increase 1.14% and 7.98% in seasons 2 and 3 if wrapping bag costs climb 10%. Importantly, the coefficients of the square term for wrapping bag cost were positive, indicating that Chu mango growers earned more by investing in wrapping bags. Similarly, the coefficients of family labor cost in seasons 1 and 3 are positive at 1% level of probability. In addition, the coefficient of interaction between fertiliser cost and family labour cost was negative in season 1 at 5% significance level, but positive in season 3 at 1% significance level.

Table 3: Determinants of cost inefficiency

Variable	**Season 1**		**Season 2**		**Season 3**	
	Coef	SE	Coef	SE	Coef	SE
Constant	0,561**	0,286	-4,149	4,806	-0,163	0,229
(Z_1) Payment for agro-input	-0,028	0,052	0,450	0,452	0,001	0,001
(Z_2) Credit access	0,052	0,060	0,403	0,446	-0,028**	0,014
(Z_3) Farming experience	0,003	0,003	0,034	0,033	0,049***	0,017
(Z_4) Age	-0,001	0,002	0,006	0,013	0,002**	0,001
(Z_5) Education	-0,008	0,007	0,061	0,061	-0,001**	0,001
(Z_6) Plant density	-0,0002	0,0002	0,001	0,001	0,0010	0,0021

Source: Field Survey Data, 2022

* Significant at 10% level, ** significant at 5% level, *** significant at 1% level

Note: A negative sign of the parameters in the inefficiency function means that the associated variable has a positive effect on profit efficiency, and vice versa.

Credit's effect on production efficiency is well established. Credit availability affects agricultural efficiency, according to studies (Inkoom and Micah, 2017; Onumah et al., 2013). The finding indicated that credit availability affected Chu mango growers' allocative efficiency. According to season 3 model results in Table 3, Chu mango growers' allocative inefficiency is negatively affected by financing. It meant that banking credit facilities boost Chu mango growers' allocative efficiency. Access to financing gives farmers more cash, making production decisions and operations faster. The observed credit access calls for the establishment of adequate credit facilities for farmers and the reengineering of bank credit criteria to make it easier for farmers to get credit to support their farming operations.

Season 2 model results showed that farming experience and age positively and significantly correlated with allocative inefficiency. This shows that farmers become less efficient with higher experience and age. Less-experienced and younger farmers were more productive. Our research found that faming experience affects farm-level efficiency differently from others (Ogunya and Tijani, 2022; Onumah et al., 2013; Khan and Ali, 2013). The finding of age were consistent with those obtained from the studies of Mbanasor and Kalu (2008), Mwita (2016). However, these results were contrary to the findings of Daniel (2016), Khan and Ali (2013), Abdur (2012), Alam (2012), Bealu et al. (2013), stated that older farmers had a negative effect on profit efficiency.

The research also found that Chu mango growers' allocative inefficiency was adversely and substantially impacted by educating. The result from season 2 of Table 3 suggested that Chu mango producers with higher education are more allocatively efficient in output. Chu mango growers are less likely to experience allocative inefficiency since education improves their cognitive capacity to produce effectively. This finding confirmed prior studies (Daniel 2016; Khan and Saeed 2011; Mwita 2016) that demonstrated a statistically significant association between education and efficiency.

Table 4 shows the predicted allocative efficiencies of Chu mango producers in seasons 1, 2, and 3. Allocative efficiency is 0–1. No farmer exhibited 100% allocative efficiency. Seasons 1 and 2 predicated allocative efficiency in study area was 0.639 and 0.693, respectively, with ranges 0.214-0.964 and 0.152-0.929. Chu mango farmers average 63.9% and 69.3% allocative efficiency. Season 3 allocated efficiency ranged from 74.8% to 99.6%. The study's Chu mango growers' mean allocative efficiency estimate was 84.0%. This suggests that the typical farmer in the sample must boost allocative efficiency by 36.1%, 31.7%, and 16.0% of seasons 1, 2, and 3 to match Dong Thap's most efficient farmer, respectively. Table 4 matches Londiwe et al (2014). South African sugarcane crop allocative efficiency was 61.5%. Hussain (1995) reported 42.5 % wheat crop allocative efficiency in Pakistan. Bashir and Khan (2005) estimated 72% mean allocative efficiency for Peshawar valley wheat crop. This matches Tchale (2009) and Magreta et. al. (2013) observed 46% and 59% allocative efficiency.

Table 4: Distribution of farm specific allocative efficiency estimates

Score	Season 1		Season 2		Season 3	
	Frequency	%	Frequency	%	Frequency	%
<0.1	0	0,00	0	0,00	0	0,00
0,1-<0,2	0	0,00	4	1,33	0	0,00
0,2-<0,3	3	1,00	7	2,33	0	0,00
0,3-<0,4	9	3,00	13	4,33	0	0,00
0,4-<0,5	49	16,33	26	8,67	0	0,00
0,5-<0,6	68	22,67	28	9,33	0	0,00
0,6-<0,7	64	21,33	37	12,33	0	0,00
0,7-<0,8	55	18,33	82	27,33	14	16,67
0,8-<0,9	37	12,33	90	30,00	59	70,24
0,9-<1,0	15	5,00	13	4,33	11	13,10
1,0	0	0,00	0	0,00	0	0,00
Number of obs (N)	300		300		84	
Minimum	0,2141		0,1525		0,7489	
Maximum	0,9644		0,9297		0,9966	
Mean	0,6390		0,6938		0,8400	
Std.deviation	0,1540		0,1787		0,0558	

Source: Field Survey Data, 2022

The allocative efficiency gaps of this study are 36.1%, 31.7%, and 16.0% in seasons 1, 2, and 3, respectively. By enhancing allocative efficiency, the typical farmer in the study region might raise revenue by 36.1% in season 1, 31.7% in season 2, and 16.0% in season 3. It intended that the average mango gardener could save 33,74% in season 1, 25.37% in season 2, and 15.71%

in season 3 to become the most efficient mango grower in production, whereas the least efficient gardener suggested an improvement in allocative efficiency of 77,79% in season 1, 83.59% in season 2, and 24.85% in season.

4 Conclusion

In this study, the stochastic frontier analysis of production function was used to assess Chu mango producers' farm-level allocative efficiency and driving variables by maximising the probability function using Frontier 4.1.

Allocative inefficiency was high among Chu mango growers. This suggests that with the present inputs, farmers were performing significantly below their optimal capacity, requiring strict effort to develop farmers' ability to achieve maximum production without additional inputs. Again, by engaging farmers in efficient farm management and optimal agronomic methods, farmers may greatly boost their income at the lowest cost. After determining that farmers were not totally efficient in output, implying a gap, it was required to determine the causes of the observed efficiency differentials. The article found that agro-input payment, credit access, farming experience, age, education, and plant density influence farm-level efficiency differentials. Allocative efficiency depends on education and financing availability. Thus, to boost Chu mango farmers' liquidity preference in production, the research proposes that the government engage with key banking institutions and fruit institutional authorities to implement suitable credit programmes. The research suggests training and educational programmes to continue improving its connection education to help them catch up in sustainable production. Education factor significantly explains farm-level efficiency differential among Chu mango farmers.

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