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Technical Efficiency and Its determinants on Conventional and Certified Organic Jasmine Rice Farms in Yasothon Province

Nitiphong Songsrirote[1]
Charuk Singhapreecha[2]

Abstract

The aim of this study is to measure and compare technical efficiency between conventional and certified organic jasmine rice farms. exploring factors affecting technical inefficiency on conventional and certified organic jasmine rice farms is also considered. Technical efficiency is measured by Stochastic Frontier Analysis (SFA) using Cobb-Douglas and translog model with half-normal distributional assumption as well as multiple regression is used for analysing factors affecting technical inefficiency. Crossectional data is randomly obtained from 330 farms in Yasothon province, which is consisted of 165 conventional farms and 165 certified organic farms. Data is collected in the crop year 2005/06. According to the results, labor, seed, and organic fertilizer are much more important factors on organic jasmine rice production than on conventional one. On the average, organic farms operate closer to production frontier than conventional farms do or

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[1] นิสิตปริญญาเอก สาขาเศรษฐศาสตร์เกษตร ภาควิชาเศรษฐศาสตร์เกษตรและทรัพยากร คณะเศรษฐศาสตร์ มหาวิทยาลัยเกษตรศาสตร์ e-mail: econ555@gmail.com, http://www.nitiphong.com

[2] อาจารย์ประจำภาควิชาเศรษฐศาสตร์เกษตรและทรัพยากร คณะเศรษฐศาสตร์ มหาวิทยาลัยเกษตรศาสตร์ e-mail: fecochs@ku.ac.th

equivalently organic farmers are using their available resource more effectively than their conventional counterparts are. In addition, on average, conventional and certified organic farms can reduce their input use by 55% and 28% or can increase their output by 29% and 13%, respectively. Based on elasticities of variables, the key factors affecting technical inefficiency on conventional farms are management characteristics, input and knowledge on agriculture supported by government, location, and agricultural training. In case of organic farm, the key factors are management characteristics, agricultural training, education, location and farm management.

บทคัดย่อ

การศึกษาครั้งนี้มีความมุ่งหมายเพื่อวัดประสิทธิภาพเชิงเทคนิค และเปรียบเทียบประสิทธิภาพเชิงเทคนิคระหว่างกลุ่มผู้ผลิตข้าวหอมมะลิอินทรีย์ที่ได้รับการรับรอง และผู้ผลิตข้าวหอมมะลิอินทรีย์แบบดั้งเดิม รวมทั้งพิจารณาปัจจัยที่มีผลต่อความไม่มีประสิทธิภาพของผู้ผลิตข้าวหอมมะอินทรีย์ที่ได้รับการรับรองและแบบดั้งเดิม เครื่องมือในการวิเคราะห์ประสิทธิภาพเชิงเทคนิคใช้วิธี Stochastic Frontier Analysis โดยใช้ตัวแบบ Cobb-Douglas และ Translog ภายใต้ข้อสมมติการกระจายของความไม่มีประสิทธิภาพแบบHalf-normal และการวิเคราะห์ปัจจัยที่กำหนดความไม่มีประสิทธิภาพเชิงเทคนิคใช้การวิเคราะห์สมการถดถอยพหุคูณ การวิเคราะห์ใช้กลุ่มตัวอย่าง จำนวน 330 ฟาร์ม ประกอบด้วยผู้ผลิตข้าวหอมมะลิอินทรีย์ที่ได้รับการรับรอง จำนวน 165 ฟาร์มและผู้ผลิตข้าวหอมมะลิแบบดั้งเดิม จำนวน 165 ฟาร์ม โดยเก็บรวบรวมข้อมูลในรอบการผลิต พ.ศ. 2548/49 ผลการศึกษาพบว่า แรงงาน เมล็ดพันธุ์ และปุ๋ยอินทรีย์เป็นปัจจัยการผลิตที่มีความสำคัญต่อการผลิตข้าวหอมมะลิอินทรีย์มากกว่าการผลิตข้าวหอมมะลิแบบดั้งเดิม โดยเฉลี่ยแล้ว การผลิตข้าวหอมมะลิอินทรีย์จะจัดสรรปัจจัยการผลิตมีประสิทธิภาพกว่าการผลิตข้าวหอมมะลิแบบดั้งเดิม โดยการผลิตข้าวหอมมะลิแบบดั้งเดิมและแบบอินทรีย์สามารถลดการใช้ปัจจัยการผลิตได้อีกร้อยละ 55 และร้อยละ 28 ตามลำดับ หรือการผลิตข้าวหอมมะลิแบบดั้งเดิมและแบบอินทรีย์สามารถเพิ่มผลผลิตได้อีก ร้อยละ 29 และร้อยละ 13 ตามลำดับ โดยพิจารณาจากค่าความยืดหยุ่นของปัจจัยที่กำหนดความไม่มีประสิทธิภาพเชิงเทคนิค พบว่า กรณีการผลิตข้าวหอมมะลิแบบดั้งเดิม ปัจจัยสำคัญที่กำหนดความไม่มีประสิทธิภาพคือ ลักษณะทางการจัดการของผู้ผลิต การได้รับการสนับสนุนด้านความรู้ทางการเกษตรและปัจจัยการผลิตทำเลที่ตั้ง และการ

ฝึกอบรมด้านการเกษตรกรณีการผลิตข้าวหอมมะลิอินทรีย์ ปัจจัยสำคัญที่กำหนดความไม่มีประสิทธิภาพเชิงเทคนิค คือ ลักษณะทางการจัดการของผู้ผลิต การฝึกอบรมด้านการเกษตร การศึกษาในโรงเรียน ทำเลที่ตั้ง และการจัดการฟาร์ม

I. INTRODUCTION

The main feature of Thai agriculture has always been small-scale farms. The average of land holding size is about 20 rai per household (National Statistical Office, 2003) (1 rai is equivalent to 0.16 hectare). There are several agricultural policies that are supposed to improve the well-being of small-scale farmers, but they are unsuccessful. The failure of the national agricultural policy to support small-scale farmers stems mainly from the misconception about agricultural development strategies. The green revolution policy is adopted to improve the productivity of the farming sector, and thus contributes to an improvement in the economic situation of farmers. However, experience has shown that the green revolution further aggravate rural impoverishment and has tremendous negative impacts on rural natural resources, undermining the basic livelihood of rural farmers (UNESCAP, 2002: 173-174).

Organic agriculture is not a recent phenomenon. Local Thai farmers have practiced traditional farming for hundreds of years. Such practices have been developed and enriched through the farmer knowledge of the local agro-ecology and environmentally sustainable way of farming. Despite the imposition of modern agriculture, traditional farms continue to exist and local indigenous knowledge of sustainable farming remains. The survival of these farms is the source of the revitalization of modern organic agriculture in Thailand today.

The emergence of organic farming can be traced back to the collapse of modern agriculture in the early 1980s. As conventional farm production is geared towards cash-crop production with heavy reliance on agrochemicals, farmers are exposed to market instability and health hazards. The dual cost price squeeze drive farmers to the edge of bankruptcy when prices of agricultural products decline sharply while production costs rise steadily. Millions of small-scale farmers are driven to indebtedness and forced off their farmlands. At the same time, the impacts of the excessive use of agrochemicals begin to unfold. Increasingly frequent incidents of health hazards to farmers and consumers are reported. Widespread freshwater fish diseases linked to agrochemical residue pollution shock the public. Against this background, many farmers and local NGOs try to search an alternative for breaking away from the vicious circle of debt and health risks.

However, no explicit targets or projects are established until the Eighth Plan (1997-2001). Until the end of the 1990s, there is no government bodies or research institutions which are officially engaged in organic agriculture. The Eighth National Economic and Social Development Plan (1997-2001) is the first and the current institutional framework at the national level that clearly describes sustainable agriculture, including organic farming. In addition, Organic Agriculture Certification Thailand (ACT) had been established since 1998 for inspecting the quality of product and certify organic products.

Currently, only organic crops, no organic livestock or wild products, are produced in Thailand. The predominant organic crops are rice and vegetables. The largest planted areas under organic agriculture are conducted in the Northeast. Yasothon and Surin province are the main area under organic jasmine rice farms. The largest grower groups that produce organic jasmine rice in Yasothon are Nature Care Club, Organic Support Project, Loeng Nok Tha-Thaicharoen Organic Agriculture Cooperative and Bakruea Farmer Group Network. These grower groups are comprised of 748 members (farms) (Organic Agriculture Certification Thailand (ACT), 2005)

As concerning about the problems of conventional agriculture production system which may harm the farmer's health through chemical substance and they also face high cost of production, Clearly, the success of any policy effort aiming to transform conventional agriculture practices into organic ones depends on, among other things, the efficiency levels achieved by the individual farms (Müller, 1974; Shapiro and Müller, 1976; Birkhaeuser et al., 1991).

Then it should be raised the question that as the conventional farmer change to join organic jasmine rice farming, whether it provides the farmer higher performance in term of higher efficiency. To enhance their efficiency level in both of certified organic and conventional jasmine rice farms, technical efficiency should be taken into account as well as identifying factors affecting technical inefficiency. Moreover, technical efficiency can provide farmers how to reallocate resources for reaching highest efficiency and cost can be reduced. The latter leads to alleviate rural poverty. The farmers who produce conventional jasmine rice and are interested in changing to organic rice farming can learn from the benchmarking productive farmer for reaching the best practice. Consequently, the aim of this study is to measure technical efficiency, compare technical efficiency between conventional and certified organic jasmine rice farms and try to explore factors affecting technical inefficiency on conventional and certified organic jasmine rice farms.

II. LITERATURE REVIEW

Efficiency Measurement

Given the original definitions of productive efficiency set forth by Debreu (1951); Koopmans (1951) and Shephard (1953), two measures of technical efficiency can be defined according to whether one adopts an output-expanding or an input-conserving approach (Kumbhakar and Lovell, 2000, pp. 46–48). The first one is the output oriented *Debreu-type* measure, defined as the ratio of the observed to maximum feasible output, given the production technology and the observed input use. The second one is the input-oriented *Shephard-type* measure, defined as the ratio of minimum feasible to observed input use, given the production technology and the level of output. Both measures of technical efficiency can be obtained from the econometric estimation of the stochastic production frontier (SPF) model suggested independently by Aigner et al. (1977) and Meeusen and Van der Broeck (1977). In this analytical framework the agricultural output is treated as a stochastic production process of the following general form:

$$y_i = f(x_i;\, A)\cdot \exp(\varepsilon_i) \; and \; \varepsilon_i \equiv v_i - u_i \qquad (1)$$

where $x \in R^{+}$ is a (N×J) matrix of the applied inputs, $y \in R^{++}$ is a $(N\times 1)$ vector of output, $f(\times)$ is the best practice production frontier, A is the technology parameter vector and i, j denote production units and applied inputs, respectively. The component v_i is a symmetric, identically and independently distributed (*iid*) error term representing random variation in output due to random exogenous factors, measurement errors, omitted explanatory variables, and statistical noise. The component u_i is a non-negative error term representing the stochastic shortfall of the *i*th farm's output from its production frontier due to output-oriented technical inefficiency. Since the producer-specific inefficiency u_i is the ultimate objective of the estimation. To achieve this objective it is required that separate estimates of statistical noise v_i and technical inefficiency u_i are extracted from estimates of ε_i for each producer. This requires distributional assumptions on u_i.

The assumptions on u_i as referred to Kumbharkar and Lovell (2000) are comprised of the normal-half normal, the normal-truncated normal, the normal-exponential and the normal-gamma. A common criticism of the stochastic frontier method is that there is no a priori justification for selection of any particular distribution form for the technical inefficiency effects, u_i. The half-normal and the exponential distributions are arbitary selections. Since both of distributions have a mode at zero, it implies that there is the highest probability that the inefficiency effects are in the neighbourhood of zero. This , in turn, implies relatively high technical efficiency. In practice, it may be possible to have a few very efficient firms, but a lot of quite inefficient firm. A few research attempted to address this criticism by specifying more general distributional forms, such as the truncated-normal (Stevenson, 1980) and the two-parameter gamma (Greene, 1990) distributions for the technical inefficiency effects. These two distributions allow for a wider range of distributional shapes (including ones with non-zero modes). The truncated-normal distribution is a generalization of the half-normal distribution. It is obtained by the truncation at zero of the normal distribution with mean, u, and variance, σ^2. If u is pre-assigned to be zero, then the distribution is half-normal. The distribution may take a variety of shapes, depending upon the size and sign of u. However, for further analysis, this paper is assumed that u is half-normal, reflecting the belief that larger values of inefficiency are less likely or relatively high technical efficiency.

In addition, Most studies of efficiency on rice production in Thailand and other countries are analyzed by using stochastic frontier analysis and there are a few papers that emphasize on the factors affecting technical inefficiency. A summary of this section is presented in Table 1.

Table 1 Studies of Efficiency on Rice Production in Thailand and Other Countries

Author	Country	Model	Major findings
Patamasiriwat and Isavilanonda (1990)	Thailand	SFA	138 households of total 295 households have the efficiency score less than 90%.
Wiboonpongse and Sriboonchitta (1999)	Thailand	SFA	- The average of efficiency on jasmine rice farming is 67.93% and non-jasmine rice is 71.58%. - The factors affecting inefficiency are the ratio of male labor/total labor, farming ecperience.
Champhech (2003)	Thailand	SFA	The key factor affecting inefficiency is farmers'experience.
Krasachat (2003)	Thailand	DEA	The key factor affecting efficiency is the diversity of natural resources.
Raicharoen (2004)	Thailand	SFA	The average of technical efficiency on organic jasmine rice production is less than that on conventional jasmine rice.
Kaliajan and Flinn (1983)	Philipines	SFA	- The efficiency scoe rang from 0.38 to 0.91 - The key factors affecting efficiency are the practice of transplanting rice seedlings, the incidence of fertilization, years of farming and a number of extension contacts.
Lingard et al. (1983)	Philipines	SFA	The least efficient farm achieved only 29% of the maximum possible output for given input level.
Dawson and Lingard (1989)	Philipines	SFA	The average of efficiency ranged between 0.60 and 0.70.
Dawson, Lingard and Woodford (1991)	Philipines	SFA	The average of efficiency ranged between 0.84 and 0.95.
Rola and Quintana-Alejandrino (1993)	Philipines	SFA	The average of efficiency on irrigated, rainfed and upland environments are 0.73,0.65 and 0.57

Note: SFA=Stochastic Frontier Analysis and DEA=Data Envelopment Analysis.

Finally, The source of efficiency differentials that were observed among rice farmers was an issue of overriding concern. Most of these studies examined factors that explain why some farmers are more efficient than others. Studies of the sources of technical inefficiency in rice farming concentrated on characteristics of the farms and farmers. The efficiency variables were related to managerial and socio-economic characteristics. By definition, managerial variables are concerned with the ability of the farmer to choose farm output mixes and patterns, for example, seed type and rates, the application of fertilizers and chemicals (rate, types and timing), and planting and harvesting techniques. From the literature, the most common socio-economic variables were farm size, the education, age and experience of the farmers, and their access to extension services and credit. (Ali and Flinn 1989; Kalirajan and Shand 1989; Xu and Jeffrey 1998). In addition, Numerous studies have identified wide variation in the physical and financial performance achieved by farmers and farm managers operating within the same environmental and economic constraints. Many instances this difference in performance is due to variation in management. However, unlike land, labor and capital, management is not directly observable; subsequently this complicates any analysis that attempts to explain the influence of management on farm performance. Kay and Edward (1994) define the functions of management as planning, implementation and control. (Wilson et al., 2001, cited in Kay and Edward, 1994). Rougoor, et al. (1998) have renewed the debate on how to measure the ability of a farmer to influence his/her farm results and broadened the definition of management and group management capacity into two components: personal aspects (e.g. drives, motivations, abilities and biographical facts) and aspects of the decision-making process (e.g. the practices and procedure in planning, implementation and control of decisions). Rougoor, et al. (1998) argues that a manager may possess high personal skills yet fail to achieve high performance if decision-making process is poor. (Wilson et al., 2001, cited in Rougoor et. al, 1998). Wilson, et al. (2001) conclude that variations in technical efficiency index across production units are explained through a number of managerial and farm characteristics variables. Moreover, those farmers who seek information, have more years of managerial experience, and have a large farm are also associated with higher levels of technical efficiency. Likewise, Inchniowski (1995) studies the effects of human resource management practices on technical efficiency finding that new work practice, including work teams, flexible job assignments, employment security, training in multiple jobs, and extensive reliance on incentive pay, produces substantially higher levels of technical efficiency. Similar to Patterson (1997), the result reveal that acquisition and development of skills (selection, induction, training and appraisal) and job design (job variety and responsibility, skill flexibility, and team working) are significant predictors of both change in profitability and change in technical efficiency. However, this study is extended into more details on the variables in management characteristics of a farm, which is based on the process approach consisted of planning also decision making, organizing, leading and controlling, which each of them is categorized into various dimensions of measurement.

III. METHODOLOGY

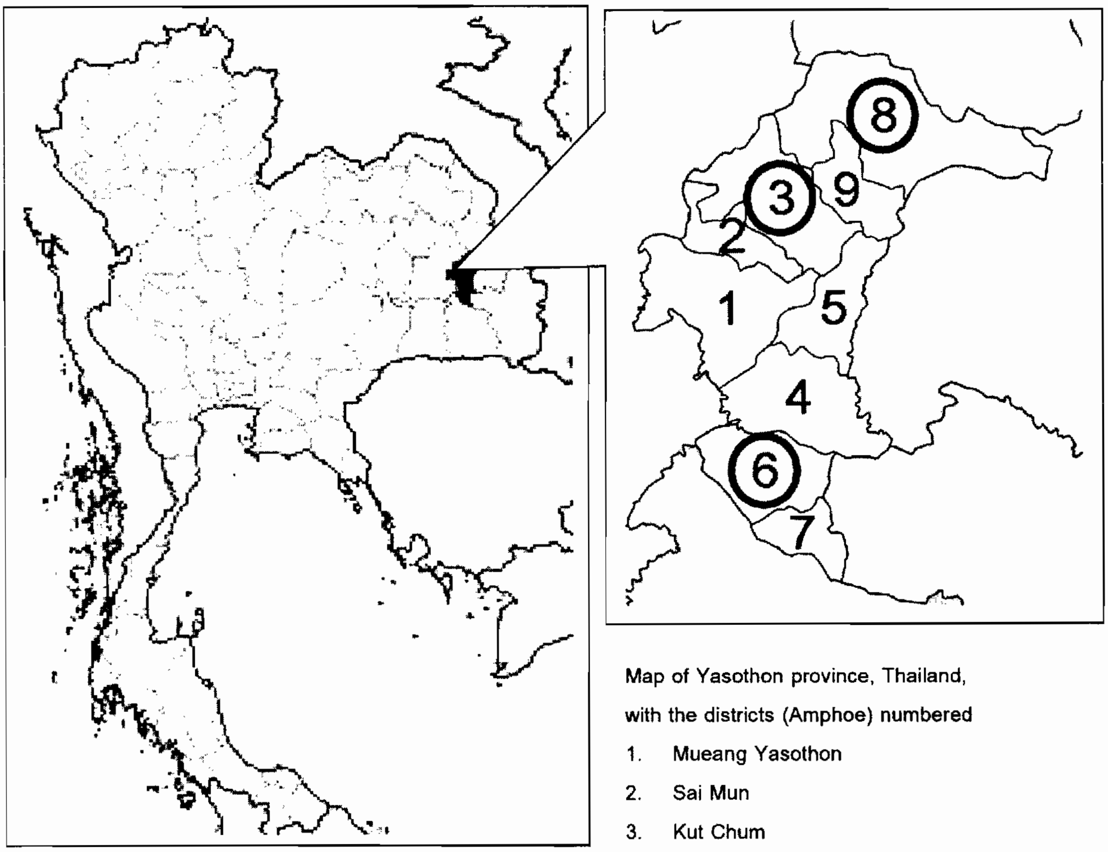
Data Collection

Data for analyzing was collected from farmers who operated certified organic and conventional jasmine rice farms in Yasothon province which was depicted in Figure 1 The farmers who operated certified organic jasmine rice farms and who became the members of the grower groups were randomly selected amounted to 55 samples for each grower-groups (Nature Care Club, Organic Support Project, Loeng Nok Tha and Thai Charoen Organic Agriculture Cooperative and Bakruea Farmer Group Network) in each area. Likewise, the farmers who operated conventional jasmine rice farming were randomly chosen amounted to 55 samples from each area which is located nearby the certified organic jasmine rice farmers . Therefore, A number of samples for certified organic jasmine rice are 165 farms and for conventional jasmine rice are 165 farms as expressed in Table 2.

Table 2 Certified organic jasmine rice producers classified by the grower-group

Area	Total Producers in each grower group	Sample Size (farms)	
		Conventional Farms	Organic Farms
Kut Chum District	324	55	55
Loeng Nok Tha District	184	55	55
Maha Chana Chai District	240	55	55
Total	748	165	165

Source: Author's Calculation.



Map of Yasothon province, Thailand,
with the districts (Amphoe) numbered

1. Mueang Yasothon 27
2. Sai Mun
3. Kut Chum
4. Kham Khuean Kaeo
5. Pa Tio
6. Maha Chana Chai
7. Kho Wang
8. Loeng Nok Tha
9. Thai Charoen

Figure 1 The Map of Yasothon Province and Areas for Collecting Data

Data Analysis

Technical efficiency of certified organic and conventional jasmine rice was measured by stochastic frontier production (output-oriented) and some production forms was specified in order to estimate parameters and calculate the efficiency score. Since different forms of frontier production function, it could yield different parameters as well as the efficiency score. Therefore, the Cobb-Douglas and translog form of the stochastic frontier production were considered and it was investigated which form it is appropriate. The parameters were obtained by maximum likelihood method and inefficiency effects were assumed as Half Normal, reflecting the belief that most producers are relatively high technical efficiency.

Cobb-Douglas form of the stochastic frontier production

$$\ln Y_i = \alpha_0 + \alpha_1 \ln X_{1i} + \alpha_2 \ln X_{2i} + \alpha_3 \ln X_{3i} + \alpha_4 \ln X_{4i} + \alpha_5 \ln X_{5i} + v_i - u_i \qquad (2)$$

Translog form of the stochastic frontier production

$$\ln Y_i = \alpha_0 + \sum_j \alpha_j \ln X_{ij} + \frac{1}{2}\left[\sum_j \beta_j \left(\ln X_{ij}\right)^2 + \sum_j \sum_{k \neq j} \gamma_{jk} \ln X_{ij} \ln X_{ik}\right] + v_i - u_i \qquad (3)$$

The subscript i=1,2,3,…,n denoted certified organic and conventional jasmine rice farms; j,k=1,2,3,…,5 stand for inputs use.

The input variables, definition and its measurement were exhibited below.

Y_i = the total output or yield (certified organic or conventional from transplanted and broadcasting farming) of jasmine rice in term of paddy measured in kilogram/rai

X_1 = the total amount of seed use in jasmine rice farming measured in kilogram/rai

X_2 = the total amount of labor use in jasmine rice farms measured in hour/rai

X_3 = the total amount of organic fertilizer applied in jasmine rice farms measured in kilogram/rai

X_4 = the total amount of chemical fertilizer applied in jasmine rice farms measured in kilogram/rai (in case of organic farms, chemical fertilizer is not applied in farms)

X_5 = the total amount of machinery use in jasmine rice farms measured in hours

Therefore, In case of conventional farms, input variables are comprised of X_1, X_2, X_3, X_4, and X_5. On the other hand, for organic farms, input variables are comprised of X_1, X_2, X_3, and X_5

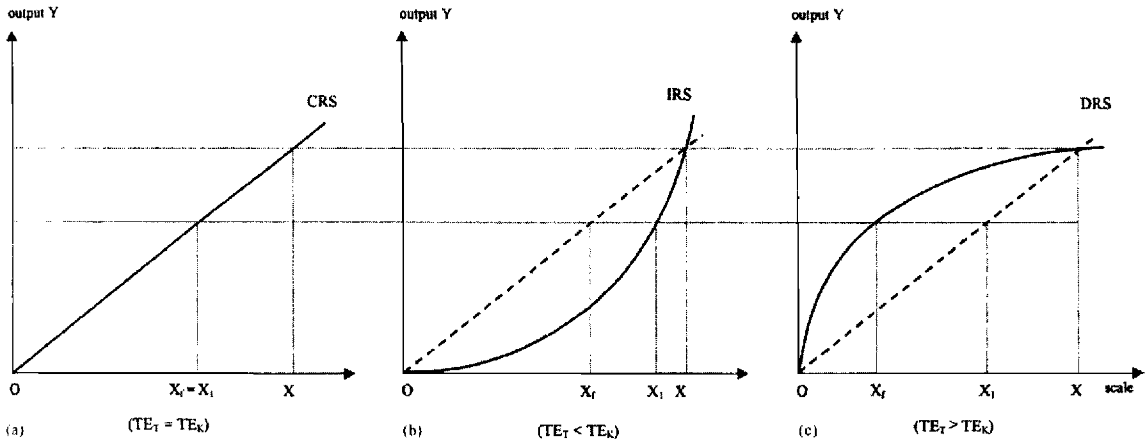
Efficiency can be defined in terms of producing a maximum amount of output, given a set of inputs; or producing a given level of output using a minimum level of inputs; or a mixture of both. Efficient farms either use less input than others to produce a given quantity of output, or for a given set of inputs they generate a greater output. The output-based Timmer (1971) index of technical efficiency TE_T is simply the ratio of the observed level of output to the potential (frontier) output, given a set of inputs. The input-based Kopp (1981) index of efficiency TE_K is defined as the ratio of frontier input (cost) to the observed level of input (cost), given the level of output. According to Llewelyn and Williams (1996), these two indices are not necessarily the same, because input efficiency does not focus on the same aspects of production as those of output efficiency. According to Fare and Lovell (1978), a unique measure of these two indexes cannot be calculated in the case of non-homothetic technology. Homotheticity — for which homogeneity is sufficient but not necessary— implies that all the isoquants have the same slope on a ray through the origin in the input space. After having obtained u_i from stochastic frontier production, technical efficiency score is calculated as follows.

The Timmer index for an individual farm is the ratio of observed output Y to frontier output Y_f, defined for $u_i = 0$, $TE_T = \dfrac{Y}{Y_f} = e^{-u_i}$ and following Russell and Young (1983) the Kopp index may be formulated (for any j) as

$$TE_K = \frac{X_{fj}}{X_j} = (e^{-u_i})^{\frac{1}{\sum \alpha_i}} = (TE_T)^{\frac{1}{\sum \alpha_i}},$$

where X_{fj} and X_j are the frontier ($u_i = 0$) and observed levels of the jth input, respectively.

Given the inefficiency component u_i, both indices may be calculated simply and directly. In the case of constant returns to scale, $\sum \alpha_i = 1$, the Kopp index equals the Timmer index, while the Kopp index is greater (less) than the Timmer index in the case of increasing (diminishing) returns to scale, $\sum \alpha_i > 1$ (<1) as shown in Figure 2



Source: Mohammad Bakhshoodeh and Kenneth J. Thomson (2001:310)

Figure 2 Technical Efficiency Score with: (a) constant returns to scale (CRS); (b) increasing returns to scale (IRS); (c) decreasing returns to scale (DRS)

To identify the factors affecting their technical inefficiency, multiple linear regression model with ordinary least square is employed to identify the relationship between technical inefficiency score and its determinants. The model on conventional and organic farm can be constructed as follows.

$$\begin{aligned} \ln TI &= \beta_0 + \beta_1 \ln HTH + \beta_2 \ln EXP + \beta_3 \ln EDU + \beta_4 \ln ATR + \beta_5 \ln HHS + \beta_6 LOC2 + \beta_7 LOC3 + \beta_8 \ln INC + \beta_9 \ln SAV \\ &+ \beta_{10} \ln LOA + \beta_{11} TRC + \beta_{12} \ln FMX + \beta_{13} \ln MGTX + \beta_{14} \ln RNF + \beta_{15} \ln IRG + + \beta_{16} \ln GKNW + \beta_{17} \ln GINPUT \end{aligned} \quad (4)$$

Table 3 Variables, Definition, and Unit of Analysis Used in the Multiple Regression

Variables			Definitions	Unit of Measurement
Technical Inefficiency		TI	Technical Inefficiency score	Ratio Scale
Farmers' Learning and Health		HTH	Illness from conducting jasmine rice farming	Rating Scale
		EXP	Agriculture farming experience (year)	Ratio scale
		EDU	Schooling (year)	Ratio scale
		ATR	Agricultural training	Rating Scale
Demographic and Location Factors		HHS	Household size (A number of family members)	Ratio scale
		LOC1	Area of rice farming in Kut Chum	Dummy variable 1,0
		LOC2	Area of rice farming in Maha Chana Chai	Dummy variable 1,0
		LOC3	Area of rice farming in Loeng Nok Tha	Dummy variable 1,0
Farm Management		TRC	Type of Rice Cultivation	Dummy variable 1=Transplanted Rice,0= Broadcasting Rice
	FMX	CRR	Crop Rotation in Farmer's Rice Field	Rating Scale
		PCR	Perennial Cultivation around Rice Field	Rating Scale
		VCR	Vegetable Cultivation around Rice Field	Rating Scale
		HRR	Animal Husbandry around Rice Field	Rating Scale
		FPR	Fishery Pond around Rice Field	Rating Scale
				CRR–HRR: Ratio scale (Mean Value)
Household's Finance		INC	Total income (Baht)	Ratio scale
		SAV	Saving (Baht)	Ratio scale
		LOA	Loan (Baht)	Ratio scale

Table 3 (Continued) Variables, Definition, and Unit of Analysis Used in the Multiple Regression

Variables			Definitions	Unit of Measurement	
Farmer's Management Characteristics (MGTX)		PLA	Planning: Setting an organization's goals and deciding how best to achieve them	Rating scale	Ratio scale (Mean Value)
		ORG	Organizing: Grouping activities and resources in a logical fashion	Rating scale	
		LEA	Leading: The set of processes used to get members of the organization to work together to further the interests of the organization	Rating scale	
		CTL	Controlling: Monitoring organizational progress toward goal attainment	Rating scale	
Infrastructure Access and Climate		IRG	Access of water source for agriculture	Rating Scale	
		RNF	Rainfall	Rating Scale	
Government Support	GNWX	KNW1	Knowledge and Information about rice production	Rating scale	Ratio scale (Mean Value)
		KNW2	Knowledge and Information of how to produce fertilizer	Rating scale	
		KNW3	Knowledge and Information of how to improve soil quality	Rating scale	
	GINPUT	FINS	Financial Support: Budget for conducting rice farming	Rating scale	
		FERS	Fertilizer support for rice production	Rating scale	
		SEDS	Rice Breed (seed) Support for rice production	Rating scale	

Note: In case of dummy variable (1, 0), 1=yes and 0=no.

The rating scales are defined as follows (Griffin and Ricky W., 1996: 26).

Very Much Like Me = 5 Somewhat Like Me = 4

Occasionally Like Me = 3 Seldom Like Me = 2

Nothing Like Me = 1

The rating scales above are exploited to ask the farmers that which item is consistent with their characters, activities and perception or they agree with.

IV. RESULTS

Descriptive Statistics of Variables Used in Production Frontier

As can be seen in Table 4, farmers used an amount of 23 (11) kg, 22 (20) hour/rai, 215 (424) kg/rai, 28 kg/rai and 8 (9) hour/rai of seed, labor, organic fertilizer, chemical fertilizer and machine, respectively during the crop year and produced about 275 (303) kg of jasmine rice on conventional (organic farm).

Table 4 Descriptive Statistics of Variables Used in Production Frontier on Conventional and Organic Jasmine Rice Farms

Variables	Description	Units	Conventional Farms		Organic Farms	
			Mean	S.D	Mean	S.D
y	Yield	Kilogram/rai	274.62	170.49	302.95[c]	312.37
x_1	Seed	Kilogram/rai	22.92[a]	57.90	11.11	9.11
x_2	Labor	Hour/rai	21.80	25.95	20.36	22.85
x_3	Organic Fertilizer	Kilogram/rai	214.99	242.10	424.05[a]	380.07
x_4	Chemical Fertilizer	Kilogram/rai	28.38	35.69	-	-
x_5	Machine	Hour/rai	7.76	10.27	9.20	12.43

Note: [a] Its mean value is greater at 1% level of significance. [b] Its mean value is greater at 5% level of significance.
[c] Its mean value is greater at 10% level of significance. In case of conventional jasmine rice farm, natural and chemical fertilizers are employed. For organic jasmine rice farm, chemical fertilizer is not employed. Famer spend 36 days for rice cultivation until transporting to the rice mill, then man-day is about 7-8 hours.
Farmers used their land about 21 rai and 18 rai for producing conventional and organic jasmine rice.
1 Hectare = 6.25 Rai (approx.). 1 Acre = 2.5 Rai (approx.). S.D=Standard Deviation.

In addition, we also test the hypothesis whether yield/rai and input use/rai are different between conventional and organic farms. It is found that jasmine rice yield and organic fertilizer on organic farms is greater than conventional ones at the 10% and 1% level of significance, respectively. In contrast, seed of organic farms is less than conventional ones at the 1% level of significance. Land and machine use are not different between conventional and organic farms.

Maximum Likelihood Estimates of Frontier Production Function

The results of stochastic frontier model on conventional and certified organic farm are shown in Table 5. Estimates of frontier production function are organized into two sections as follows.

Conventional Farms

Of the six estimated parameters, three were found to be statistically significantly in the Cobb-Douglas model. Of the twenty-one estimated parameters, eight were found to be statistically significantly in the translog model. At the point of approximation, the Cobb-Douglas model with Half-Normal is well behaved since monotonicity conditions are satisfied or peripheral products are all positive. The production function is well behaved if it has useful marginal products for all inputs and is quasi-concave. In case of translog model, these conditions are not satisfied. In addition, a specification error is also tested. It is found that Cobb-Douglas model with Half-Normal is appropriate one. Therefore, the Cobb-Douglas production frontier with Half-Normal is employed to calculate the efficiency scores. In fact, Taylor et al. (1986) argrued that as long as interest rests on efficiency measurement and not on the analysis of the general structure of the production technology, the Cobb-Douglas production function provides an adequate representation of the production technology. Moreover, in one of the very few studies examining the impact of operational form on efficiency, Kobb and Smith (1980) concluded "... that functional specification has a discernible but rather small impact on estimated efiiciency". That is why the Cobb-Douglas functional form has been widely used in farm efficiency analyses both in developing and developed countries (Battese, 1992; Brovo-Ureta and Pinheiro, 1993).

Organic Farms

The results of stochastic frontier model on organic farm are as follows. Of the five estimated parameters, four were found to be statistically significantly in the Cobb-Douglas model. Of the twenty-one estimated parameters, three were found to be statistically significantly in the translog model. Likewise in case of Conventional farm, at the point of approximation, the Cobb-Douglas model with all assumption on inefficiency effect (u_i) is well behaved. A specification error is also tested. It is found that Cobb-Douglas model is appropriate one. Therefore, the Cobb-Douglas production frontier is employed to calculate the efficiency scores.

Table 5 Maximum Likelihood Estimates of Stochastic Frontier Production on Conventional and Certified Organic Farms

Variables (parameter)	Conventional Farm		Organic Farm	
	Coefficient		Coefficient	
	Cobb-Douglas Model	Translog Model	Cobb-Douglas Model	Translog Model
Constant (α_0)	5.1930[a]	4.5735[a]	4.2045[a]	5.4558[a]
	(0.1847)	(0.5756)	(0.3460)	(0.7626)
$\ln x_1 (\alpha_1)$	0.1778[a]	-0.0252	0.1829[a]	0.1035
(Seed)	(0.0402)	(0.1126)	(0.0374)	(0.2177)
$\ln x_2 (\alpha_2)$	0.0274	-0.1664	0.0579	-0.0722
(Labor)	(0.0414)	(0.1112)	(0.0387)	(0.2320)
$\ln x_3 (\alpha_3)$	0.0034	-0.0567	0.1425[a]	-0.3771[c]
(Organic Fertilizer)	(0.0234)	(0.1112)	(0.0349)	(0.2084)
$\ln x_4 (\alpha_4)$	0.0326	0.1391		
(Chemical Fertilizer)	(0.0378)	(0.1381)	-	-
$\ln x_5 (\alpha_5)$	0.1305[a]	0.8707[a]	0.0618[c]	0.2457
(Machine)	(0.0373)	(0.1366)	(0.0343)	(0.2239)
$0.5(\ln x_1)^2 (\alpha_6)$	-	0.0059	-	0.0483
		(0.0546)		(0.0526)
$0.5(\ln x_2)^2 (\alpha_7)$	-	0.0437	-	0.0766
		(0.0579)		(0.0484)
$0.5(\ln x_3)^2 (\alpha_8)$	-	0.0433[c]	-	0.0975[b]
		(0.0237)		(0.0390)
$0.5(\ln x_4)^2 (\alpha_9)$	-	0.0463	-	-
		(0.0409)		
$0.5(\ln x_5)^2 (\alpha_{10})$	-	-0.0693[c]	-	0.0512
		(0.0377)		(0.0517)
$\ln x_1 \ln x_2 (\alpha_{11})$	-	0.0163	-	-0.0120
		(0.0475)		(0.0428)
$\ln x_1 \ln x_3 (\alpha_{12})$	-	0.0497[b]	-	0.0125
		(0.0228)		(0.0390)
$\ln x_1 \ln x_4 (\alpha_{13})$	-	-0.1789	-	-
		(0.0395)		
$\ln x_1 \ln x_5 (\alpha_{14})$	-	-0.0583	-	-0.0357
		(0.0361)		(0.0455)
$\ln x_2 \ln x_3 (\alpha_{15})$	-	0.0019	-	0.0100
		(0.0206)		(0.0359)

Table 5 (Continued) Maximum Likelihood Estimates of Stochastic Frontier Production on Conventional and Certified Organic Farms

Variables (parameter)	Conventional Farm Coefficient		Organic Farm Coefficient	
	Cobb-Douglas Model	Translog Model	Cobb-Douglas Model	Translog Model
$\ln x_2 \ln x_4 (\alpha_{16})$	-	0.0226 (0.0413)	-	-
$\ln x_2 \ln x_5 (\alpha_{17})$	-	-0.0521[c] (0.0292)	-	-0.0602 (0.0589)
$\ln x_3 \ln x_4 (\alpha_{18})$	-	-0.0348 (0.0289)	-	-
$\ln x_3 \ln x_5 (\alpha_{19})$	-	-0.0402[b] (0.0174)	-	-0.0083 (0.0352)
$\ln x_4 \ln x_5 (\alpha_{20})$	-	-0.8035[c] (0.0417)	-	-
σ_v^2	0.1543	0.1929	0.2134	0.1954
σ_u^2	0.3561	0.0002	0.00003	0.00001
$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.5103	0.1931	0.21340	0.19540
$\gamma = \sigma_u^2 / \sigma^2$	0.6979[b]	0.0008	0.00020	0.00006
Log Likelihood	-128.4800	-98.4146	-106.6985	-99.4303
Likelihood-ratio (test of $\sigma_u = 0$)	5.15[b]	0.0000	0.0000	0.0000

Note: [a]Significant at 1%. [b]Significant at 5%. [c]Significant at 10%
Figures in parenthesis in coefficiecnt column are standard errors.

Heteroscedasticity of Error Component and Multicollinearity in Input Variables

Among the assumption underlying the stochastic production frontier model is that of homoscedasticity of both error components. But the symmetric noise error component might be heteroscedastic if the sources of noise vary with the size of producers. And the one-sided technical inefficiency error component might be heteroscedastic if, as suspect, the sources of inefficiency vary with size of producers. It is therefore desirable to investigate the consequences of heteroscedasticity in either error component and consider how to remedy this problem. It is found that there is heteroscedastic in both of v_i and u_i for conventional farms and there is heteroscedastic v_i for organic farms. Unmodeled heteroscedasticity in v_i does not lead to biased in estimates of parameters describing the structure of the production frontier, although it does lead to bias in estimate of technical efficiency and Unmodeled heteroscedasticity in v_i and u_i lead to biased in estimates of parameters describing the structure of the production frontier and estimate of technical efficiency. Therefore, heteroscedasticity will be included in model in order to obtain correct estimates. The corrected production frontier estimates are exhibited in Table 6. In case of multicollinearity on input variables, It is found that there is no multicollinearity among inputs.

Table 6 Corrected Production Frontier Estimates on Cobb-Douglas Model with Half-Normal

Variables (parameter)	Unmodeled heteroscedasticity		Modeled heteroscedasticity	
	Conventional Farms	Organic Farms	Conventional Farms	Organic Farms
Constant (α_0)	5.1930[a]	4.2045[a]	4.8101[a]	4.4353[a]
	(0.1847)	(0.3460)	(0.2124)	(0.3408)
$\ln x_1(\alpha_1)$	0.1778[a]	0.1829[a]	0.0869[c]	0.1694[a]
(Seed)	(0.0402)	(0.0374)	(0.4486)	(0.0386)
$\ln x_2(\alpha_2)$	0.0274	0.0579	0.0305	0.0663[c]
(Labor)	(0.0414)	(0.0387)	(0.0339)	(0.0391)
$\ln x_3(\alpha_3)$	0.0034	0.1425[a]	0.1070[a]	0.1270[a]
(Organic Fertilizer)	(0.0234)	(0.0349)	(0.0345)	(0.0309)
$\ln x_4(\alpha_4)$	0.0326	-	0.0787	-
(Chemical Fertilizer)	(0.0378)		(0.0493)	
$\ln x_5(\alpha_5)$	0.1305[a]	0.0618[c]	0.0719[b]	0.0653[b]
(Machine)	(0.0373)	(0.0343)	(0.0299)	(0.0315)

Note: Figures in parenthesis (coefficiecnt column) are standard errors.

Production Elasticities and Returns to Scale on Conventional and Certified Organic Farms

Based on the production parameter estimates in Table 6, production elasticities and returns to scale for each farming method as shown in Table 7. The production elasticity estimates indicate that organic fertilizer, seed, chemical fertilizer, machine, and labor contributed the most to conventional jasmine rice production, respectively. Seed, organic fertilizer, labor and machine contributed the most to organic jasmine rice production, respectively. The magnitude of production elasticities on conventional and organic farming method is different. The largest difference appears in the case of labor, seed, and organic fertilizer. The average production elasticity of which is about 2.17, 1.94, and 1.19 times larger in organic than in conventional farms. As expected, this is a rather interesting finding as it suggests that labor, seed, and organic fertilizer are much more important factors in organic jasmine rice production. Regarding the average scale elasticities, they are clearly diminishing in both of farming method.

Table 7 Production Elasticities and Returns to Scale of the Conventional and Organic Farms

Input Variables	Conventional Farms	Organic Farms
Mean elasticities with respect of output		
Seed	0.0869	0.1694
Labor	0.0305	0.0663
Organic Fertilizer	0.1070	0.1270
Chemical Fertilizer	0.0787	-
Machine	0.0719	0.0653
Returns to Scale	0.3750	0.4280

Technical Efficiency on Conventional and Certified Organic Jasmine Rice Farms

Efficiency scores obtained with SFA method are exhibited in Table 8. Of the 165 farms studied on conventional farms, 103 farms (62%) under SFA (TE_T) showed a performance above 0.70 and 31 farms (19%) showed a performance below 0.60. The highest efficiency score was 0.9330 and the mean value of SFA (TE_T) was 0.7145. 27 farms (16%) under SFA (TE_k) showed a performance above 0.70. 124 farms (76%) under SFA (TE_K) showed a performance below 0.60. The highest efficiency score was 0.8311 and the mean value of SFA (TE_K) was 0.4499. In case of organic farm, 165 farms (100%) under SFA (TE_T) showed a performance above 0.70 and no farms showed a performance below 0.70. The highest efficiency score was 0.9260 and the mean value of SFA (TE_T) was 0.8666. 121 farms (74%) under SFA (TE_k) showed a performance above 0.70. 6 farms (4%) under SFA (TE_K) showed a performance below 0.60. The highest efficiency score was 0.8357 and the mean value of SFA (TE_K) was 0.7165. This section we consider hypothesis test whether technical efficiency on organic jasmine rice is greater than technical efficiency on conventional jasmine rice. It is found that technical efficiency on certified organic jasmine rice is greater than technical efficiency of conventional jasmine rice. Hence, organic farms may be viewed, in general, as more technically efficient than conventional farms. It means that, on the average, organic farms operate closer to production frontier than conventional farms do or equivalently organic farmers are using their available resource more effectively than their conventional counterparts are. In addition, on average, conventional and certified organic farms can reduce their input use by 55% and 28% or can increase their output by 29% and 13%, respectively.

Table 8 Frequency Distributions of Technical Efficiency Scores Obtained by SFA Model

Technical Efficiency (%)	Conventional Farm				Organic Farms			
	TE_T		TE_K		TE_T		TE_K	
	N	%	N	%	N	%	N	%
Less than 40	10	6	64	39	0	0	0	0
40-50	10	6	31	19	0	0	0	0
50-60	11	7	29	18	0	0	6	4
60-70	31	19	14	8	0	0	38	23
70-80	50	30	22	13	6	4	115	70
80-90	33	20	5	3	150	91	6	4
90-100	20	12	0	0	9	5	0	0
Total	165	100	165	100	165	100	165	100
Mean	0.7145		0.4499		0.8666		0.7165	
S.D	0.1583		0.2118		0.0250		0.0474	
Minimum	0.2043		0.0145		0.7707		0.5442	
Maximum	0.9330		0.8311		0.9260		0.8357	

Note: TE_T is output-orientated technical efficiency of SFA approach, TE_K is input-orientated technical efficiency of SFA approach. N is number of farms.

Factors Affecting Farm Technical Inefficiency

Descriptive Statistics of Variables Used in the Analysis

As can be seen in Table 9, the average of HTH (conventional farms) is 2.33 implying that most of farmers are ill from their activities in conventional farms being more ill than organic farms. The average of RNF is 3.45 and 3.65 for conventional and organic farms respectively implying that a mount of rainfall on organic farms is more suitable than conventional farms. In case of variables which are ratio scale or quantitative scale consists of EXP, EDU, HHS, INC, FMX (derived from rating scale), and MGTX (derived from rating scale), the average of schooling year is about 5 year. The average of FMX and MGTX except INC in organic farms are higher than conventional implying that farm management and management characteristics of organic farm are more intensive than conventional farms. Access to the water (IRG) on organic farms is easier than conventional farms. Similarly, Government support on knowledge (GKNW) on organic farms is higher than conventional farms but Government support on inputs (GINPUT) on conventional farms is greater than organic farms.

Table 9 Descriptive Statistics of Variables Used in the Analysis

Variables	Conventional Farms (n=165)		Organic Farms (n=165)	
	Mean	S.D	Mean	S.D
TI	0.39[a]	0.28	0.15	0.03
HTH	2.33[a]	1.01	1.91	0.99
EXP	23.90	13.14	5.04	1.72
EDU	5.29	2.23	5.08	2.43
ATR	2.22	1.07	3.87[a]	0.96
HHS	4.49	1.71	4.48	1.78
LOC1	0.33	0.47	0.33	0.47
LOC2	0.33	0.47	0.33	0.47
LOC3	0.33	0.47	0.33	0.47
INC	64,820.81[c]	62,175.23	56,157.01	42,879.48
SAV	7,682.67	15,099.43	9,303.64	17,564.94
LOA	35,037.58	53,524.07	41,869.70	52,352.09
TRC	0.41	0.48	0.42	0.49
FMX	2.42	0.83	3.22[a]	0.97
MGTX	3.35	0.49	3.56[a]	0.44
RNF	3.45	1.05	3.65[b]	0.94
IRG	3.00	1.26	3.37[a]	1.18
GKNW	2.41	1.08	2.71[a]	1.25
GINPUT	2.03[c]	1.06	1.87	1.08

Note: [a] Its mean value is greater at 1% level of significance. [b] Its mean value is greater at 5% level of significance.
[c] Its mean value is greater at 10% level of significance.

Determinants of Technical Inefficiency

Scio-economics, demographical factors, farm characteristics, environmental factors and non-physical factors are likely to affect the efficiency (Kumbhakar and Bhattacharya, 1992, Ali and Chaundry, 1990). Using the specification of equation (4), the study is attempted to capture determinants of technical efficiency. After having diagnosing the regression and correcting the regression (multicollinearity, outlier, leverage, normality, model specification error, heteroscedasticity). The Results of estimates using ordinary least square estimation of the equation for conventional and organic farms and rank of elasticies are exhibited in Table 10 and Table 11.

Farmers' Learning and Health

Experience of agricultural farming (LnEXP), farmers' schooling year (LnEDU) and agricultural training (LnATR) are included to estimate the impact of farmers' learning on technical inefficiency. The expectation of LnEXP and LnEDU are supported by negative and insignificant estimated coefficient for conventional and organic farms. The expectation of LnATR is supported by positive and significant estimated coefficient for conventional and organic farms. The positive sign of LnATR is implied that farmer with poor agricultural training can lower inefficient.

Illness from conducting jasmine rice farming (LnHTH) on conventional and organic farms has a positive and insignificant impact on inefficient in similar to a prior expectation which is implying that illness provide them inefficiency.

Demographic and Location Factors

A prior expectation on household size (LnHHS) was made with argument that the more household size it has, the lower or higher inefficiency farms are. LnHHS has a positive and insignificant impact on inefficiency on conventional farms but has a negative and insignificant impact on organic farms. Location (LOC2 and LOC3) of the farm has a negative and significant impact on inefficiency for both of farming method, that is, Maha Chana Chai and Loeng Nok Tha are efficient for producing jasmine rice.

Household's Finance

Total family income (LnINC), family saving (LnSAV) and loan (LnLOA) are hypothesized that they affect the inefficiency. The estimated value of LnINC on conventional farms is positive and insignificant in contrary to a prior expectation implying that conventional farms' income allocation may be spent inefficient. For organic farms, LnINC has a negative and significant impact on inefficiency. In case of LnSAV and LnLOA, LnSAV is negative and insignificant estimated coefficient for conventional farms but it is significant for organic farms implying that a farmer with more saving can be lower inefficient. In the both of farming method, LnLOA has a positive effect on efficiency but it is not significant. This indicates that allocation of loan is likely to be inefficient.

Farm Management

Farm management is consisted of TRC being transplanted or broadcasting rice farm and LnFMX. LnFMX is calculated from crop rotation in rice farm (CRR), Perennial Cultivation around rice farm (PCR), vegetable cultivation around rice farm (VCR), Animal Husbandry around Rice Field (HRR), and Fishery Pond around Rice Field (FPR). TRC is positive but insignificant on conventional farms but negative on organic farms. This implies that method of boardcasting rice cultivation may be appropriate for conventional farms and method of tranplanted rice cultivation may be appropriate for organic farms.

As expected, the results also revealed a consistent pattern of negative relationships between farm management (LnFMX) and inefficiency on organic farms implying that high-insentive farm management (LnFMX) provides farms more efficient. In contrast, for conventional farm, it implied that although being low-insentive farm management (LnFMX), they can lower inefficient.

Farmers' Management Characteristics

Management characteristics (LnMGTX) are constructed from the concept of the process approach or based on the management activities (planning (PLA), organizing (ORG), leading (LEA) and controlling (CTL)). LnMGTX is hypothesized that it has a negative impact on inefficiency. In accordance with the expectation, LnMGTX is negative and statistically insignificant for organic farms but it has a positive effect on inefficiency for conventional farms. For conventional farms, this indicates that the low-intensive management characteristics can lower inefficiency. On the other hand, high-intensive management characteristics on organic farms lead to lower inefficiency.

Infrastructure and Climate

Infrastructure is defined as access to the water source for production (LnIRG). Climate is defined as appropriate rainfall for rice farm (LnRNF). Estimated coefficient of LnIRG is negative and insignificant for conventional and organic farms. This indicates that being access to the water sources, inefficiency of rice farms can be lower. LnRNF have a positive and insignificant impact on inefficiency on conventional and organic farm implying that over-rainfall may higher inefficiency.

Government Support

Government support is defined as knowledge support (LnGKNW) and input support (LnGINPUT). LnGKNW are related positively to inefficiency for conventional and organic farms complying with a prior expectation indicating that farms can lower inefficiency without knowledge support from government sector. It can be explained because farmers might have already known about rice production, fertilizer production, and soil quality improvement. LnGINPUT are related negatively to inefficiency for conventional and organic farm and they are consistent with prior expectation. In addition, as shown in Table 11, The (negative) elasticity estimates indicates that management characteristics on organic farms contributed the most to lower inefficiency, followed by education, location, farm management, and income. For conventional, government input support contributed the most to lower inefficiency, followed by location, education, and access to the water source.

Table 10 Linear Regression Estimates on Conventional and Certified Organic Farms

Variables	Parameters	Conventional Farms (n=165)		Organic Farms (n=165)	
		Coefficients	S.E	Coefficients	S.E
Constant	β_0	-2.1277[b]	0.8229	-1.1714[a]	0.3104
LnHTH	β_1	0.0489	0.1170	0.0128	0.0329
LnEXP	β_2	-0.0435	0.0759	-0.0213	0.0493
LnEDU	β_3	-0.0900	0.1525	-0.0679	0.0491
LnATR	β_4	0.2395[b]	0.1194	0.1449[b]	0.0669
LnHHS	β_5	0.1714	0.1256	-0.0306	0.0415
LOC2	β_6	-0.3811[b]	0.1783	-0.1701[a]	0.0453
LOC3	β_7	-0.7514[a]	0.1509	-0.1513[a]	0.0511
LnINC	β_8	0.0100	0.0521	-0.0344[c]	0.0194
LnSAV	β_9	-0.0172	0.0136	-0.0087[b]	0.0039
LnLOA	β_{10}	0.0007	0.0116	0.0031	0.0035
TRC	β_{11}	0.1574	0.1129	-0.0080	0.0337
LnFMX	β_{12}	0.0173	0.1454	-0.0347	0.0540
LnMGTX	β_{13}	0.8044[c]	0.4344	-0.2044	0.1778
LnRNF	β_{14}	0.0746	0.1654	0.0178	0.0624
LnIRG	β_{15}	-0.0719	0.1120	-0.0087	0.0443
LnGKNW	β_{16}	0.3441[c]	0.1852	0.0290	0.0419
LnGINPUT	β_{17}	-0.3745[b]	0.1520	-0.0094	0.0419
F-Statistic		4.00[a]		1.70[b]	
R^2		0.32		0.16	
Adjusted R^2		0.24		0.07	
Sum Squared Residual		53.01		5.42	

Note: [a]Significant at 1%. [b]Significant at 5%. [c]Significant at 10%. S.E=Standard Error of Coefficient

Table 11 Elasticities of Variables on Conventional and Certified Organic Farms

Conventional Farms			Organic Farms		
Rank	Variable	Elasticities (sign)	Rank	Variable	Elasticities (sign)
1	LnMGTX	0.8044[c] (+)	1	LnMGTX	0.2044 (-)
2	LnGINPUT	0.3745[b] (-)	2	LnATR	0.1449[b] (+)
3	LnGKNW	0.3441[c] (+)	3	LnEDU	0.0679 (-)
4	LOC3	0.2480[a] (-)	4	LOC2	0.0561[a] (-)
5	LnATR	0.2395[b] (+)	5	LOC3	0.0499[a] (-)
6	LnHHS	0.1714 (+)	6	LnFMX	0.0347 (-)
7	LOC2	0.1258[b] (-)	7	LnINC	0.0344[c] (-)
8	LnEDU	0.0900 (-)	8	LnHHS	0.0306 (-)
9	LnRNF	0.0746 (+)	9	LnGKNW	0.0290 (+)
10	LnIRG	0.0719 (-)	10	LnEXP	0.0213 (-)
11	TRC	0.0645 (+)	11	LnRNF	0.0178 (+)
12	LnHTH	0.0489 (+)	12	LnHTH	0.0128 (+)
13	LnEXP	0.0435 (-)	13	LnGINPUT	0.0094 (-)
14	LnFMX	0.0173 (+)	14	LnSAV	0.0087[b] (-)
15	LnSAV	0.0172 (-)	15	LnIRG	0.0087 (-)
16	LnINC	0.0100 (+)	16	TRC	0.0034 (-)
17	LnLOA	0.0007 (+)	17	LnLOA	0.0031 (+)

Note: [a]Significant at 1%. [b]Significant at 5%. [c]Significant at 10%.
Elasticities of LOC2, LOC3 and TRC are derived from coefficient multiplied by mean of that variable.

V. CONCLUSIONS

The aim of this study is to measure technical efficiency, compare technical efficiency between conventional and certified organic jasmine rice farms and exploring factors affecting technical inefficiency on conventional and certified organic jasmine rice farms. It is found that labor, seed, and organic fertilizer are much more important factors in organic jasmine rice production. On the average, organic farms operate closer to production frontier than conventional farms do or equivalently organic farmers are using their available resource more effectively than their conventional counterparts are. In addition, on average, conventional and certified organic farms can reduce their input use by 55% and 28% or can increase their output by 29% and 13%, respectively.

Based on elasticities of variables, the key factors affecting technical inefficiency on conventional farms are management characteristics, input and knowledge on agriculture supported by government, location, and agricultural training. In case of organic farm, the key factors are management characteristics, agricultural training, education, location and farm management.

As findings above, farmers and agencies that are involved in agricultural development programs needs to appreciate there is an inefficiency problem. Operating at best practice, farm families would be able to release inputs for use in alternative economic activities to generate extra income for the family's welfare, or cost-saving to purchase new technologies such as improved seeds, fertilizers and land improvement.

Benchmarking using the efficient farms would be helpful for setting targets and finding the weakness of the current practices. The relatively efficient farms can also improve their efficiency further through learning the best allocation decision from other efficient farms.

Efficiency improvement program should be flexible enough to accommodate the diversity of both farmers and their need for improvement. For example, creating separate groups of high, medium and low efficiency might be required for educational purposes. Similarly, developing and implementing separate programs for farmers who are inefficient in fertilizer, seed, labor use and so on would be probably be useful.

According to determinants of technical inefficiency, for organic farms, management characteristics and education are the important factors. Therefore, if farmers are trained on the knowledge of planning, organizing, leading, and controlling, it would provide farmers higher efficiency. Likewise, In the long run, increasing private and public investment in education might lead to better performance. However, in the short run, inefficient farmers may be better off by learning from the benchmarking practices of the relatively efficient farms in their locality, perhaps using extension tools such as field days on the efficient farms.

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