CHAPTER II

LITERATURE REVIEW

This chapter deals with a systemization of the productive efficiency study. Alternative approaches of the frontier analysis are presented such deterministic and stochastic frontier production function, and data envelopment analysis (DEA). The articles related to the study are also reviewed in this section.

2.1 Approaches of frontier production function and productive efficiency study

In microeconomic theory a production function is defined in terms of the maximum output that can be produced from a specified set of inputs, given the existing technology available to the firms involved. However, up until the late 1960s, most empirical studies used traditional least-squares methods to estimate production functions. Hence the estimated functions could be more appropriately described as response (or average) functions (Battese, 1992).

Productive efficiency has been adopted in production analysis for years. Generally, technical efficiency refers to the ability to minimize input used in the production of a given output vector, or the ability to obtain maximum output from a given input vector. Farrell (1957) defined the sample of farm productive efficiency that accounted for multiple inputs consisting of two components: technical and allocative efficiencies. The frontier methodology has become a widely used tool in applied production analysis and played an important landmark in technical measurement of production efficiency.

The large number of studies in different areas on frontier models, especially in agricultural economics that have been developed, based on Farrell's work. They can be divided into two basic types: parametric and non-parametric approaches as addressed in Figure 2.

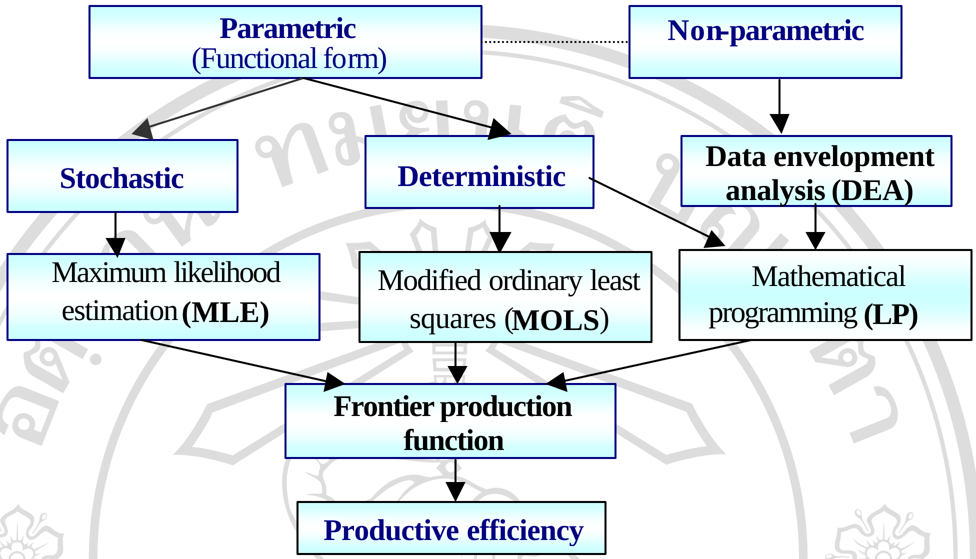

Figure 2 Alternative approaches of the frontier analysis

Parametric frontiers, which rely on a specific functional form, can be separated into two kinds of model: deterministic and stochastic. The deterministic model assumes that any deviation from the frontier is only due to inefficiency, while the stochastic approach allows for symmetric statistical noise. There are two essential differences between the econometric approach and mathematical programming methods to the construction of a production frontier and the calculation of efficiency relative to the frontier as stated below

The econometric approach has the virtue of being stochastic, and so attempts to distinguish the effects of statistical noise from those of productive inefficiency. However, the econometric approach is parametric, and so can confound the effects of misspecification of (even flexible) functional forms (of both technology and inefficiency) with inefficiency. In addition, a flexible form is susceptible to multicollinearity, and theoretical restrictions may be violated. A main attraction of the econometric approach is the possibility it offers for a specification in the case of panel data. It also allows for a formal statistical testing of hypotheses and the construction of confidence intervals (Hjalmarsson *et al*., 1996). Coelli (1995) concluded that the stochastic frontier method is recommended for use in agricultural applications, because measurement error, missing variables and weather, etc. are likely to play a significant role in agriculture.

The mathematical programming approach is nonstochastic, and lumps noise and inefficiency together and calls the combination inefficiency. The Data Envelopment Analysis (DEA) version of the mathematical programming approach is nonparametric, and less prone than the Stochastic Frontier Analysis (SFA) to specification error, meaning that it does not require a specific functional form. It also imposes regularity conditions a *priori* rather than testing them *ex-post*. DEA has the additional advantage over SFA that it can accommodate many inputs and many outputs, although it generates more efficient firms when the number of variables increases (Tauer and Hanchar, 1995).

Nevertheless, a major drawback of this method is that it does not allow for random noise as do parametric frontiers and DEA does not support panel data estimation, and so for each year a new production possibility set is calculated. Every observation is compared with the frontier of the production possibility set of each year. Another characteristic of DEA method is the potential sensitivity of the efficient scores to the number of observations and as well as to the number of outputs and inputs that can point out the solutions to input optimization to each specific farm (Shafip and Reman, 2000).

In order to estimate a frontier production function and draw productive efficiency of the specific farms, parametric approach in the stochastic frontier form uses maximum likelihood estimation (MLE) to come up with the frontier function. Meanwhile, non-parametric approach with the DEA (Coelli *et al.*, 2001; Thanassoulis, 2001) uses linear programming, and parametric approach in the deterministic frontier form uses both linear programming (LP) and modified ordinary least squares (Figure 2).

Deterministic frontier approach

The procedure of deterministic frontier estimation was addressed by Aigner and Chu (1968) that the deterministic production frontier model can be converted into either a pair of mathematical programming models as follows:

$y_i = f(x_i, a_i)\exp(-Ui)$

where, $TE = \exp(-Ui) = y_i / \hat{yi}$

exp = exponential term

It requires that TE ≤ 1, so Ui ≥ 0. Next, assuming that f(Xi, a_i) takes a log-linear Cobb-Douglas form, the deterministic production frontier model becomes

$$Y_j = a_0 + \Sigma a_i X_{ij} - Ui, \qquad (1)$$

where, $Y_j = \ln y_j$ and $X_{ij} = \ln x_{ij}$

The objective is to obtain estimates of the parameter vector of a_i for which the sum of proportionate deviations of the observed output of each producer beneath maximum feasible output is minimized. The resulting deviations are then converted to measures of technical efficiency for each producer. Such a model can be addressed as

$$\text{Min} \sum_{j=1}^{n} Uj = \sum_{j=1}^{n}\sum_{i=0}^{m} \hat{a}iXij - \sum_{j=1}^{n} Yj \quad \leftrightarrow \quad \text{Min } \hat{U} = \sum \overline{\hat{ai}\,\bar{X}j} - \bar{Y}$$

$$\text{S.t} \quad \hat{Yi} = \sum \hat{ai}\, Xij \geq Yi \qquad (j = 1 \text{ to } n)$$

$$a_i, X_{ij} \text{ and } Y_j \geq 0$$

where, $\bar{Y} = \sum_{j=1}^{n} Yj/n$; $\bar{X} = \sum_{j=1}^{n} Xj/n$; $\hat{U} = \sum_{j=1}^{n} \overline{Uj}/n$

$\hat{ai}$ = coefficients estimated

n = number of observations

U = one sided error term,

X_{ij} = ln-value of input i used by farm j

Y_j = ln-value of output of farm j

There is another method of the deterministic frontier production function estimation, namely corrected ordinary least squares (MOLS) that was addressed in

Afriat (1972) and Richmond (1974). The authors suggested that the deterministic production frontier model could be estimated in two steps. Firstly, OLS is used to estimate parameters under the assumption that disturbances follow an explicit one-sided distribution such as exponential or half normal. Secondly, the estimated intercept is shifted up by the mean of the assumed one-sided distribution, $E(\hat{u})$. The OLS residuals can then be used to provide consistent estimates of the technical efficiency of each producer. However, there is no guarantee that the modification of OLS shifts the estimated intercept up by enough to ensure that all producers are bounded from above by the estimated production frontier. If this happens, it is uncomfortable to explain for the cases that technical efficiency score is greater than unity.

In short speaking, the above deterministic frontier model exists a serious deficiency: it did not take into account of the possible influence of random shocks. Therefore, a fundamental problem with deterministic frontier is that any measurement error, any other sources of stochastic variation in the dependent variable, is embedded in the one-sided error component. As a consequence, outliers can have profound effects on the estimates and any shortcoming in the specification of the model could translate into increased inefficiency measures.

DEA approach

Charnes *et al.* (1978) first introduced DEA that was extended the Farrell (1957) technical efficiency measure from a single-input, single-output process to a multiple-input, multiple-output process. Since then, DEA has been used to assess efficiency in many different areas. The authors proposed a method in which the multiple-input, multiple output model was reduced to a ratio with a single "virtual" input and single "virtual" output by estimating a set of weights depicting each DMU (decision making unit) in the most favorable position relative to other DMUs. In equation form, the model is addressed as follows:

$$\text{Max } w_o = \sum_{r=1}^{s} u_r y_{ro}$$

$$\sum_{i=1}^{m} v_i x_{io} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \qquad j=1\ldots o\ldots N$$

$$u_r \geq \varepsilon \text{ , and } v_i \geq \varepsilon \qquad r = 1\ldots s;\ i = 1\ldots m$$

where, y_{rj} = quantity of output r produced by firm j,

x_{ij} = quantity of input i used by firm j,

u_r = weight for output r,

v_i = weight for input i, and

ε = small positive quantity.

Färe *et al.* (1994) proposed the input-oriented and output-oriented DEA models to measure technical efficiency. The models can be expressed as below:

Input-oriented technical efficiency model examines the vector of inputs used in the production of any output bundle, and measures whether a firm is using the minimum inputs necessary to produce a given bundle of outputs. Linear programming for measuring input-oriented technical efficiency of any DMU is modeled as

Min λ

s.t. $u_{jm} \leq \sum_{j=1}^{J} z_j u_{mj}$, $(m = 1,2,\ldots,M)$

$$\sum_{j=1}^{J} z_j x_{nj} \leq \lambda x_{nj}, \qquad (n = 1,2,\ldots,N)$$

$$z_j \geq 0, \qquad (j = 1,2,\ldots,J)$$

where, λ = efficiency measure to be calculated for each DMU_j,

u_{jm} = quantity of output m produced by DMU_j,

x_{jn} = quantity of input n used by DMU_j, and

z_j = intensity variable for DMU_j.

Output-oriented technical efficiency is a measure of the potential output of a DMU given that inputs are held constant. Färe *et al.* (1994) modeled the output technical efficiency measure for any DMU using linear programming as follows:

$$\text{Max } \theta$$

$$\text{s.t.} \quad \theta u_{jm} \leq \sum_{j=1}^{J} z_j u_{jm}, \qquad m = 1, 2, \ldots, M$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}, \qquad n = 1, 2, \ldots, N$$

$$z_j \geq 0, \qquad j = 1, 2, \ldots, J$$

where, θ = output technical efficiency measure,

u_{jm} = quantity of output m produced by DMU j,

x_{jn} = quantity of input n used by DMU j, and

z_j = intensity variable for DMU j.

The problem of returns to scale can be dealt with by using the Banker *et al.* (1984) extension to the Constrained Categorical Regression (CCR) model as: (a) for constant returns to scale (CRS), the condition $\Sigma z_j \geq 1$ is added; and (b) for variable returns to scale (VRS), the constraint $\Sigma z_j = 1$ is imposed.

Since the variable λ, θ is calculated for each DMU, the preceding formulation is estimated once for each DMU in the data set. A value of λ =1.0 means that a firm is considered efficient, while a value λ <1.0 means a firm is inefficient. The θ values from the output-oriented model indicate how much each DMU could be able to increase output production given that the inputs are held constant. If θ = 1, firm is considered efficient but θ >1 (e.g. θ =1.1) meaning that firm should have been able to increase its outputs by 10%.

Stochastic frontier approach

Aigner, Lovell and Schmidt (1977), and Meeusen and van den Broeck (1977) simultaneously introduced the stochastic production frontier function models, in which an additional random error, V_i, is added to the non-negative random variable, U_i. These models allow for technical inefficiency but they also acknowledge the fact that random shocks outside the control of producers can affect output. The great virtue of stochastic production frontier models is that the impact on output of shocks due to variation in labor and machinery performance, vagaries of the weather, and just plain luck can at least in principle be separated from the contribution of variation in technical efficiency (Kumbhakar and Lovell, 2000). Assume that stochastic frontier function takes a log-linear Cobb-Douglas form so it can be written as follows:

$$LnY_j = \beta_0 + \Sigma \beta_i lnX_{ij} + V_j - U_j \qquad (2)$$

where, Y_j = output level of farm j,

X_{ij} = input i used by farm j,

$V_j - U_j = \varepsilon j$ (error terms,)

V_j = two sided error terms representing random error of farm j independently and identically distributed as $N(0,\sigma_v^2)$

U_j = one sided error term-nonnegative, independently and identically distributed as $N^+(\mu,\sigma_u^2)$ representing technical inefficiency of farm j

$\beta_{0,}\ \beta_{ij}$ = parameters to be estimated,

Crucial difference from the deterministic frontier approach is that the stochastic production function model incorporates a composed error structure with a two sided symmetric term (V) and a one sided component (-U). The one sided component reflects inefficiency while two sided error captures the random effects (exogenous events) beyond the control of the production unit, including measurement errors and other statistical noise typical of empirical relationships. Hence, stochastic frontier models address the noise problem (Thiam *et al.*, 2001).

The main different characteristics between traditional estimation, OLS and maximum likelihood estimation, MLE is that OLS implicitly assumes that all firms are fully efficient. Meanwhile, in reality even there were many cases that used the same technology of production and the same level of inputs but produced different levels of output. Therefore, the stochastic frontier analysis with association of MLE was employed to explain this issue as the existence of inefficiency of production caused by management ability throughout the frontier analysis. OLS shows information on production function of average practice farmers while MLE provides information on production function of the best practice farmers. The estimated frontier function is then used to measure technical efficiency.

Given the virtues of the stochastic frontier approach, the author selected this approach to apply for the study. Procedures of maximum likelihood estimation for the stochastic frontier production function are presented in detail in Chapter III.

2.2 Related studies to frontier production and technical efficiency, and others using quantitative methods in horticultural crops

Schmidt and Lovell (1979) obtained evidence bearing total inefficiency and its technical and allocative components by mean of a straightforward extension of analysis of Aigner, Lovell and Schmidt (1977). Meeusen and van den Broeck (1977) assumed that the farmers tried to minimize the cost of producing its desired rate of output, subject to a stochastic production frontier. If the farmer is technically inefficient, it operates below the stochastic production function. They used MLE to estimate the stochastic production function and then calculated the average technical inefficiency. The price inefficiency parameters were derived from the minimum cost.

Kalirajan (1981) estimated a stochastic Cobb-Douglas frontier production function and drew technical efficiency using data from 70 rice farmers located in the state of Tamil Nadu, India. The variance of farm effects was found to be a highly significant component in describing the variability of rice yields (the estimate for the γ-parameter was 0.81). The author proceeded to investigate the relationship between the difference between the estimated 'maximum yield function' and the observed rice yields and such variables as farmer's experience, educational level, number of visits by extension workers, etc. The study showed that management practices and contacts with local extension agents had a significant positive impact on technical efficiency.

In this second-stage analysis, he noted the policy implications of these findings for improving crop yields of farmers.

Huang and Bagi (1984) assumed a modified translogarithmic stochastic frontier production function to estimate the technical efficiencies of individual farms in India. It was found that the stochastic Cobb-Douglas frontier was not an adequate representation for describing the value of farm products, given the specifications of the translog model. The variance of the random effects was a significant component of the variability of value of farm outputs. Individual technical efficiencies ranged from about 0.75 to 0.95, but there appeared to be no significant differences in the technical efficiencies of small and large farms.

Kalirajan and Shand (1986) investigated the technical efficiency of rice farmers within and without the Kemubu Irrigation Project in Malaysia during 1980. Given the specifications of a translog stochastic frontier production function for the output of the rice farmers, the Cobb-Douglas model was not an adequate representation of the data. Maximum-likelihood methods were used for estimation of the parameters of the models and the frontiers for the two groups of farmers were significantly different. The authors reported that the individual technical efficiencies ranged from about 0.40 to 0.90, such that the efficiencies for those outside the Kemubu Irrigation Project were slightly narrow. However, given the relatively large estimated standard errors for the variances of the random errors in the stochastic frontiers, it may be the case that the stochastic model is not significantly different from the deterministic model. Hence this would suggest that the results obtained from the deterministic frontiers are more encouraging as to the positive impact of the credit program on participant farmers, even though the absolute levels of technical efficiencies were quite small. They concluded that their results indicated that the introduction of new technology for farmers does not necessarily result in significantly increased technical efficiencies over those for traditional farmers.

Ekanayake and Jayasuriya (1987) estimated both the deterministic and stochastic frontier production functions of Cobb-Douglas type for two groups of rice farmers in an irrigated area in Sri Lanka. The parameters of the two frontiers were estimated by maximum-likelihood and corrected ordinary least-squares methods. In only the 'tail reach' irrigated area, the stochastic frontier appeared to be significantly different from the deterministic model. Individual farm technical efficiencies were estimated for both regions. The estimates obtained for the farms in the 'head reach' area (for which the stochastic frontier appeared not to be significantly different from the deterministic frontier) were vastly different for the two different stochastic frontiers. These results are not intuitively reasonable.

Battese and Coelli (1988) used the stochastic frontier Cobb-Douglas function to define for panel data for the three years, 1978-79, 1979-80 and 1980-81 on sample fims of dairy farms in New Wales and Victoria, Australia to estimate technical efficiencies and to test whether the mean technical efficiencies in the two states are equal, and to predict individual technical efficiencies of dairy farms. The hypothesis that nonnegative effects had half normal distribution was rejected for both states, and Cobb-Douglas production function was not a suitable model, since the half-normal distribution was not an adequate representation for the individual firm effects, which determine technical efficiencies of farms. The estimates of mean technical efficiencies based on frontier production function showed that dairy farms in South Wales were about 77 percent technically efficient, whereas those in Victoria have technical efficiency of about 63 percent with a significant difference at the 20 percent level for a one sided asymptotic t-test. The individual farm technical efficiencies ranged from 0.54 to 0.93 for New Wales Farms, whereas for Victorian farms, the range was 0.296 to 0.934.

Kumbhakar *et al.* (1989) used a system approach to estimate technical, allocative and scale inefficiencies for Utah dairy farmers. The stochastic frontier production function which was specified included both endogenous and exogenous variables. The endogenous variables included were labor (including family and hired labor) and capital (the opportunity cost of capital expenses on the farm), whereas the exogenous variables included level of formal education, off-farm income and measures of farm size for the farmers involved. Both types of explanatory variables were found to have significant effects on the variation of farm production. Technical efficiency of farms was found to be positively related to farm size.

Kalirajan and Shand (1989) estimated the time-invariant panel-data model using data for Indian rice farmers over five consecutive harvest periods. The farm effects were found to be a highly significant component of the variability of rice output, given the specifications of a translog stochastic frontier production function. Individual technical efficiencies were estimated to range from 0.64 to 0.91, with an average of 0.70. A regression of the estimated technical efficiencies on farm-specific variables indicated that farming experience, level of education, access to credit and extension contacts had significant influences on the variation of the farm efficiencies.

Bravo-Ureta and Rieger (1990) estimated both deterministic and stochastic frontier production functions for a large sample of dairy farms in the northeastern states of the U.S.A. for the years 1982 and 1983. The Cobb-Douglas functional form was assumed to be appropriate. The parameters of the deterministic frontiers were estimated by linear programming, corrected ordinary least-squares regression and maximum-likelihood methods (assuming that the non-negative farm effects had gamma distribution). The stochastic frontier model was estimated by maximum-likelihood techniques (given that the farm effects had half-normal distribution). The stochastic frontier model had significant farm effects for 1982 but it was apparently not significantly different from the deterministic frontier in 1983. The estimated technical efficiencies of farms obtained from the three different methods used for the deterministic model showed considerable variability but were generally less than those obtained by use of the stochastic frontier model. However, the authors found that the technical efficiencies obtained by the different methods were highly correlated and gave similar ordinal rankings of the farms.

Ali and Chaudry (1990) measured farm efficiency in four irrigated cropping regions in Punjab province, Pakistan using an estimate probabilistic frontier production function. A Cobb-Douglas production function was estimated from the data of whole farm survey in the years 1984-1985. Farm efficiency was estimated in terms of technical efficiency, allocative efficiency and economic efficiency using OLS. Then it was transformed into a probabilistic production function using linear programming by deleting outliers one by one until all coefficients stabilized. They found that the average technical efficiency ranges from 0.8 in the rice region to 0.87 in the sugar cane region. The study showed that there exists a 13-20 percent potential for increasing the gross income of the farmers at the existing levels of farmers' resources and technology.

Kumbhakar (1990) used a panel-data framework and models firm-specific technical inefficiency which is allowed to vary over time to estimate economic efficiency of the production units. The specification is flexible enough to accommodate increasing, decreasing, and time-invariant behavior of technical inefficiency. Based on the assumption of cost minimization, time-varying firm- and input-specific allocative inefficiency is also incorporated. The estimation method suggested uses a parametric production function and cost-minimization hypothesis. The ML estimation method, based on a parametric production function, is developed to estimate the parameters. Estimates of technical and allocative inefficiency based on the ML parameter estimates are also suggested. Finally, formulas for calculating costs of technical and allocative inefficiency are derived.

Bravo-Ureta and Rieger (1991) estimated technical efficiency of diary farms in New England region of the U.S using the Cobb-Douglas frontier production function based on the cross-sectional data of a sample of 511 dairy farms. They obtained technical efficiency ranging from 0.5 to 1.0 with an average of 0.82. The authors concluded that technical efficiency of individual farm was statistically independent of size of the dairy farms as measured by the number of cows.

Battese and Coelli (1992) applied the panel-data model incorporating time-varying firm effects in the analysis of data for paddy farmers in an Indian village who were observed for up to ten years. Given the specifications of a stochastic frontier production function with time-invariant parameters, the hypothesis of time-invariant technical efficiencies of the paddy farmers was rejected. However, given that a linear time trend was included in the stochastic frontier model (Hicksian neutral technical change), and then the hypothesis of time-invariant technical efficiencies was accepted. In addition, the stochastic frontier production function with the time trend included was not significantly different from the average response function (i.e., technical inefficiencies could be considered absent from the model).

Seyoum *et al.* (1998) investigated the technical efficiency of two samples of maize producers in eastern Ethiopia, one involving farmers within the Sasakawa-Global 2000 project and the other involving farmers outside this program. The study used the stochastic frontier functions in which technical inefficiency effects were assumed to be functions of age and education of the farmers, together with the time spent by extensionists in assisting farmers. The stochastic Cobb-Douglas frontiers were found to have adequate representations of the data, given the specifications of the translog stochastic frontiers for farmers within and outside the project. The empirical results indicated that farmers within the project were more technically efficient than those outside the project. The mean frontier output of maize for farmers within the project was more significant than that for the farmers outside the project.

Shafiq and Rehman (2000) examined the sources of resource use inefficiency for cotton production in Pakistan's Punjab. The use of a non-parametric method, Data Envelopment Analysis (DEA), was developed to study the relative technical and allocative efficiencies of individual farms which used similar inputs, to produce the same product and operated under comparable circumstances. In the 'cotton–wheat' system of Pakistan, there were a considerable number of farms that were both technically and allocatively inefficient. The use of DEA showed that the technique provides a clear identification of both the extent and the sources of technical and allocative inefficiencies in cotton production. However, both the interpretation of the farm level results generated and the projection of these results to a higher level require care, given the technical nature of the agricultural production processes.

Sriboonchitta and Wiboonpongse (2001) analyzed factors affecting outputs of the jasmine and nonjasmine rice production in Thailand. The stochastic production frontier estimation method was thus used with self-selectivity variables. The factors included production inputs, physical and environmental factors, disease occurrence and technical efficiency. The method of estimation was modified to include a self-selectivity variable to eliminate biases of the estimated parameters. The empirical results showed that the average technical efficiency for jasmine and nonjasmine rice were 60.72 and 62.81 percent respectively. The percents of the output reduction due to the drought were 35.13 and 26.13 while due to the neck blast were at 18.38 and insignificantly different from zero for jasmine and nonjasmine rice respectively,

Sriboonchitta and Wiboonpongse (2001) also used both the Cobb-Douglas and translog models alternatively to estimate the stochastic frontier functions for both jasmine and nonjasmine rice yields in order to examine the effects of production inputs, technical efficiency and other factors on both jasmine and nonjasmine rice yields. The results showed that the Cobb-Douglas function was chosen to draw policy implications, and the crucial factors influencing jasmine rice yield were technical efficiency, chemical fertilizer, labor, irrigation, severe drought and neck blast. The factors affecting technical inefficiency for nonjasmine rice in a negative relationship were male labor to total labor ratio and farming experience while the labor influenced positively. For jasmine rice, there is only one variable male-labor ratio influencing technical inefficiency significantly.

Zaibet and Dharmapala (1999) analyzed horticultural growers' technical efficiency in Oman using the stochastic production frontier (SPF) and the data envelopment analysis (DEA) methods. Different methods were used because the determinants of technical efficiency may be influenced by the method used and also by the assumptions (i.e. returns to scale) maintained. Results from the stochastic parametric frontier (SPF) and DEA-Charnes, Cooper and Rhodes (CCR) models showed that the percentage of farmers that could qualify as technically efficient was as low as 17 percent. When the DEA- Banker, Charnes and Cooper (BCC) method was used, this percentage increased to about 46 percent. Factors such as off-farm income and soil quality were found to be positively correlated to productivity. On the other hand, small farm size and farmer's age showed a negative relationship with productivity.

Vandeveer (2001) examined the need for litchi crop insurance in northern Vietnam. Hypothetical insurance programs were developed which proposed all-risk coverage based on area yields. The author used different premiums of two-guaranty average yield levels (85 and 90 percent) and indemnity prices to measure farmer's responses to insurance selection. Binomial logit models were estimated for the yield insurance decision probabilities of farmers, including variables (e.g. premium, dummy for yield guarantee, indemnity price, schooling level, farming experience, ratio of minimum farm income to average farm income, average total income, number of risks happened, number of risk management responses, number of died litchi trees, and standard deviation of litchi yield). Results indicated that while farmer participation would be significant, crop insurance is not needed to achieve policy goals like raising farmer income or guaranteeing subsistence levels of income. Crop insurance is not needed to promote litchi production, which is already expanding rapidly due to its high profitability relative to other farm enterprises. Estimated premiums were quite low when expressed as a percent of expected revenue, and farmers were not responsive to changes in premiums. Econometric analysis indicated that high income farmers were more likely to participate, but other farmer characteristics seemed to matter little.