ELSEVIER

Agricultural Economics 15 (1996) 113-126

AGRICULTURAL ECONOMICS

Nonparametric analysis of technical, pure technical, and scale efficiencies for food crop production in East Java, Indonesia [1]

Richard V. Llewelyn *, Jeffery R. Williams

Department of Agricultural Economics, Kansas State University, Manhattan, Kansas, USA

Accepted 1 August 1996

Abstract

Nonparametric analysis of technical efficiency for irrigated farms in the Madiun regency in the west-central part of East Java, Indonesia is conducted using linear programming techniques. This procedure allows the relative technical efficiency for each farm to be determined and for inefficiencies to be decomposed into pure technical inefficiency and scale inefficiency and does not require restrictions or assumptions regarding functional form to be placed on the data.

Farmers in Madiun generally are efficient relative to each other. Farmers operating inefficiently do so more often because of scale inefficiencies rather than pure technical inefficiencies. A majority of the farms operate in the region of decreasing returns to scale rather than increasing returns to scale. Farmer age, the level of diversification of cropping activities, and high school education were found to be related to technical efficiency in the rainy season under irrigated conditions. Other socioeconomic factors were not statistically significant.

The results imply that inefficient farms use excessive levels of inputs, particularly nitrogen fertilizer. This is perhaps due to the lingering effects of past input subsidization policies, particularly of fertilizers, in Indonesia, or to risk-reducing behavior. The results also imply that current government policies to encourage diversification of cropping practices in Java may lead to greater technical inefficiencies in production. In addition, extension education targeted to younger farmers with low levels of formal education would improve efficiency.

Nonparametric analysis of technical efficiency for irrigated farms in the Madiun regency of East Java, Indonesia is conducted using linear programming techniques. Though relatively common in high income countries, efficiency analysis in low income countries has been hampered by lack of data and poor understanding of the production process and often is limited to analysis of a single crop. Whole-farm analysis of technical efficiency that includes multiproduct production is rare. The use of nonparametric techniques makes it possible to evaluate technical, pure technical, and scale efficiencies for multiproduct farms in Madiun and to then identify factors associated with inefficiencies.

Efficiency may be described as the relation between ends and means (Afriat) and has application in production analysis as well as consumption theory and demand analysis. Economists widely distinguish between technical efficiency and allocative or price efficiency, following pioneering work by Farrell in 1957. The concept of technical efficiency relates to whether a firm uses the best available technology in its production process (Chavas and Cox, 1988). In

* Corresponding author at: Kutisari Indah Selatan IV/48, Surabaya, Indonesia.

[1] Contribution no. 96-308-J from the Kansas Agricultural Experiment Station.

PII S0169-5150(96)01202-9

economic terms, technical inefficiency refers to failure to operate on the production frontier and generally is assumed to reflect inefficiencies caused by the timing and method of application of production inputs (Byerlee, 1987). Potential causes of technical inefficiency are inadequate information or insufficient technical skills.

A variety of methods have been used to measure efficiency. The concept of the efficient frontier has often been used, where deviations from the frontier are assumed to represent inefficiencies. Various types of frontier efficiency analysis exist. These methods differ with respect to the assumptions on the outer bound of the frontier, which may be deterministic or stochastic, and to the method of measurement, parametric or non-parametric.

For the parametric approach, estimation of production functions (or profit or cost functions) consists of specifying a parametric form for the function and then fitting it to observed data by minimizing some measure of their distance from the estimated function. This method attributes variation from the most efficient farms to technical inefficiency. As Chavas and Aliber (1993) note, the parametric approach provides a consistent framework for analyzing efficiency, however, this approach has an important weakness, in that the maintained hypothesis of parametric form can never be detected directly (Varian, 1984; Banker and Maindiratta, 1988). This method thus imposes restrictions on the technology that may not hold and that affect the distribution and measurement of the efficiency terms (Chavas and Aliber, 1993). An advantage of the parametric approach is that it can segregate deviations from the frontier technology into the systematic or actual inefficiencies of the firm and the random components, such as weather, that are stochastic and not due to operator inefficiency. Some stochastic formulations of frontier production functions have been developed that sort out the effects due to random errors from those caused by technical inefficiencies.

An alternative approach is to apply nonparametric techniques to analyze production efficiency. A deterministic nonparametric frontier model was developed by Farrell (1957) in his groundbreaking work. This model cannot separate deviations from the frontier technology into their systematic and random components and thus, attributes all deviations from the frontier technology to inefficiency of the observed firm and may overstate inefficiencies. However, this methodology has the advantage of imposing no a priori parametric restrictions on the underlying technology, because it does not require a specific functional form for the frontier to be specified. Therefore, it does not impose unwarranted structure on the technology that might create a distortion in the efficiency measures (Färe et al., 1985). Also, it can handle disaggregated inputs and multiple output technologies and can be used in evaluating technical, allocative, scale and scope efficiencies.

This study utilizes nonparametric techniques to provide a direct analysis of technical efficiency of irrigated food-crop production in East Java, Indonesia. A nonparametric, whole-farm, production frontier that includes multiple outputs is estimated for each farm in each of three distinct cropping seasons: rainy, middle, and dry. The crops included in this study are paddy rice, corn, soybeans, peanuts, mungbeans, cassava, and a pepper-onion intercrop. Relative overall technical efficiency for each farm is determined as well as pure technical efficiency and scale efficiency. Efficiency indices obtained from the nonparametric analysis are then regressed on socioeconomic variables to help identify factors associated with technical inefficiencies.

1. Agricultural production and efficiency in Indonesia and Asia

Efficiency analysis of agricultural production in Indonesia has focused primarily on irrigated rice production (Widodo, 1986; Erwidodo, 1990) using stochastic parametric approaches. Widodo used a stochastic production function methodology with panel data to estimate average technical efficiencies, found to be between 83% and 96%. These values are similar to those found by Dawson et al. (1991) in the Philippines for lowland irrigated rice. In a similar study, Erwidodo used two stochastic production functions, the Cobb-Douglas and the translog, to examine farm-level efficiency in West Java. Technical efficiencies for wetland rice production averaged 93.5% and ranged from 88% to 96.4%. This methodology revealed no significant difference in the level of technical efficiency between small and large farms.

Byerlee cites six other studies that have taken place in Asia, five of which examined irrigated rice production and one that looked at corn production, all using stochastic production frontier methodology. Average efficiencies for rice production ranged from 47% to 80% in India, the Philippines, and Pakistan. For corn, the average efficiency in a study by Peng and Chen in Taiwan (cited by Byerlee, 1987) was 72%. The major factors explaining differences in efficiency were variables that dealt with farmers' information and skills, such as education, experience, and contact with extension agents.

A study of irrigated, high-yielding rice varieties in India by Kalirajan (1981) used Cobb-Douglas technology in estimating a profit function to evaluate the relative efficiency of large and small farmers who had adopted modern varieties. He concluded that small farmers were as efficient in adopting the new technologies as large farmers in terms of both technical efficiency and allocative efficiency.

In a study of rice production in the Philippines, Bernsten (1977) included a measure of farmers' technical knowledge in the production function. The effect of this variable was significant and positive. He also found that age, experience, and extension contact were significant factors in farmers' efficiency, but education was not significant.

Dawson et al. (1991) evaluated technical, allocative, and overall economic efficiencies for 22 rice farms in the Philippines with panel data from the International Rice Research Institute using a frontier production function approach. Overall efficiencies ranged from 84% to 95% across the farms. Azhar (1991) found technical efficiency in rice and wheat production in Pakistan to be related positively and very significantly to education levels, with primary education providing the greatest increase in efficiency.

Little has been done concerning efficiency of secondary food-crop production in Indonesia. In addition, the application of nonparametric techniques to Indonesian agriculture is virtually nonexistent, and these methodologies have potential for providing useful information regarding technical and scale efficiencies in production as well as factors associated with inefficiencies that may exist. These techniques are useful where data are more limited and production technologies not well understood, since they do not require a priori specification of a functional form.

2. Methodology and model development

Although the use of parametric techniques is prevalent, the use of nonparametric techniques is more limited, particularly in low income countries, despite the fact that nonparametric methodologies can be used in situations where data is more limited and where production technologies are less well understood. There are two nonparametric approaches to production analysis. One is based on the works of Afriat, 1972; Hanoch and Rothschild, 1972; and Varian, 1984. This approach deals with four types of concerns in the neoclassical theory of production: consistency, restriction of form, recoverability, and extrapolation, without maintaining any hypotheses of functional form. This methodology is applied to time series data and has been used in several studies to evaluate technical efficiency in agriculture (e.g. Chavas and Aliber, 1993; Chavas and Cox, 1988).

Alternatively, Farrell decomposed efficiency into technical efficiency and allocative efficiency. Färe et al. (1985) introduced a nonparametric method of calculating efficiency across farms, which extended Farrell's approach by relaxing the restrictive assumptions of constant returns to scale and of strong disposability of inputs, the major criticisms of the method.

Färe et al. note that efficiency by a firm in inputs does not imply that the firm is necessarily efficient in outputs. Technical, allocative, and other efficiency measures of outputs cannot be determined from corresponding efficiency measures of inputs or vice versa because output and input efficiencies focus on different aspects of production. The type of efficiency that is being evaluated should be clearly specified.

Technical efficiency may be defined as the ability of a firm to produce as much output as possible with a specified level of inputs, given the existing technology. Graphically, this is illustrated in Fig. 1. Six observed data points with associated levels of input and output are shown. The frontier for this production process is defined by the line ABC. Observations A, B, and C lie on the frontier while observa-

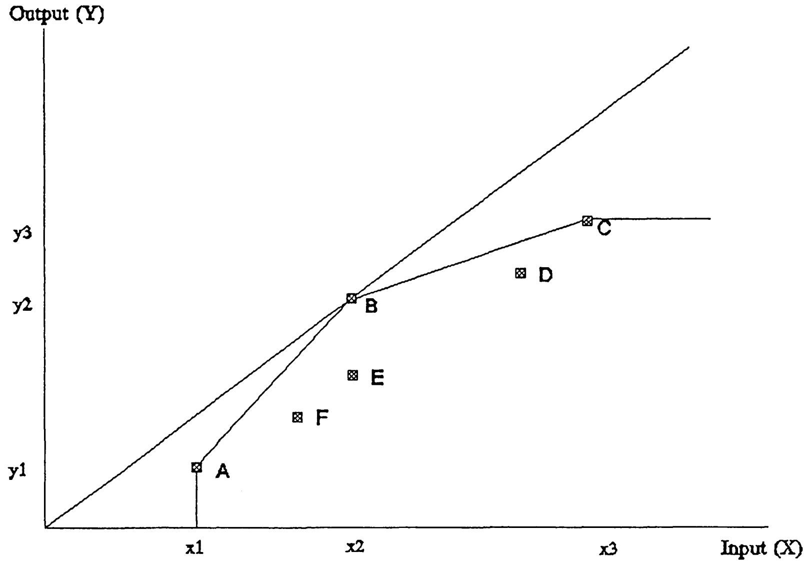

Fig. 1. Technical efficiency illustrated.

tions D, E, and F lie within the frontier. A ray from the origin is tangent to the frontier at Point B. This ray represents constant returns to scale for the technology represented by these data observations. In this example, Observation B is overall relatively technically efficient, which implies that this firm is also purely technically efficient and scale efficient. It lies on the frontier and has constant returns to scale.

Although a firm may be technically inefficient in an overall sense, it is possible for it to be purely technically efficient, while experiencing inefficiencies in scale. This is also illustrated in Fig. 1. Observations A and C are purely technically efficient, since they lie on the frontier, but exhibit scale inefficiencies. Observation D is both scale inefficient and purely technically inefficient since it lies below the frontier. Theoretically, the same level of input could be used to achieve a higher level of output, which would allow this producer to be on the frontier between Points B and C. Observation E is purely technically inefficient since it is not on the production frontier, but is scale efficient, because it produces at input level $x2$, the scale-efficient level of input.

The model utilized in this study is based on a model developed by Grabowski and Pasurka (1987) to examine relative efficiency of farms in the northern and southern United States prior to the Civil War. Using this methodology, overall technical efficiency for a farm is determined and then is decomposed into pure technical efficiency and scale efficiency for multiproduct, farm-level, crop production in Madiun, Indonesia. With this approach, a nonparametric production frontier is constructed, with inefficiency being measured by the extent to which firms operate below the frontier. Using this approach, the cause of the inefficiency can be allocated as either inappropriate scale (scale inefficiency) or off-isoquant production (pure technical inefficiency).

It should be noted that this procedure involves relative technical efficiency, that is, the production frontier is constructed from the data and each farm's performance is compared with the frontier to indicate overall technical efficiency of the individual farm. Risk is not included explicitly in the model. The model assumes that the degree of risk aversion is consistent across all farms in the sample, but does not assume the degree of risk aversion, that is, whether this group of farmers are risk-taking, risk-neutral, or risk averse. If this assumption of constant risk preference does not hold, the estimated inefficiencies will be overstated. It has been suggested that risk preferences may be different particularly between large and small farms. However, the regression analysis conducted to evaluate factors associated with inefficiency includes farm size as a possible factor, but as shown later, this is not statistically related to inefficiency.

This analysis also assumes homogeneous inputs. Land is not included explicitly in the model and it is assumed that variations in soil types and fertility do not exist. This is a rather strong assumption, but necessary in order to proceed. Though data for variation in land quality were not collected, the data for each of the four villages surveyed were tested separately to evaluate whether there might be large differences in land quality. These results are reported below, but no significant differences in technical efficiency are found to exist between villages. Homogeneity of other inputs, including labor, chemicals, seed, and management, is assumed as well. Differences in labor and management quality would be very difficult to determine and include in the model.

In the model, it is assumed that x represents a vector of n inputs, $x=(x_1, x_2,\ldots, x_n) \in R^n_+$; that y represents the output vector of m outputs, $y=(y_1, y_2,\ldots, y_m) \in R^n_+$; and that there are k farms. It is also assumed that firms face output prices $p^k \in R^n_+$, input prices $r^k \in R^n_+$, target cost $C^k > 0$, and revenue $R^k > 0$. The matrix of observed inputs, X, of dimension (n,k) and the matrix of observed outputs, Y, of dimension (m,k) form a transformation set written as:

$$T=\{(x,y): y \leq Yz, Xz \leq x, z \in R^{k+}\} \tag{1}$$

where z is the vector of intensity variables of activity (x_i, y_i). The transformation set corresponds to the total product curve and shows maximum feasible output for a function exhibiting constant returns to scale.

For observation (x_i, y_i), overall technical efficiency can be illustrated as follows:

$$\theta^*(x_i, y_i) = \max\{\theta: (x_i, \theta_i y_i) \in T\} \tag{2}$$

where θ is the level of inefficiency and $\theta_i y_i$ is the actual output of the ith farm. The farm is technically efficient if θ equals 1. θ can be interpreted as the ratio of potential to actual output or alternatively, $1/\theta$ is the ratio of efficiency relative to the potential frontier output. Technical efficiency can be determined by solving the following linear programming problem:

$$\begin{gathered}
Max\theta \\
subject\,to: \\
x_{11} z_1 + x_{12} z_2 + \ldots + x_{1k} z_k \leq x_{1i} \\
x_{21} z_1 + x_{22} z_2 + \ldots + x_{2k} z_k \leq x_{2i} \\
\ldots\ldots \\
x_{n1} z_1 + x_{n2} z_2 + \ldots + x_{nk} z_k \leq x_{ni} \\
y_{11} z_1 + y_{12} z_2 + \ldots + y_{1k} z_k - y_{1i}\theta \geq 0 \\
y_{21} z_1 + y_{22} z_2 + \ldots + y_{2k} z_k - y_{2i}\theta \geq 0 \\
\ldots\ldots\ldots \\
y_{m1} z_1 + y_{m2} z_2 + \ldots + y_{mk} z_k - y_{mi}\theta \geq 0
\end{gathered} \tag{3}$$

where there are n input constraints and m output constraints. The output constraint $(y_{i1} z_1 + y_{i2} z_2 + \ldots + y_{ik} z_k)$ measures the output level of the (hypothetical) overall technically efficient farm for a particular output. This is the maximum output that can be produced by the ith farm, given its actual level of inputs. For a single output situation, only one output constraint is needed.

The term, $y_{mi}\theta$, is the actual production of output m for the ith farm multiplied by the level of inefficiency, θ. In a multi-output situation, y_{mk} is the level of m output produced by firm k. Multi-input, multi-output analysis of technical efficiency is conducted for each firm in each of the three seasons. This analysis evaluates overall efficiency of the farm and not efficiency in the production of individual outputs. If the farm is overall technically efficient, then $\theta = 1$. However, if the farm is technically inefficient, $\theta \rangle 1$. When this is the case, the theoretical maximum output is greater than the actual output of the ith farm, making the ith farm inefficient relative to the production frontier by a factor of $1/\theta$.

This model allows for the decomposition of technical inefficiency between scale inefficiency (not producing at constant returns to scale) and pure technical efficiency (operating off of the isoquant). To determine the source of the inefficiency, a new transformation set is needed:

$$T' = \{(x,y): y \leq Yz, Xz \leq x, z \in R^{k+}, \Sigma^{k}{}_{i=1} z_i = 1\} \tag{4}$$

where the intensity variables, z, are restricted to being summed to 1. This modification allows for increasing and decreasing returns to scale.

Pure technical efficiency for observation (x_i, y_i) can be shown as:

$$\lambda^*(x_i, y_i) = \max\{\lambda : (x_i, \lambda y_i) \in T'\} \tag{5}$$

and is determined by solving the following linear programming problem:

$$\begin{aligned} &Max\lambda \\ &subject\,to: x_{11} z_1 + x_{12} z_2 + \ldots + x_{1k} z_k \leq x_{1i} \\ &x_{21} z_1 + x_{22} z_2 + \ldots + x_{2k} z_k \leq x_{2i} \\ &\ldots\ldots \\ &x_{n1} z_1 + x_{n2} z_2 + \ldots + x_{nk} z_k \leq x_{ni} \\ &y_{11} z_1 + y_{12} z_2 + \ldots + y_{1k} z_k - y_{1i}\lambda \geq 0 \\ &y_{21} z_1 + y_{22} z_2 + \ldots + y_{2k} z_k - y_{2i}\lambda \geq 0 \\ &\ldots\ldots\ldots \\ &y_{m1} z_1 + y_{m2} z_2 + \ldots + y_{mk} z_k - y_{mi}\lambda \geq 0 \\ &z_1 + z_2 + \ldots + z_k = 1. \end{aligned} \tag{6}$$

where the last constraint restricts the intensity variables to sum to 1. If $\lambda^* = 1$, the firm is purely technically efficient and operating on the production frontier, indicating that any inefficiencies that exist are due to scale inefficiencies, that is, the incorrect level of input use along the frontier. This measure evaluates the ratio of potential to actual output based on the transformation set, T'. Using θ^* and λ^*, it is possible to determine scale efficiency for observation (x_i, y_i), which can be written as follows:

$$\Phi^*(x_i, y_i) = \theta^*(x_i, y_i)/\lambda^*(x_i, y_i) \tag{7}$$

When $\Phi^*(x_i, y_i)$ is equal to 1, the ith farm operates at constant returns to scale. If $\Phi^*(x_i, y_i) \neq 1$, the firm is operating at nonconstant returns to scale. However, using this measure, it is not possible to know whether a farm operating at nonconstant returns to scale is operating at increasing or decreasing returns to scale. Thus, another measure is needed.

To accomplish this, the transformation set is modified again by imposing nonincreasing returns to scale. The new transformation set can be written as:

$$T^* = \{(x, y) : y \leq Yz, Xz \leq x, z \in R^{k_+}, \Sigma^{k_{i=1}} z_i \leq 1\} \tag{8}$$

where the sum of the value of the intensity variables, z, is restricted so that it is less than 1.

The calculation of efficiency for observation (x_i, y_i) is now:

$$\gamma^*(x_i, y_i) = \max\{\gamma : (x_i, \gamma y_i) \in T^*\} \tag{9}$$

where γ^* can be calculated by using the following linear programming problem:

$$\begin{aligned} &Max\gamma \\ &subject\,to: \\ &x_{11} z_1 + x_{12} z_2 + \ldots + x_{1k} z_k \leq x_{1i} \\ &x_{21} z_1 + x_{22} z_2 + \ldots + x_{2k} z_k \leq x_{2i} \\ &\ldots\ldots \\ &x_{n1} z_1 + x_{n2} z_2 + \ldots + x_{nk} z_k \leq x_{ni} \\ &y_{11} z_1 + y_{12} z_2 + \ldots + y_{1k} z_k - y_{1i}\gamma \geq 0 \\ &y_{21} z_1 + y_{22} z_2 + \ldots + y_{2k} z_k - y_{2i}\gamma \geq 0 \\ &\ldots\ldots\ldots \\ &y_{m1} z_1 + y_{m2} z_2 + \ldots + y_{mk} z_k - y_{mi}\gamma \geq 0 \\ &z_1 + z_2 + \ldots + z_k \leq 1. \end{aligned} \tag{10}$$

This problem indicates that if $\Phi^* \neq 1$, two alternatives exist. If $\Phi^* \neq 1$ and $\theta^* = \gamma^*$, the farm produces at increasing returns to scale. If $\Phi^* \neq 1$ and $\theta^* \neq \gamma^*$, then the farm operates at decreasing returns to scale. A firm operating at increasing returns to scale should increase input use in order to achieve economies of scale. This would mean moving from Point A to Point B in Fig. 1 to increase efficiency. A situation in which farms are operating at decreasing returns to scale suggests that small farms are viable and that large farms would be better off to decrease input levels or at least not increase them, because to do so would be to further increase inefficiency associated with returns to scale.

Economic efficiency tests only evaluate actual productivity relative to potential productivity and do not imply irrationality on the part of farmers who are inefficient. The failure of farmers to use the most efficient techniques of production may be due to the cost of the acquisition of information for an individual farmer being greater than the benefits or perhaps due to fixed assets, property rights, and tenancy, as well as non-monetary objectives of the farmers (Byerlee, 1987).

To help identify possible factors related to inefficiencies, the efficiency indices determined from the linear programming problems are regressed on explanatory variables of age, education, farm size, and tenure using a Tobit analysis to investigate the effect of these variables on the technical efficiency of the individual farms.

This analysis can be helpful in targeting extension activities to deal with technical inefficiencies in production. The linear Tobit regression in Eq. (11) is used to identify possible factors associated with inefficiency. Tobit analysis is used because the dependent variables, overall technical efficiency, pure technical efficiency, and scale efficiency, are censored variables, having an upper limit of 1.00. Each of these indices is regressed on the explanatory variables of age, education, farm size, percent of land owned, and diversification. Dummy variables are used for education, representing junior high school and high school. The parameters, β_3 and β_4, provide an idea of how much additional levels of education after the primary level affect efficiency. The variable percent of land owned is an attempt to evaluate the effects of land tenure on technical efficiency.

$$EFF_i = \alpha + \beta_1 Age_i + \beta_2 (Age_i)^2 + \beta_3 ED2_i + \beta_4 ED3_i + \beta_5 FS_i + \beta_6 OL_i + \beta_7 DV_i + \epsilon_i \tag{11}$$

where:

EFF_i is Efficiency index for farmer i.
Age_i is Farmer age in years.
$ED2_i$ is Education dummy variable = 1 if junior high education, 0 otherwise.
$ED3_i$ is Education dummy variable = 1 if high school education, 0 otherwise.
FS_i is Farm size in hectares for firm i.
OL_i is Percent of operated land owned by farmer i.
DV_i is Diversification variable expressed by Herfindahl index.
α, β is Parameters.
ϵ_i is Error term.

It is hypothesized that younger, better educated farmers are more technically efficient, due to better skills and access to information. Farm size may positively affect efficiency, if farmers are able to achieve some economies of scale. Efficiency may be higher for farmers who own their land, because of greater incentives for efficiency relative to those who are renting. Farmers who produce only one crop in a season may be more technically efficient in production than those who are more diversified.

3. Description of data and study area

The study area is the Madiun regency in the west-central part of East Java, Indonesia, about 170 km west of Surabaya. The total area is 101 086 ha, of which 44 122 ha were tilled with 32 407 ha being irrigated in 1992. Dryland agriculture accounts for about 24% of cropland in this regency (Kantor Statistik, 1993). Land holdings are small, averaging 0.72 ha (Kantor Statistik, 1993). Annual rainfall during 1988–1992 ranged from 1511 mm in 1991 (a drought year) to 2329 mm in 1989. There are three cropping seasons annually on irrigated land, March to June, July to October, and November to February.

Data from 77 farms collected from interviews in four villages in the Madiun regency of East Java, Indonesia in 1994 are used in analyzing technical efficiency of food crop production. A nonparametric, whole-farm, production frontier that includes multiple crops is estimated for each farm in each of the three distinct cropping seasons: rainy, middle, and dry. The crops included in this study represent the major commodities grown in this area: paddy rice, corn, soybeans, peanuts, mungbeans, cassava and a pepper-onion intercrop.

Average age of all respondents was 44.4 years and ranged from 26 to 76 years. A total of 78% of the respondents had an elementary school education or less, 16% were junior high school graduates, and 6% were high school graduates. Average farm size for the survey was 0.82 ha, slightly larger than the regency average of 0.72, and varied from 0.13 ha to 2.28 ha. Of the 77 total farms, 14 farms (18%) included nonirrigated cropping, and these are evaluated separately. A total of 87.0% of the farmers owned land and 50.6% had land that was cash rented whereas only 9.1% had a share rent arrangement, figures comparable with those found in other studies (Brotonegoro et al., 1986; Sendjaja and Choliq, 1986).

The nine crops in this study covered 72% of the arable land in the Madiun regency in 1992 (Kantor Statistik, 1993). A comparison of the proportion of crop acreages for the entire regency and for the farmer sample is shown in Table 1. Rice is the most commonly planted crop both in the sample and across all farms in the regency. Corn, soybeans, and sugar cane are the next most important crops in terms of harvested acreage both in the sample and for all farmers in the regency. The regency data do not provide information about multicropping.

Table 1
Proportion of crops grown in Madiun Regency and in the survey sample

Madiun Regency (source: Kantor Statistik, 1993)		
	Arable land area (%)	Food crops grown (%)
Rice	42	58.1
Corn	6	6.4
Soybeans	9	12.4
Peppers/onions	< 1	0.5
Peanuts	3	4.5
Mungbeans	2	2.8
Cassava	3	5.6
Sugar cane	7	9.4
Survey farmers		
	Crops in sample (%)	Acreage in sample (%)
Rainy season		
Rice	68	58
Corn	12	13
Peppers/onions	9	6
Sugar cane	14	16
Corn/cassava	5	7
Middle season		
Rice	38	35
Corn	21	18
Sugar cane	14	16
Soybeans	17	19
Soybean/mungbean	3	4
Soybean/peanut	6	6
Cassava	3	2
Dry season		
Rice	11	9
Pepper/onion	14	8
Soybeans	23	18
Corn	18	16
Corn-soybean	14	10
Corn-mungbean	10	6
Corn-peanut	8	5
Fallow	18	12
Sugar cane	14	16
Other	2	1

The inputs used for crop production include seed, measured in kilograms; three fertilizer inputs: urea, TSP, and an aggregated fertilizer input of other fertilizers used, all in kilograms; an aggregated chemical input in kilograms of active ingredient per hectare; aggregated labor input in man-days; and irrigation in hours per crop. Output data for the model is yield in kilograms per hectare for each crop. These values also were determined from the data collected from the farmer interviews. A more detailed description of the data is included in Llewelyn (1995).

Data for the regression analysis are also from the farmer interviews. Farmers were questioned regarding age, education and farm size. Education was recorded as elementary school (6 years or less), junior high school (9 years), and high school (12 years). None of the farmers interviewed had attended post-secondary education. Farm size is recorded in hectares of land operated, both owned and rented. The variable for tenure is measured in terms of the percentage of land owned (i.e. zero to 100). Diversification was measured using the Herfindahl index represented as:

$$DV = \sum_{i=1}^{n} P_i^2 \tag{12}$$

where P_i is the proportion of the farm acreage involved in a particular enterprise. A value approaching 1.0 indicates specialization whereas smaller values reflect increasing diversification. For this sample, values ranged from 0.405 to 1.0 in the rainy and middle seasons and from 0.337 to 1.0 in the dry season and averaged 0.919, 0.879, and 0.814 for the rainy, middle and dry seasons respectively.

4. Analysis and results

Using the linear programming methodology outlined earlier, nonparametric analysis of relative technical efficiency is performed for food crop production on irrigated farms in each of the three seasons. Three linear programs (Eq. (3), Eq. (6), and Eq. (10)) are solved to provide the values of θ, λ, and γ for each individual farm. Table 2 summarizes the crops evaluated in each seasonal analysis and the number of farms in the sample which produce each crop. A total of 61 farms is evaluated for technical efficiency in this analysis.

Average, minimum, and maximum overall technical efficiency, pure technical efficiency, and scale efficiency are reported for each season in Table 3, as well as the number of farms operating at constant, increasing, and decreasing returns to scale. The average overall efficiency is calculated by dividing $1/\theta$ for each farm to obtain the overall efficiency level for that farm. This level of efficiency then is averaged over all the farms in the sample. A farm that is technically efficient has an efficiency of 100%. Average pure technical efficiency is calculated by dividing $1/\lambda$ for each farm and averaging these values, and average scale efficiency is determined by dividing λ/θ for each farm and averaging these values for the entire sample. Scale efficient farms operate at constant returns to scale in inputs (input level $x2$ on Fig. 1), whereas those with decreasing returns have input levels that are too high and those with increasing returns to scale have input levels that are too low. Scale-inefficient firms may be purely technically efficient (operating on the frontier) but are not using the correct level of input.

Table 2
Crops by season and number of farms evaluated for technical efficiency

	Number of farms
Rainy season	
Rice	53
Corn	9
Peppers/onions	7
Middle season	
Rice	33
Corn	14
Soybeans	13
Soybean/mungbeans	2
Soybean/peanuts	5
Dry season	
Rice	9
Corn	14
Soybeans	18
Corn/soybeans	11
Peppers/onions	11
Corn/peanuts	6
Soybean/mungbean	7
Corn/mungbean	8

Table 3
Efficiency analysis results

	Mean	SD
Rainy season		
Overall technical efficiency [a]	0.981	0.043
Minimum	0.844	
Maximum	1.000	
Number technically efficient	44 (72.1%)	
Pure technical efficiency [b]	0.988	0.029
Minimum	0.876	
Maximum	1.000	
Number technically efficient	50 (82.0%)	
Scale efficiency [c]	0.992	0.019
Minimum	0.904	
Maximum	1.000	
Number CRS farms [d]	45 (73.8%)	
Number IRS farms [d]	1 (1.6%)	
Number DRS farms [d]	15 (24.6%)	
Middle season		
Overall technical efficiency	0.955	0.083
Minimum	0.646	
Maximum	1.000	
Number technically efficient	41 (67.2%)	
Pure technical efficiency	0.977	0.054
Minimum	0.749	
Maximum	1.000	
Number technically efficient	48 (78.7%)	
Scale efficiency	0.977	0.058
Minimum	0.711	
Maximum	1.000	
Number CRS farms	43 (70.5%)	
Number IRS farms	8 (13.1%)	
Number DRS farms	10 (16.4%)	
Dry season		
Overall technical efficiency	0.977	0.063
Minimum	0.738	
Maximum	1.000	
Number technically efficient	50 (82.0%)	
Pure technical efficiency	0.989	0.045
Minimum	0.745	
Maximum	1.000	
Number technically efficient	58 (95.1%)	
Scale efficiency	0.987	0.040
Minimum	0.746	
Maximum	1.000	
Number CRS farms	50 (82.0%)	
Number IRS farms	1 (1.6%)	
Number DRS farms	10 (16.4%)	

[a] Calculated using Eq. (3).
[b] Calculated using Eq. (6).
[c] Calculated using Eq. (7).
[d] Determined using Eq. (7) and Eq. (10).

Results of the efficiency analysis in the rainy season are summarized in Table 3. Overall and pure technical efficiencies are high, as are scale efficiencies. The average overall technical efficiency of 98.1% is slightly higher than but quite similar to values in other studies in Indonesia and Asia that used a parametric approach in evaluating rice production (Widodo, 1986; Erwidodo, 1990; Dawson et al., 1991). This study had a much larger sample size than Dawson et al., and slightly larger than the other two studies. In a small sample, a few inefficient farms would influence the results more than in a larger sample.

The range in overall technical efficiency is between 84.4% and 100%, with 44 of the 61 farms (72.1%) being overall technically efficient, that is $\theta = 1$. An additional six farms are purely technically efficient, meaning they operate on the production frontier but not at constant returns to scale. The average pure technical efficiency is 98.8%, with a minimum of 87.6%, indicating that the most purely technically inefficient farm could only increase output by about 12.4% through more efficient use of inputs. Average scale efficiency is 99.2% with a minimum of 90.4%. Little variation in these measures is evident, with the standard deviations ranging from 0.019 to 0.043. Constant returns to scale are evident for 45 of the farms. Increasing returns to scale hold for only one farm and 15 farms experience decreasing returns to scale.

In the middle season, average overall efficiency is 95.5% with the minimum efficiency of 64.6%, as shown in Table 3. Forty-one farms are technically efficient, with seven of the remaining farms being purely technically efficient. Forty-three farms have constant returns to scale, whereas eight have increasing returns to scale and ten have decreasing returns. The lower efficiencies associated with the middle season for these farms may be explained by a situation where rainfall may vary across farms leading to production responses which would not be captured by the efficiency analysis. The low rainfall in the dry season is consistent for all parts of the regency, while in the rainy season, rainfall is more consistent across all farms than in the middle season. Rainfall data by village are not available for analysis.

Relative technical efficiency in the dry season is summarized in Table 3. Average efficiency is 97.7%, with the minimum efficiency at 73.8%. Fifty of the farms are overall technically efficient, with all but three farms being purely technically efficient. Average pure technical efficiency is 98.9%, and average scale efficiency is 98.7%. The 50 overall technically efficient farms operate at constant returns to scale, whereas 10 of the 11 remaining farms have decreasing returns to scale, and one farm shows increasing returns to scale.

Higher fertilizer use, particularly of urea, seems to be associated with the least efficient farms in each season, with average urea use of farms found to be overall technically inefficient higher than the average for the entire sample, with the least efficient farm in each season having the highest use of urea. High fertilizer use may reflect a risk evasive action, though some studies have found that producers with higher levels of risk aversion would be less likely to prefer high levels of nitrogen fertilization (Williams et al., 1992; SriRamaratnam et al., 1987).

Because of the assumption of homogeneity of inputs, particularly of land quality, the efficiency analysis was conducted for each of the four villages where data were collected. If homogeneous land quality is incorrectly assumed and land differences actually account for the measured inefficiencies found in the above analysis, the average efficiencies for each village should be 100% or nearly so, since the frontier for each individual village would be less than or equal to the aggregate production frontier for all farms.

However, in each season, the average efficiencies for each individual village are only slightly higher than the averages for the aggregate sample and none are equal to 100%. In the rainy season, the average overall technical efficiencies for the four villages are 98.2%, 98.8%, 98.7%, and 98.4%, respectively, compared with the average for the entire sample of 98.1%. The overall technical efficiencies by village in the middle season average 95.7%, 96.1%, 96.1%, and 95.8%, respectively, while the average overall technical efficiency for the dry season for each village is equal to 97.9%, 97.8%, 98.2%, and 98.4%. The average overall efficiency for the entire sample is equal to 95.5% for the middle season and 97.7% for the dry season. The results are similar for pure technical and scale efficiencies for each village as well. This indicates that assuming homogeneous land

Table 4
Regression analysis testing inefficiency for rainy-season farms

Variable	Overall technical efficiency	Pure technical efficiency	Scale efficiency
Intercept	0.946	0.952	0.993
	(4.84) *** [a]	(2.97) ***	(3.15) ***
Age	0.0359	0.0356	0.0359
	(17.55) ***	(19.87) ***	(20.38) ***
Age^2	−0.0004	−0.0003	−0.0003
	(−15.45) ***	(−17.41) ***	(−17.89) ***
Farm size	0.0071	0.0031	0.0017
	(0.42)	(0.21)	(0.12)
Percent owned land	−0.0003	−0.0003	−0.0002
	(−1.36)	(−1.38)	(−0.86)
Diversification	0.1388	0.1497	0.1396
(Herfindahl index)	(3.32) ***	(4.08) ***	(3.87) ***
Dummy variable	0.0057	0.0014	0.0086
Junior High School	(0.24)	(0.07)	(0.43)
Dummy variable	0.0274	0.057	0.053
High School	(0.82)	(1.95) *	(1.84) *
Sigma	0.0603	0.0528	0.0519
	(11.05)	(11.05)	(11.05)
Log likelihood	84.77	92.77	93.83
Number of observations	61	61	61

[a] Numbers in parentheses are t-statistics.
* Indicates significance at $\alpha = 0.10$. *** Indicates significance at $\alpha = 0.01$.

Table 5
Regression analysis testing inefficiency for middle-season farms

Variable	Overall technical efficiency	Pure technical efficiency	Scale efficiency
Intercept	0.928	0.993	1.002
	(4.12) *** [a]	(5.73) ***	(6.29) ***
Age	0.0372	0.0391	0.0358
	(11.65) ***	(16.17) ***	(14.11) ***
Age^2	−0.0004	−0.0004	−0.0004
	(−10.61) ***	(−14.64) ***	(−12.89) ***
Farm size	−0.0145	−0.0057	−0.0146
	(−0.43)	(−0.22)	(−0.55)
Percent owned land	−0.0002	−0.1030	−0.0001
	(−0.53)	(−0.35)	(−0.33)
Diversification	0.0920	0.0419	0.1493
(Herfindahl index)	(1.45)	(0.87)	(2.95) ***
Dummy variable	0.0183	0.0177	0.0188
Junior High School	(0.49)	(0.62)	(0.63)
Dummy variable	0.0633	0.0917	0.0435
High School	(1.00)	(1.92) *	(0.87)
Sigma	0.0977	0.0741	0.0777
	(11.05)	(11.05)	(11.05)
Log likelihood	55.27	72.21	69.25
Number of observations	61	61	61

[a] Numbers in parentheses are t-statistics.
* Indicates significance at $\alpha = 0.10$. *** Indicates significance at $\alpha = 0.01$.

quality across the regency for this sample of farms does not distort the results unnecessarily.

5. Factors associated with inefficiency

A censored regression or tobit model is used in each of the above multiproduct situations to assess the factors associated with technical inefficiencies. The Tobit regression defined in Eq. (11) is estimated using the Tobit procedure in TSP Version 4.2B (TSP International, 1993). Efficiency measures are regressed on age, farm size, percent of owned land, a diversification dummy variable, and two dummy variables representing education levels. Results for rainy season irrigated farms are presented in Table 4.

In the rainy season, farmers' age shows a significant quadratic relationship with all three measures of efficiency. Efficiency increases with age, then eventually decreases. In addition, diversification, represented by the Herfindahl index described in Eq. (12), is shown to have a significant relationship with technical efficiency. The value of the estimated coefficient is positive, indicating that greater specialization in production is associated with higher relative efficiency. As diversification increases and more crops are grown, efficiency declines. It is possible that the increased inefficiency with diversification may be transitory as farmers improve their ability to grow new crops. Both the age and diversification variables are statistically significant at $\alpha = 0.05$. High school education is found to be related significantly in a positive way with pure technical and scale efficiencies at $\alpha = 0.10$. A statistical relationship is not found to exist between education and overall technical efficiency. All of the other variables are statistically not significant for any of the efficiency indices.

In the middle season, age again is related significantly to efficiency (Table 5). However, the diversification variable is found to be associated only with scale efficiency, with greater diversification leading to lower scale efficiencies. Also, the dummy variable for high school education is found to be significant at $\alpha = 0.10$ for the equation with pure technical efficiency. No other variables are statistically significant.

The results for the dry season are similar to those of the rainy season, as found in Table 6. Farmers' age again shows a statistically significant quadratic

Table 6
Regression analysis testing inefficiency for dry-season farms

Variable	Overall technical efficiency	Pure technical efficiency	Scale efficiency
Intercept	1.045	1.011	1.045
	(7.27) *** [a]	(5.80) ***	(6.98) ***
Age	0.0328	0.0345	0.0350
	(11.63) ***	(14.20) ***	(15.57) ***
Age^2	−0.0003	−0.0003	−0.0003
	(−10.35) ***	(−12.64) ***	(−13.84) ***
Farm size	0.0323	0.0336	0.0122
	(1.23)	(1.48)	(0.58)
Percent owned land	−0.000005	0.0001	−0.1441
	(−0.02)	(0.39)	(−0.06)
Diversification	0.1948	0.1525	0.1604
(Herfindahl index)	(3.52) ***	(3.21) ***	(3.64) ***
Dummy variable	−0.0038	−0.0096	0.0098
Junior High School	(−0.12)	(−0.35)	(0.39)
Dummy variable	0.0660	0.0624	0.0675
High School	(1.34)	(1.48)	(1.73) *
Sigma	0.0858	0.0737	0.0683
	(11.05)	(11.05)	(11.05)
Log likelihood	63.24	72.46	77.13
Number of observations	61	61	61

[a] Numbers in parentheses are t-statistics.
* Indicates significance at $\alpha = 0.10$. *** Indicates significance at $\alpha = 0.01$.

type of relationship with efficiency measures. Greater diversification is found to be associated with lower efficiency for all three efficiency indices, and high school education has a significant ($\alpha = 0.10$) relationship with scale efficiency but not with overall technical or pure technical efficiency. Other variables, such as farm size, percent of land owned, or junior high school education, are not found to have a significant association with technical efficiency as measured for this sample of farmers.

6. Summary and conclusions

Nonparametric analysis of technical efficiency for irrigated farms in Madiun, Indonesia is conducted using models based on techniques developed and used by Grabowski and Pasurka (1987). This procedure allows the relative technical efficiency for each farm to be determined and for inefficiencies to be decomposed into pure technical inefficiency (operating off of the isoquant or production frontier) and scale inefficiency (not producing at constant returns to scale in input use). This methodology also allows for multi-input, multi-output situations and does not require restrictions or assumptions regarding functional form to be placed on the data. This analysis provides information on the technical efficiency of multiproduct food-crop producing farms in Indonesia and some of the factors associated with inefficiency.

Evaluating farms for each season under irrigated conditions shows that average overall technical efficiency is 98.1% in the rainy season, while in the middle season it is 95.5% and is slightly higher at 97.7% in the dry season. In each case, the majority of farms are technically and scale efficient, operating at constant returns to scale. Most farms that are scale inefficient are operating at decreasing returns to scale, indicating excessive input levels.

Tobit analysis to evaluate inefficiency shows that farmers' age and the level of diversification are the most statistically significant factors associated with technical efficiency measures. A quadratic relationship between age and efficiency exists in each season, with efficiency increasing with age initially, then decreasing. Greater diversification is associated with lower efficiency levels in the rainy and dry seasons for each of the three efficiency indices. The same relationship occurs in the middle season only for scale efficiency.

In addition, having a high school education is related positively to higher levels of pure technical efficiency in the rainy and middle seasons and with scale efficiency in the rainy and dry seasons but at a lower confidence level than age or diversification ($\alpha = 0.10$). None of the other variables, including farm size, tenure arrangements, or junior high school education is statistically significant in any season.

Farmers operating inefficiently are doing so more often because of scale inefficiencies rather than pure technical inefficiencies, and the majority of these farmers are operating at decreasing returns to scale in inputs rather than increasing returns to scale, often using higher levels of fertilizer, particularly nitrogen, than more efficient farmers. In Indonesia, relatively high fertilizer subsidies have been in place until the early 1990s and since have declined by over 20%. The data in this study were collected in 1994, after the reduction in the fertilizer subsidy began. Some farmers may still be using higher levels of fertilizer than are efficient, perhaps due to continuing production techniques which began when fertilizers were subsidized. This may account for the decreasing returns to scale found to exist. Another possibility is that this is a risk-reducing strategy, Williams et al. (1992) and SriRamaratnam et al. (1987) have shown this may not be true. It should be noted that the majority of farms in this sample operate at constant returns to scale, indicating that they are using correct levels of inputs, relative to other farms in the sample.

Efficiency increases, then eventually declines with age. This is consistent with what would be expected. Targeting younger and older farmers for extension activities could increase their levels of technical efficiency relative to middle aged farmers.

Higher levels of diversification in cropping practices are associated with lower technical efficiency, particularly in the rainy and dry seasons. Farmers who are more specialized with only one or two crops grown in a season have higher levels of technical efficiency. Thus, government programs that have attempted to divert cropland away from rice production toward secondary food crop production may actually lead to increased technical inefficiency in production.

Having a high school education is associated with higher technical efficiency in production in this study. Only 7% of the sample of farmers have a high school education, but these farmers apparently are able to operate at significantly higher technical efficiency than other farmers. These results imply that extension education could be effective, particularly if targeted to farmers who have had limited educational opportunities. Those with higher education levels may have access to information that farmers with only elementary or junior high school education do not. Providing access to information to farmers with lower levels of education may help them to increase technical efficiency in production relative to farmers with higher levels of education.

Acknowledgements

The authors wish to acknowledge the University of Merdeka, Madiun and particularly Ir. Wuryantoro for the assistance in collecting data for this study. The helpful comments of Allen Featherstone and Michael Langemeier and two anonymous referees are also gratefully acknowledged.

References

Afriat, S.N., 1972. Efficiency estimation of production functions. Internat. Econ. Rev., 13: 568–598.

Azhar, R.A., 1991. Education and technical efficiency during the green revolution in Pakistan. Econ. Develop. Cult. Change, 39: 651–665.

Banker, R.D. and Maindiratta, A., 1988. Nonparametric analysis of technical and allocative efficiencies in production. Econometrica, 56: 1315–1332.

Bernsten, R.H., 1977. Constraints to higher rice yields in the Philippines. Ph.D. Dissertation. University of Illinois, Champaign, Urbana, IL.

Brotonegoro, S., Laumans, Q.J. and Van Staveren, J.Ph., 1986. Palawija: food crops other than rice in East Java agriculture. Monograph No. 2. Malang Research Institute for Food Crops, Malang.

Byerlee, D., 1987. Maintaining the momentum in post-green revolution agriculture: a micro-level perspective from Asia. Department of Agricultural Economics, Michigan State University, East Lansing, MI.

Chavas, J.P. and Aliber, M., 1993. An analysis of economic efficiency in agriculture: a nonparametric approach. J. Agric. Resour. Econ., 18: 1–16.

Chavas, J.P. and Cox, T.L., 1988. A nonparametric analysis of agricultural technology. Am. J. Agric. Econ., 70: 303–310.

Dawson, P.J., Lingard, J. and Woodford, C.H., 1991. A generalized measure of farm-specific technical efficiency. Am. J. Agric. Econ., 73: 1098–1104.

Erwidodo, 1990. Panel data analysis on farm-level efficiency, input demand and output supply of rice farming in West Java, Indonesia. Ph.D. Dissertation, Michigan State University.

Farrell, M.J., 1957. The measurement of production efficiency. J. Roy. Statist. Soc., Ser. A, Part 2: 252–267.

Färe, R., Grosskopf, S. and Lovell, C.A.K., 1985. The Measurement of Efficiency of Production. Kluwer-Nijhoff Publishing, Boston, MA.

Grabowski, R. and Pasurka, C., 1987. The relative technical efficiency of Northern and Southern U.S. farms in 1860. Southern Econ. J., 54: 598–614.

Hanoch, G. and Rothschild, M., 1972. Testing the assumptions of production theory: a nonparametric approach. J. Polit. Econ., 80: 256–275.

Kalirajan, K., 1981. The economic efficiency of farmers growing high yielding, irrigated rice in India. Am. J. Agric. Econ., 63: 566–570.

Kantor Statistik, 1993. Kabupaten Madiun. Buku Statistik Kabupaten Madiun, Tahun 1993. Madiun, Indonesia.

Llewelyn, R.V., 1995. Optimal cropping combinations: an economic analysis of food crop production in East Java, Indonesia. Kansas State University, Unpublished Ph.D. Dissertation.

Sendjaja, T.P. and Choliq, A., 1986. The cropping patterns on small farmers' land in West Java, Indonesia. An economic study of rice farming in West Java. A. Fujimoto and T. Matsuda (Editors). Nodai Research Institute, University of Agriculture, Tokyo.

SriRamaratnam, S., Bessler, D.A., Rister, M.E., Matocha, J.E. and Novak, J., 1987. Fertilization under uncertainty: an analysis based on producer yield expectations. Am. J. Agric. Econ., 69: 349–357.

TSP International, 1993. TSP Version 4.2B. Palo Alto, CA.

Varian, H., 1984. The nonparametric approach to production analysis. Econometrica, 52: 579–597.

Widodo, S., 1986. An econometric study of production efficiency among rice farmers in irrigated lowland villages in Java, Indonesia. M.S. Thesis, Tokyo University of Agriculture.

Williams, J.R., Maddux, L.D., Barnes, P.L. and Rowell, C.P., 1992. Risk analysis of nitrogen fertilization rates for corn and soybeans. J. Prod. Agric., 5: 226–232.