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METAFRONTIER ANALYSIS OF FARM-LEVEL EFFICIENCIES AND ENVIRONMENTAL-TECHNOLOGY GAPS IN PHILIPPINE RICE FARMING

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Abstract

Rice producers in the Philippines operate in different physical environments that are largely beyond their control, especially in terms of the agroclimatic conditions they face. Each rice area requires a unique set of location-specific technologies to match its location-specific needs. The rice production frontier is expected to vary, depending on the degree of yield-enhancing interventions implemented by the government and adopted by farmers. Understanding differences in specific production frontiers in different production systems should provide better assessments of yield performance across different locations and enable rice scientists to develop location-specific technologies as well as disseminate appropriate technologies to farmers in different climatic zones. A precise analysis of productive efficiencies, technology gaps and technical change among these zones may contribute to a more accurate targeting and effective design of the government's rice program.

We measure technical efficiencies and technological gaps in rice production for farmers in four agroclimatic zones in the Philippines who may employ different production technologies according to environmental conditions. Climatic zone 3 is considered most favourable for rice production based on the intensity and distribution patterns of rainfall. A stochastic metafrontier function is used to compare mean technical efficiency and the environmental and technological gap ratio (ETGR) across climatic zones. We estimated four regional stochastic frontiers using the standard stochastic frontier model based on a translog functional form. A deterministic metafrontier production function was then fitted to the regional frontiers. Farm-level panel data were used from a three-round survey covering six cropping periods – the wet seasons of 1996, 2001 and 2006 and the dry seasons of 1997, 2002 and 2007.

Results show surprisingly little interzonal variation in productivity. First, the production frontiers are quite stable across the different agroclimatic zones. The mean ETGR is quite high in all zones and varies in a narrow range from 0.83 to 0.87. Farmers operating in agroclimatic zone 3 are the most productive group followed by those operating in agroclimatic zone 2. Mean technical efficiencies of farmers in respect of their group frontiers are also closely grouped, ranging from 0.74 to 0.76. It appears that Philippine rice producers have been able to adapt their crop management strategies well to suit their particular agroclimatic conditions.

Keywords: Technical efficiency, technology gap, Metafrontier, stochastic production frontier, Philippine rice farming productivity

1. Introduction

Rice is one of the most important crops in the Philippines, as in many Asian countries. It accounts for a fifth of agricultural gross value added and employs a substantial part of the agricultural labour force. Around 90 million Filipinos depend mainly on 2.4 million farmers for their rice consumption. The increasing demand for the country's staple food has put pressure on both farmers and the government to ensure the availability of rice on every consumer's plate.

Rice is one of the commodities where technical advancement has occurred. Measuring technological change and technical efficiencies provides an empirical indicator of the current status of rice productivity. Moreover, information on the technology gap between producers in different physical environments helps rice scientists to develop new technologies and/or improve existing ones that will significantly increase farmers' yields. A precise analysis of productive efficiencies, technology gaps and technical change may contribute to a more accurate targeting and effective design of the government's rice program.

This paper aims to measure technical efficiencies and technological gaps in rice production for farmers in four agroclimatic zones in the Philippines who may employ different production technologies according to environmental conditions. Sections of this paper are organised as follows. We start with a discussion on the productivity growth and climate adaptation in Philippine rice farming. This is followed by a description of the methodologies employed. Then the empirical findings are analysed and the implications of the results are discussed in the next two sections. The paper ends with a few concluding remarks and some policy recommendations.

2. Productivity growth and climate adaptation in Philippine rice farming

Productivity is a key element of economic growth as it expands the production of output from any given amount of resources. More importantly, rice productivity growth translates to the country's ability to feed an ever increasing population despite limited resource endowments. Understanding the direction and sources of rice production growth over the years can provide useful insights on how to boost rice production further and consequently to mitigate malnutrition and poverty.

2.1 Output growth of rice production in the Philippines

The Philippines have taken significant strides in rice production despite its natural disadvantages in land endowments and water resources. Table 1 shows the exponential growth rates of rice production, area harvested and yield over the past four decades. Between 1970 and 2008, good performances in rice production were achieved during the 1970s and 2000s. Yield was the major contributor to output growth over the 38-year period. In the 1970s, 1980s and 2000s, more than 70% of the growth in production was due to yield increase. Only in the 1990s did area have a significant role in production growth.

Table 1. Production, area harvested and yield annual growth rates and sources of output growth

Time period	Annual growth rate (%)			% contribution to output growth		Significant interventions in rice production
	Production	Yield	Area	Yield	Area	
1970 to 1980	3.62%	2.51%	1.11%	69%	31%	- modern varieties, high irrigation investments, fertilisers subsidies and rural credit provision (*Masagana 99* rice program)
1980 to 1990	1.98%	2.43%	-0.45%	123%	-23%	- spillovers of the green revolution era - intensive cropping systems - closure of land frontier
1990 to 2000	2.85%	0.89%	1.96%	31%	69%	- development of small-scale irrigation systems - rice production trainings - decentralisation of extension services
2000 to 2008	3.82%	2.58%	1.24%	67%	33%	- hybrid seed technology - certified seed subsidies - integrated crop management practices

Basic source of data: Bureau of Agricultural Statistics (BAS), Philippines

The massive introduction of high-yielding varieties during the late 1960s triggered the Green Revolution in Philippine rice production. During the peak of the Green Revolution era from 1970 to 1980, the Philippines had a 3.62% annual growth in rice production. The Marcos regime made yield-enhancing interventions through the national rice program, *Masagana 99*. The word *Masagana* literally means bountiful and 99 refers to the government yield target of 99 sacks per hectare (50 kg each). The rice crisis of 1973 was the reason behind the emergence of the M99 rice program which resulted in rice surpluses and paved the way for the country's entry into the export market. The government made major investments in irrigation infrastructure and provided subsidised fertilisers and rural credit to farmers

(Panganiban, 2000). Hence, it is not surprising that the production growth during this period was due to yield increases. Overall, yield grew by 2.51% per year while the area harvested increased at 1.11% annually.

The Rice Production Enhancement Program (RPEP) in 1986-1990 was launched by the Aquino administration. The government maintained the package-of-technology approach from the M99 program and continued the fertiliser subsidy under a "buy two-take one" scheme. The RPEP also pursues irrigation development, integrated pest management and marketing support services. But despite these rice program interventions, production growth rates decelerated during the 1980s, mainly due to the closure of the land frontier which had a big impact on the decline of cultivated area. The Comprehensive Agrarian Reform Program (CARP) resulted in the conversion of agricultural lands to non-agricultural uses, which had partly caused the decline in *palay* area harvested. The annual growth of 1.98% during this period was exclusively attributed to increase in yield at 2.43% annually. Mundlak et al. (2002) emphasised that this poor performance in rice production history was a result of a drop in world rice prices, exhaustion of the productivity potential from modern varieties, and soil degradation due to intensive land cultivation. Umetso et al. (2003) added that rice farming was affected by the country's macroeconomic conditions such as volatile political conditions, high inflation and peso devaluation.

From 1990 to 2000, productivity rebounded increasing at an annual rate of 2.85%. Interestingly, this output growth was attributed mostly to the increase in land area harvested growing at 1.98% per year. This peculiar growth seems unsustainable because it was due to the intensification of existing rice area rather than the opening of new areas. Llanto (2003) pointed out that this decade was marked by the construction of small-scale irrigation systems such as surface water pumps, shallow tube wells and small diversion dams that allowed farmers to increase their cropping intensity. Figure 1 shows that productivity stagnated during this period because of the occurrence of natural calamities such as the El Niño and La Niña phenomena in 1997 and 1998, respectively. This decade was ruled during the presidency of Ramos and Estrada. The Ramos administration launched two different rice programs – the Grains Production Enhancement Program (GPEP, 1993-1995) and the *Gintong Ani Program* for rice and corn (GAP, 1996 to 1998) while Estrada implemented the *Agrikulturang Makamasa* (1998-2001) rice program.

Figure 1. Annual production (mt) and yield (mt/ha) from 1990 to 2007

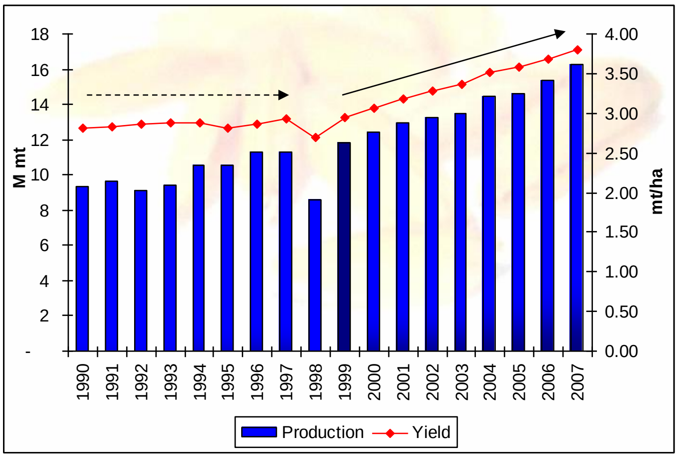


Figure 1 also illustrates that yield accelerated in the 2000s. From 2000 to 2008, yield improvement contributed around 70% of output growth at 3.82% per year. Surprisingly, rice farmers were able to reach the level of production growth identical to that of the Green Revolution era of the 1970s. The subsidies on high quality seeds such as certified inbred and hybrid seeds seem to contribute the biggest chunk of this good performance. In addition, the government conducted farmers' training, technical assistance and technology demonstrations. The *Ginintuang Masaganang Ani* for rice (GMA Rice) is the current national rice program under the Arroyo administration (2001 to 2009). The goals of the program include the attainment of national food security, reduction of poverty incidence, increased rice profitability and sustainability of natural resources. The rice program focuses on interventions such as infrastructure development, research and technology development and extension services which are considered as the powerhouses for achieving higher levels of rice farm productivity.

Despite the recent achievements of farmers, there are still many issues of concern emerging in the rice sector. Many farmers are using modern rice varieties but there is still a low adoption of certified and hybrid seeds that would give higher yield than farmer seeds. Moreover, there is an increasing concern about the competition for water for irrigation and home consumption as well as the denudation of watersheds. Another issue is on the conversion of rice farms to subdivisions and commercial establishments. Moreover, high fertiliser and fuel prices discourage their use and constrain productivity growth. Many farmers are unable to apply the recommended fertiliser rates due to the high cost.

2.2 Productivity growth of rice production in the Philippines

The importance of rice in rural development in the Philippines and other Asian countries has led to the fascination of economists to measure productivity performance in developing countries. The following section provides a comprehensive review of studies in rice productivity in the Philippines. Results of productivity growth and efficiency scores as well as the methods used are presented in Table 2.

Fulginiti and Perrin (1998) estimated productivity growth using parametric and non-parametric approaches for 18 developing countries from 1961 to 1985. Using the non-parametric approach, the Philippines had a positive growth in technical efficiency but a decline in technological growth. Nin et al. (2003) also examined technological and technical efficiency changes in the Philippines in a longer period from 1961 to 1994. They found a similar trend of declining technological change but their result showed no improvement in technical efficiency. Furthermore, Umetso et al. (2003) measured technical efficiency and technological change in 20 years (1971-1990). They observed positive changes in technical efficiency in the first ten years of their sample period (1971-1980) while technical efficiency declined from 1981 to 1990. On the other hand, technological progress was evident from the mid-1970s to the mid-1980s while the rest of the study period showed negative technological change. A more recent study is that by Rao and Coelli (2003). They measured technological change and technical efficiency change from 1980 to 2000. Their finding shows stagnant growth in both technical efficiency and technological progress.

At the subnational level, the work of Kalirajan and Flinn (1983) is one of the pioneering efficiency studies on Philippine rice production that employed stochastic frontier models. They estimated the rice productive efficiencies in Bicol region ranging from 0.38 to 0.91. In the 1990s, Dawson et al. (1991) estimated the technical efficiencies of rice farmers in Central Luzon during the period 1970-1985, which ranged from 0.84 and 0.95. Rola et al. (1993), on the other hand, observed lower mean technical efficiencies of 0.72, 0.65 and 0.57 for irrigated, rainfed and upland ecosystems, respectively, in the provinces of Central Luzon, Western Visayas, Central Mindanao, Bicol, and Cagayan Valley from 1987-1990. The most recent study on technical efficiencies using the stochastic frontier approach is that by Villano and Fleming (2004). In Central Luzon, Villano and Fleming (2004) estimated an average technical efficiency of 0.79 from 1990 to 1997.

Table 2. Selected productivity studies in Philippine rice farming

At the national level			
Author(s)	Study coverage	Model	Annual productivity
Fulginiti and Perrin (1998)			
Technological change (1961-1985)	Philippines	Non-parametric	0.981
Efficiency change (1961-1985)	Philippines	Non-parametric	1.016
Nin, Arndt and Preckel (2003)			
Technological change (1961-1994)	Philippines	Non-parametric	0.999
Efficiency change (1961-1994)	Philippines	Non-parametric	1.000
Umetso, Lekprichakul and Chakravorty (2003)			
Technological change (1971-1975)	Philippines	Non-parametric	0.978
Efficiency change (1971-1975)	Philippines	Non-parametric	1.002
Technological change (1976-1980)	Philippines	Non-parametric	1.023
Efficiency change (1976-1980)	Philippines	Non-parametric	1.001
Technological change (1981-1985)	Philippines	Non-parametric	1.037
Efficiency change (1981-1985)	Philippines	Non-parametric	0.999
Technological change (1986-1990)	Philippines	Non-parametric	0.986
Efficiency change (1986-1990)	Philippines	Non-parametric	0.996
Technological change (1971-1990)	Philippines	Non-parametric	1.007
Efficiency change (1971-1990)	Philippines	Non-parametric	0.999
Rao and Coelli (2003)			
Technological change (1980-1985)	Philippines	Non-parametric	1.007
Efficiency change (1980-1985)	Philippines	Non-parametric	1.000
Coelli and Rao (2003)			
Technological change (1980-2000)	Philippines	Non-parametric	1.008
Efficiency change (1980-2000)	Philippines	Non-parametric	1.000
At the sub-national level			
Author(s)	Study Coverage	Model	Mean TE score
Kalirajan and Flinn (1983)			
Technical efficiency (1982)	Bicol	Stochastic	0.50
Dawson, Lingard & Woodford (1991)			
Technical efficiency (1970-1985)	Central Luzon	Stochastic	0.89
Rola & Quintana-Alejandrino (1993)			
Technical efficiency (1987-1990)	Central Luzon, West Visayas, Central Mindanao, Bicol, Cagayan	Stochastic	
Irrigated			0.72
Rainfed			0.65
Upland			0.57
Villano and Fleming (2004)			
Technical efficiency (1990-1997)	Central Luzon	Stochastic	0.79

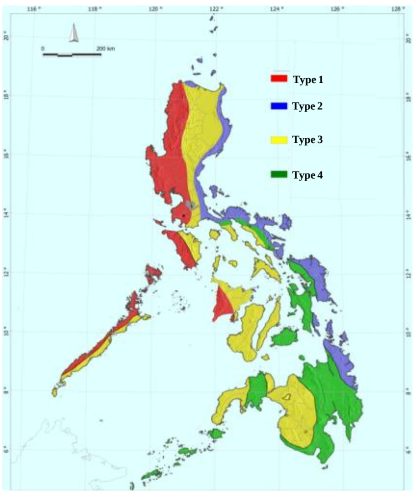
2.3 Climate adaptation in Philippine rice farming

Efforts are being made continuously to exploit the application of science in rice production in the Philippines. New varieties, more irrigation infrastructure, efficient extension services, better crop management techniques, state-of-the-art machinery and other technological innovations have been continually developed to enhance rice productivity. Due to the diverse ecosystems, the provision of different rice technology options to rice farmers suitable to environmental conditions and to their capability is a key strategy in improving productivity and sustaining growth.

Farmers are constrained by their resource endowments and are faced with environmental constraints that influence their decision-making as well as their production. Such constraints should be controlled if feasible or adaptive production strategies should be introduced that will mitigate their negative impacts. Among others, climatic conditions highly influence the operations of rice farmers. Unlike traditional inputs, climatic constraints are beyond the farmer's direct control but the production system and management strategy can be adapted to such adverse conditions of the farming environment. Different climatic zones have varying intensity of sunlight, temperature and rainfall. Farmers should consider how to fit their cropping system to the variation in hydrological and thermal growing seasons. They can choose location-specific technologies that suit their environmental conditions. Given the differences in technology sets and resource endowments, farmers have diverse sets of feasible input-output combinations which explain the variations in technical efficiencies. It is therefore necessary to estimate separate production frontiers for different groups of farmers in order to measure their level of technical inefficiency accurately.

In this paper, we measure technical efficiencies and technological gaps in rice production for farmers in four agroclimatic zones in the Philippines who may employ different production technologies according to environmental conditions. The geographical classification of climatic zones is based on the intensity and distribution patterns of rainfall (Figure 2). Type 1 climate has two pronounced seasons – dry from November to April and wet during the rest of the year. For Type 2 climate, there is no dry season but minimum monthly rainfall occurs from March to May and maximum rainfall is pronounced from November to January. In contrast, Type 3 climate has no very pronounced maximum rain period with a short dry season lasting only from one to three months. Lastly, Type 4 climate has rainfall evenly distributed throughout the year and it has no dry season.

Figure 2. Geographical distribution of based on climatic zones.



3. Analytical framework

3.1 Study area and coverage

The Philippines is composed of 16 regions and 80 provinces. The scope of this study is concentrated on 30 provinces that comprise the bulk of rice production in the country. In addition, the Philippine Department of Agriculture gives priorities to these provinces on its rice program agenda and this is where the government interventions in rice production are intensive. Table 3 shows that about 70% of the total production is coming from the top 30 rice-producing provinces included in the sample; hence it is a good representation of the rice farming population. Ignoring the variation in production technologies used in different climatic zones could lead to biased estimates of the technical efficiency scores. Hence, to reiterate, these sampled provinces are subdivided into four groups based on their climatic zones to understand the impact of agroclimatic variation on technical efficiencies.

Table 3. Production distribution of sample provinces in tonnes by climatic zone in the survey periods

Time period	Production by climatic zone of sample provinces					National production
	1	2	3	4	Pooled	
1996	3,432,154 (30)	713,239 (6)	2,997,772 (27)	1,075,044 (10)	8,218,209 (73)	11,283,568 (100)
1997	3,603,285 (32)	697,448 (6)	2,943,143 (26)	1,049,817 (9)	8,293,693 (74)	11,268,963 (100)
2001	3,832,643 (30)	768,911 (6)	3,152,329 (24)	746,637 (6)	8,500,520 (66)	12,954,870 (100)
2002	4,025,795 (30)	804,585 (6)	3,138,581 (24)	982,881 (7)	8,951,842 (67)	13,270,653 (100)
2006	5,087,212 (33)	1,148,756 (7)	3,594,621 (23)	1,248,827 (8)	11,079,416 (72)	15,326,706 (100)
2007	4,892,523 (30)	1,012,198 (6)	4,048,961 (25)	1,755,833 (11)	11,709,515 (72)	16,240,194 (100)
All Periods	24,873,768 (31)	5,145,169 (6)	19,875,531 (25)	6,859,079 (9)	56,753,547 (71)	80,345,454 (100)

Values in parenthesis are the percentage contribution to national production of the sample provinces in each climatic zone.
Source of basic data: BAS-Philrice Philippine Rice Statistics Handbook and http://www.bas.gov.ph

3.2 The empirical model

3.2.1 Parametric estimation of the group-frontier production function

A method of estimating a production frontier is to envelop the data points using an arbitrarily chosen function. Stochastic frontier analysis (SFA) employs econometric estimation of the production function to allow the frontier to vary with random disturbances. The stochastic frontier production model has two error components: one is associated with technical efficiency and the other represents random noise. The model is represented by equation (1) where Y_i represents the output of the i^{th} farmer in the k-th group, x_i is an N x 1 vector containing the logarithms of inputs, β is a vector of unknown parameters, u_i is a non-negative variable associated with technical inefficiency and v_i is a symmetric random error that accounts for statistical noise. This study utilises a three-year panel data and we assume that all firms have access to the same technology in every period and that the covariances between all error terms are zero, hence, a time variable is no longer specified in the model.

$$(1)\quad Y_i^k = f(x_i, \beta^k)e^{(v_i^k - u_i^k)}$$

Aigner et al. (1977) noted that the error component v_i^k is assumed to be independently and identically distributed *iid* $N(0,\sigma_v^2)$ while the error component u_i^k is assumed to be distributed independent of v_i and satisfying $u_i^k \leq 0$. The economic relationship for this error term specification signifies that the production process is subject to a non-positive component that makes the actual production lie on or below the frontier ($i.e. y_i^k \leq f(x_i, \beta^k)e^{-u_i^k}$) and a random disturbance which makes the frontier variable as a result of luck, weather or even measurement errors. The random error v_i can be positive or negative and the stochastic frontier outputs vary about the deterministic component of the model.

The parametric approach specifies some functional form to represent the relationship between output and inputs. A preferred functional form has the properties identified by Coelli et al. (2005) as flexibility, linearity in parameters, regularity and parsimony. The transcendental logarithmic (translog) function developed by Christensen et al. (1973) satisfies these properties and it is widely used in econometric estimation. A Cobb-Douglas functional form was also considered to represent the production model. However, a hypothesis test result suggests that it is not an adequate representation of the data and therefore the Cobb-Douglas will not be further discussed in this paper. The translog production function is defined in equation (2) where v_i is the double-sided error component which is *iid* as $N(0,\sigma_v^2)$, u_i represents the technical efficiency of i^{th} firm, and $\beta_{nm}=\beta_{mn}$ to satisfy the concavity property of the translog production function. Equation (2) can be estimated parametrically using the maximum likelihood estimation procedure with the assumption that the error terms have a truncated-normal distribution.

$$(2)\quad \ln y_i^k = \underbrace{\alpha_0 + \sum_{n=1}^{N}\beta^k \ln x_{ni}^k + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{M}\beta_{nm}^k \ln x_{ni}^k \ln x_{mi}^k}_{deterministic\ component} \underbrace{+v_i^k}_{\substack{systematic\\ random\ error}} \quad \underbrace{-u_i^k}_{inefficiency}$$

Following Battese and Coelli (1995), the estimated technical inefficiency model can be specified as:

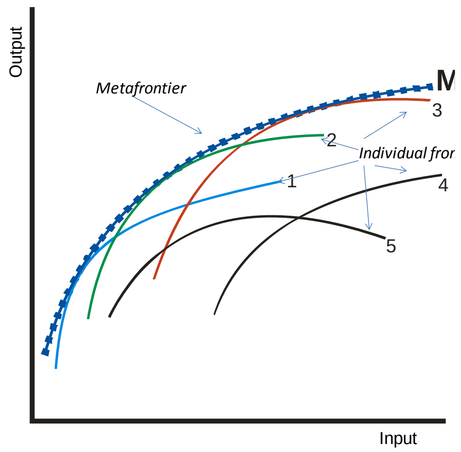
$$(3)\quad \mu_i = \delta_0 + \sum_{j=1}^{J}\delta_j Z_{ji} + \sum_{k=1}^{K}\delta_k D_{ki}$$

where $\mu_i = \delta_j s(j = 0,1,....J)$ are unknown parameters, Z_j are the inefficiency variables, and D_k denote the dummy variables for the last two periods of the data set (discussed below).

3.2.2 *Estimation of the metafrontier production function*

The metafrontier analysis proposed by O'Donnell, Rao and Battese (2004) is adopted in this study to take into account the potential environmental variation of rice production frontiers as well as to obtain comparable technical efficiencies for each climatic zone. In this approach, technical efficiencies are measured relative to a common metafrontier, defined as the boundary of the unrestricted technology set. The metafrontier production function is a frontier function that envelops all group frontiers, as shown in Figure 3. These group frontiers are boundaries of restricted technology sets. The efficiency measure is the distance between the group frontier and the metafrontier as represented by the restrictive nature of the production environment.

Figure 3. Metafrontier illustration



O’Donnell et al. (2007) also provided an econometric estimation of the metafrontier parameters using SFA. To estimate the metafrontier, there is a need to find the function that best envelops the deterministic components of the estimated stochastic group-frontiers. Formally, the metafrontier production function is:

(4) $Y_i^* = f(x_i, \beta^*) = e^{x_i\beta^*}, i = 1,2,..., N$

where Y_i^* is the metafrontier output and β^* denotes the vector of parameters for the metafrontier function satisfying the constraints $x_i\beta^* \geq x_i\beta^k, k = 1,2,..., K$.

3.2.3 Calculation of farm-level efficiencies and environmental technology gap ratios

After estimating the stochastic frontier production function in equation (2), the technical efficiency of the *k*-th group can be computed as the ratio of observed output to the corresponding stochastic frontier output given inputs, existing technologies and environmental factors as denoted by equation (5):

(5) $TE_i^k = \dfrac{y_i^k}{f(x_i, \beta^k)e^{-u_i^k}} = \exp(-u_i^k)$

The group frontier represents the state of technology pertaining to the transformation of inputs into rice output in a particular climatic zone. The metafrontier, on the other hand, represents the state of technology at the national level. In deriving the environmental technology gap ratios (ETGRs) and technical efficiencies relative to the metafrontier, we note that:

(6) $Y_i = e^{-u_i^k} \cdot \dfrac{e^{x_i\beta^k}}{e^{x_i\beta^*}} \cdot e^{x_i\beta^* + v_i^k}$

Accordingly, the ETGR defined by equation (7) is bounded from zero to one because the technical efficiency relative to the metafrontier (TE_M) is always less than the technical efficiency relative to the group frontier (TE_k). O’Donnell et al. (2007) used the term, meta-technology gap ratio (MTGR), to illustrate the gap between the production frontier for a particular group in an industry and the metafrontier for the industry. For this study, we follow the term ETGR proposed by Boshrabadi et al. (2006) as a more accurate description of the constraints placed on the potential output by the environment, and the interactions between production technology and the environment.

(7) $ETGR_k = \dfrac{e^{x_i\beta^k}}{e^{x_i\beta^*}} = \dfrac{TE_M}{TE_k}$

Lastly, the technical efficiency with respect to the metafrontier is the product of the technical efficiency relative to the group frontier and the ETGR given by equation (8). This implies that the technical efficiency with respect to the metatechnology can be decomposed into technical efficiency measured with reference to the group technology and the technology gap ratio between the group and metatechnology.

(8) $\hat{TE}_M^* = \hat{TE}_k \times E\hat{T}GR_k$

3.3 Data source and instrument

This study utilises a farm-level panel data set from the Rice-Based Farm Household Survey (RBFHS) conducted by the Philippine Rice Research Institute (PhilRice). The number of farmer-respondents in each survey period is around 2000. The RBFHS is a three-round survey covering six cropping periods – the wet seasons of 1996, 2001 and 2006 and the dry seasons of 1997, 2002 and 2007. These sets of primary data contain information on rice production and socioeconomic variables. The use of farm-level panel data in estimating the production function provides a more precise assessment of the relationships between inputs and outputs. Moreover, the availability of such a database makes the measurement of productivity more accurate.

3.3.1 Variable selection and description

Chen and Song (2008) conducted a metafrontier analysis of efficiency and technology gaps in China's agriculture using the variables GVA output, labour use, sown area, mechanical power and fertiliser use. Pate and Cruz (2007) estimated the technical efficiency of rice-producing regions in the Philippines. They derived the frontier function using inputs such as area of production, fertiliser application, labour costs, seeds costs, crop protection products, other miscellaneous inputs, year of observation, and dummy variables for natural calamities such as drought and typhoons. A more specific evaluation on the technical change and productive efficiency of irrigated rice in the Philippines was undertaken by Yao and Shively (2007). The variables incorporated in their production model included rice yield, labour, fertiliser quantity, pesticide costs, and binary variables for season, irrigation, asset ownership and time. Their inefficiency model was estimated by physical and socioeconomic factors of production such as education, age, farm size and number of workers. Lastly, Villano and Fleming (2004) analysed the technical efficiency in rainfed rice production in the Philippines and the variables used to generate their production function were the quantity of freshly threshed rice paddy, total area planted, fertiliser, herbicide applied, labour input and time.

The variation in output levels largely depends on the quantity of inputs used in production while differences in technical efficiencies are explained by productivity-enhancing factors. The variables used in this paper, summarised in Table 4, are now described.

3.3.2 Production variables

The dependent variable is total rice production in kilograms of paddy rice. Area, seed, fertiliser, other chemicals, labour and machinery are inputs traditionally used by farmers in rice production. Land is the rice area devoted to rice cultivation expressed in hectares while seed quantity is measured in kilograms. Fertiliser is the total kilograms of NPK applied. Other chemical inputs constitute herbicide and insecticide used, which are quantified based on active ingredients (AIs). Different sources of labour are hired, family or exchanged and they are all quantified in terms of person days per hectare. Machinery refers to the number of machines rented in land-preparation and threshing activities.

Non-conventional inputs that directly affect output are irrigation facilities, seed quality and source of power. These variables are included in the production function as dummy variables. The ecosystems of farmers are classified as irrigated or rainfed. It is expected that farmers with access to irrigation facilities produce more output than those famers who rely on rain. Seed quality refers to the use of certified seeds or farmer seeds. It has been proven that the use of high-quality certified seeds yields more output than the use of farmer seeds. The power source is a dummy variable that takes the value of one if the farmer uses a tractor or thresher in land preparation and threshing, respectively. And to account for time effects and eliminate possible sources of autocorrelation, year dummies are added in the model.

Table 4. Production and inefficiency variables

Variables	Description
Total production	Kilograms of paddy rice
Production variables:	
Area	Total area planted (hectares)
Seed	Total kilograms of seed used
Fertiliser	Total kilograms of nitrogen, phosphate and potash applied
Pesticides	Total kilograms of active ingredients used
Labour	Total person-days used in farm activities from land preparation to threshing
Machinery	Total machine rent cost in land preparation and threshing activities
Power source	1 if the farmer used tractor in land preparation or thresher in threshing activities and 0 otherwise
Seed quality	1 if the farmer used certified, registered or foundation seeds and 0 otherwise
Irrigation	1 if the farm is irrigated by public systems or privately own pumps and 0 if farm totally relies on rainfall
Inefficiency variables:	
Age	Age of farmer
Household size	Number of family members living in one house
Non-rice income	Total income from other sources of income aside from rice farming (in '000 pesos)
Education	Number of years of formal education
Experience	Number of years of rice farming experience
Training	1 if farmer attended rice production training in the past five years and 0 otherwise
Land ownership	1 if farmer is cultivating own land and 0 otherwise
Machine ownership	1 if farmer owned tractor or thresher and 0 otherwise
Distance	Farm distance to nearest market in kilometres

3.3.3 Inefficiency variables

Aside from describing the relationship between inputs and rice output, we are also concerned about those factors that influence farmers' technical efficiency in making decisions. Efficiency variables included in the estimation process are human capital, infrastructure, resource ownership and socioeconomic variables. Human capital refers to the level of education, farm experience and attendance at training courses by the farmers. Distance from the farm to market (infrastructure) expressed in kilometres may also affect farming operations, especially the timing of input application. The ownership of farm assets such as land and machinery is also considered in assessing the farm-level efficiencies. Lastly, socioeconomic variables included are age, household size and non-rice income.

3.4 Descriptive statistics

Descriptive statistics of the variables included in the stochastic production frontier model for the three survey rounds are summarised in the succeeding tables. First, we characterise the farmers using the efficiency variables (Table 5). On average, rice farmers are 50 years old, have a household size of 5 members, 7 years of formal education and a non-rice annual income of P38,000. Almost 30% of the farmers have attended training on rice production and have been farming for 23 years on average. The number of trained farmers in 1996 (20%) had doubled by 2007 (44%). Almost half of the respondents cultivate their own land and 23% have their own machine. Lastly, the average distance of farms to the nearest market is 7.29 kilometres.

Table 5. Farmer characteristics

All climatic zones	Crop year average 1996/1997	2001/2002	2006/2007	Average for all years
Number of observations	3770	4143	3164	11077
Age	48	50	53	50
Education	7	7	7	7
Experience	21	24	25	23
Rice production training (%)	20	22	44	27
Household size	6	5	5	5
Non-rice income ('000 pesos)	28	37	52	38
Land ownership (%)	47	50	57	51
Machine ownership (%)	21	18	30	23
Farm to market distance (km)	7.68	7.14	7.01	7.29

The farm output and conventional input use are presented in Table 6. Rice production was around 4.28 tonnes per farm in crop year 1996/1997. It declined to 3.65 tonnes/farm in 2001/2002 and increased to 4.07 tonnes/farm in 2006/2007. The mean yields of farmers increased from 3.25 t/ha in the first year to 3.34 t/ha and 3.75t/ha in the next two years, respectively. Over the whole period, rice output per farm was approximately 3.99 tonnes, which is equivalent to a mean yield of about 3.43 t/ha.

Interestingly, the quantity of seed use declined, due to the increasing adoption of high-quality seeds that require a much lower seeding rate per hectare than farmers' seeds. Lower seeding rates indicate greater efficiency in seed use. On the other hand, fertiliser application became more intensive over the years. The average amount of NPK applied by farmers in the first period (79 kg/ha) increased by approximately 16% in the second period (92 kg/ha) and doubled in the third year (158 kg/ha).

Table 6. Trends in output produced and inputs used from 1996 to 2007

Output/input variables	Crop year 1996/1997	2001/2002	2006/2007	All
Number of observations	3770	4143	3164	11077
Production (kg)	4,287	3,647	4,071	3,986
Standard deviation	5,543	3,697	4,369	4,593
Area (hectare)	1.30	1.08	1.07	1.15
Standard deviation	1.51	0.96	0.94	1.18
Yield (kg/ha)	3,253	3,336	3,751	3,426
Standard deviation	1,449	1,367	1,546	1,463
Seed (kg/ha)	137	116	99	118
Standard deviation	137	116	99	118
Fertiliser (kg NPK/ha)	79	92	158	106
Standard deviation	59	61	288	166
Pesticide (kg AIs/ha)	0.20	0.59	0.24	0.35
Standard deviation	0.54	2.16	0.59	1.41
Labour (person-days/ha)	74	58	53	62
Standard deviation	58	30	26	42
Machine cost (peso/ha)	2,756	2,537	3,177	2,794
Standard deviation	1,324	1,004	1,631	1,342
Irrigated farms (%)	67	65	72	68
High quality seed users (%)	10	18	30	19
Machine as power source (%)	26	21	13	21

Pesticide use varied over time, which suggests that the application of pesticide is not dependent on time but rather on the magnitude of pest infestation. In the crop year 2001/2002, pesticide use was twice as high as the application in 1996/1997 and 2006/2007. The increase in pesticide application reflects higher pest infestation which could explain the reduction in production during the second year.

Labour use declined over time due to mechanisation in land preparation, harvesting and threshing activities, as indicated by the increase in machine rent cost. The average labour use was 62 person-days per hectare and farmers spent around 2794 pesos per hectare for machine rent. More than 60% of the farmers have access to irrigation infrastructure. There has been an increasing percentage of high-quality seed adopters from 10% in 1996/1997 to 18% in 2001/2002 and 30% in 2006/2007. Nevertheless, such an adoption rate is still very low.

Lastly, many farmers are still using animal draft as a power source for land preparation as indicated by the low percentage share of purely mechanised farmers. The increasing price of fuel over the years had a negative impact on farm mechanisation.

Table 7 shows the differences in output produced and inputs used across climatic zones. Climatic zone 3 produces more rice output followed by zones 1, 4 and 2. However, such production ranking changes on a per hectare basis in which zone 1 had the highest mean yield of about 3.6 t/ha. The input use of farmers in zone 1 was also more intensive than in the other groups. Farmers in zone 3 rank second in amount of input used while those farmers in climatic zone 2 were the least intensive users of inputs. The percentages of irrigated farms and high quality seed users do not vary much across farmers' classifications. Finally, more farmers in zone 1 practise purely mechanised land preparation. Again, pure mechanisation in land preparation activities is less popular in zone 2.

Table 7. Variation of output produced and input used by climatic zone

Output/input variables	**Climatic zone**			
	Type 1	**Type 2**	**Type 3**	**Type 4**
Number of observations	3021	1285	3160	3611
Production (kg)	4,423	3,270	4,555	3,376
Standard deviation	4,724	3,176	5,330	4,074
Area (hectare)	1.20	1.13	1.29	1.00
Standard deviation	1.37	1.01	1.21	1.01
Yield (kg/ha)	3,689	3,056	3,469	3,301
Standard deviation	1,408	1,403	1,430	1,514
Seed (kg/ha)	136	87	131	103
Standard deviation	136	87	131	103
Fertiliser (kg NPK/ha)	158	60	94	91
Standard deviation	268	121	83	97
Pesticide (kg AI/ha)	0.35	0.28	0.40	0.35
Standard deviation	1.84	0.52	1.31	1.29
Labour (person-day/ha)	59	64	57	68
Standard deviation	33	32	33	55
Machine cost (peso/ha)	3,185	2,559	2,679	2,652
Standard deviation	1,389	1,194	1,327	1,296
Irrigated farms (%)	71	60	70	66
High quality seed users (%)	20	20	18	18
Machine as power source (%)	36	7	20	13

4. Empirical results

4.1 Production frontier estimates

To verify if there are technology differences across groupings, we tested the null hypothesis that there is no difference between the pooled frontier model and the four group frontiers. With a generalised likelihood ratio test statistic of 657.31, the test rejected the null hypothesis suggesting that there is technological variation among the climatic zones. Accordingly, this justifies the estimation of the metafrontier production model. The maximum-likelihood parameter estimates and standard errors of the translog stochastic frontier production function using the pooled data and data in each climatic zone are summarised in Table 8.

Table 8. Maximum-likelihood estimates for parameters of the stochastic frontier production model by climatic zones

Production variables	Stochastic frontier production					Meta-frontier
	Climatic zone 1	Climatic zone 2	Climatic zone 3	Climatic zone 4	Pooled	
Constant	0.2494 [a]	0.2389 [a]	0.1609 [a]	0.1363 [a]	0.1882 [a]	0.2887
	(0.0179)	(0.0338)	(0.0196)	(0.0225)	(0.0113)	(0.0181)[a]
Area	0.6113 [a]	0.4266 [a]	0.5427 [a]	0.4973 [a]	0.5230 [a]	0.5212
	(0.0202)	(0.0314)	(0.0199)	(0.0193)	(0.0108)	(0.0209)[a]
Seed quantity	0.0152 [c]	0.0469 [b]	0.0447 [a]	0.0800 [a]	0.0570 [a]	0.0403
	(0.0119)	(0.0249)	(0.0133)	(0.0124)	(0.0069)	(0.0122)[a]
Fertiliser	0.0908 [a]	0.0397 [a]	0.0943 [a]	0.1229 [a]	0.0979 [a]	0.0763
	(0.0089)	(0.0109)	(0.0087)	(0.0087)	(0.0044)	(0.0078)[a]
Pesticide	0.0183 [a]	0.0220 [a]	0.0160 [a]	0.0031	0.0138 [a]	0.0162
	(0.0051)	(0.0085)	(0.0054)	(0.0059)	(0.0029)	(0.0059)[a]
Labour	0.0305 [a]	-0.0408 [c]	-0.0029	-0.0272 [b]	0.0010	-0.0011
	(0.0129)	(0.0271)	(0.0131)	(0.0141)	(0.0075)	(0.0112)
Machine cost	0.2924 [a]	0.4872 [a]	0.3412 [a]	0.3604 [a]	0.3542 [a]	0.3743
	(0.0160)	(0.0274)	(0.0152)	(0.0164)	(0.0088)	(0.0219)[a]
Ecosystem	0.0536 [a]	0.1270 [a]	0.1702 [a]	0.2063 [a]	0.1521 [a]	0.1293
	(0.0131)	(0.0220)	(0.0133)	(0.0140)	(0.0074)	(0.0135)[a]
Seed class	0.1195 [a]	0.0623 [a]	0.0657 [a]	0.1247 [a]	0.1111 [a]	0.1165
	(0.0147)	(0.0250)	(0.0153)	(0.0167)	(0.0086)	(0.0139)[a]
Source of power	0.0513 [a]	0.0732 [b]	0.0579 [a]	0.0192	0.0421 [a]	0.0363
	(0.0115)	(0.0351)	(0.0137)	(0.0185)	(0.0078)	(0.0132)[a]
Year 2 (01/02)	-0.0629 [a]	-0.0500 [b]	-0.0204	0.0286 [b]	-0.0262 [a]	-0.0182
	(0.0159)	(0.0304)	(0.0182)	(0.0167)	(0.0100)	(0.0151)
Year 3 (06/07)	0.0098	0.0151	0.0539 [a]	-0.0156	0.0026	0.0122
	(0.0187)	(0.0371)	(0.0206)	(0.0246)	(0.0119)	(0.0184)
Cropping season	0.0996 [a]	0.0636 [a]	0.0762 [a]	0.0394 [a]	0.0653 [a]	0.0652
	(0.0126)	(0.0187)	(0.0114)	(0.0121)	(0.0066)	(0.0097)[a]
Fertiliser dummy	0.1755 [c]	-0.2012 [a]	0.1097 [c]	0.1354 [a]	0.0522 [b]	-0.1013
	(0.1136)	(0.0568)	(0.0704)	(0.0471)	(0.0270)	(0.0663)
Pesticide dummy	-0.0758 [a]	-0.1054 [a]	-0.0503 [a]	-0.0077	-0.0580 [a]	-0.0571
	(0.0158)	(0.0327)	(0.0155)	(0.0189)	(0.0091)	(0.0171)[a]
Sigma squared	3.9493 [a]	1.5969 [a]	2.8785 [a]	3.7161 [a]	3.9112 [a]	
	(0.3370)	(0.3066)	(0.2644)	(0.9138)	(0.1615)	
Gamma	0.9915 [a]	0.9763 [a]	0.9889 [a]	0.9831 [a]	0.9884 [a]	
	(0.0008)	(0.0049)	(0.0014)	(0.0042)	(0.0005)	
Log likelihood	-1042.46	-510.29	-1162.64	-1659.2	-4703.3	

Standard errors are in parenthesis.
[a] denotes significance at the 1% level, [b] denotes significance at the 5% level, [c] denotes significance at the 10% level

The values of the input and output variables were mean corrected to have unit means so the first-order coefficients can be regarded as the estimates of partial output elasticities at the mean input levels. In the pooled dataset, all estimated first-order coefficients have values from zero to one which suggests that the monotonicity condition is satisfied (i.e. all marginal products are positive and diminishing at the mean of inputs). Moreover, all estimated first-order parameters except for labour are highly significant at the 1% significance level. On the other hand, the relevance of each input to the output produced varies across climatic zones. The metafrontier parameter estimates were also significant at the 1% level, but labour has a negative coefficient albeit insignificant and at a negligible value.

Nonconventional inputs such as irrigation infrastructure (ecosystem), adoption of high-quality seeds, use of mechanical power and dry cropping season make a positive contribution to rice output and most of them are significant at the 1% level. As expected, irrigation infrastructure has a substantial impact on rice production. On average, irrigated farms yield 15% more production than rainfed farms. Those farmers who used high-quality seeds were also found to have higher production by around 10% than those who used farmer's seeds. Furthermore, dry season cropping is more favourable to rice production than cropping in the wet season, with output higher by an average of 6%. The use of tractor and thresher as mechanical sources of power in land preparation and threshing was also found to have positive impacts on rice production.

In general, the coefficients of the year dummy variables indicate a reduction in technological change for the second year (2001/2002), significant at the 1% level. Conversely, the coefficient of the year 3 dummy variable in the pooled data has a positive sign indicating technological progress, but it is not significant. Across groupings, climatic zones 1, 2 and 3 have negative technological change in the second year while climatic zone 4 had positive technological change. And for crop year 2006/2007, only climatic zone 3 had significant technological change relative to the other groupings and with respect to the pooled data.

The estimated gamma parameters are close to unity and are highly significant, which implies that almost all variability in rice output is due to technical inefficiency effects. Table 9 shows the estimated coefficients of the inefficiency variables in the translog model.

With the pooled estimate, all the parameters except for farm to market distance are significant at the 1% level. The age variable has a positive sign indicating that older farmers tend to be more inefficient. The negative coefficient of education suggests that more formal education is associated with higher technical efficiency in rice farming. Similarly, farming experience and attendance at rice production training courses improve technical efficiency as indicated by the negative coefficient of these inefficiency variables. On the other hand, the non-rice income of farming households reduces technical efficiency. Such a finding reflects the fact that farmers tend to be less efficient in rice farming if they engage in other non-rice and non-farming activities to earn additional income for the family. The number of household members also had a positive relationship with inefficiency, probably reflecting underemployment of family members. Resource ownership such as land and machines has a positive impact on the efficiency of farming operations. Generally, the land preparation and threshing activities of those farmers who owned tractors and threshers are more timely than those of farmers who are renting. The timeliness of such farming activities reduces pest incidence and postharvest losses.

Table 9. Maximum-likelihood estimates for parameters of the inefficiency effects model of the translog production function by climatic zones

Inefficiency variables	Climatic zone 1	Climate zone 2	Climate zone 3	Climate zone 4	Pooled
Constant	-11.6146 [a]	-4.0346 [a]	-4.2136 [a]	-9.8689 [a]	-8.6463 [a]
	(0.8313)	(1.0725)	(0.6948)	(2.6753)	(0.3283)
Age	0.0797 [a]	0.0093 [b]	0.0211 [a]	0.0121 [a]	0.0325 [a]
	(0.0073)	(0.0050)	(0.0040)	(0.0041)	(0.0018)
Education	0.0463 [b]	-0.0033	-0.2648 [a]	-0.2860 [a]	-0.2015 [a]
	(0.0227)	(0.0155)	(0.0120)	(0.0791)	(0.0155)
Experience	-0.0518 [a]	0.0013	-0.0060 [b]	0.0090 [a]	-0.0123 [a]
	(0.0063)	(0.0043)	(0.0033)	(0.0032)	(0.0029)
Training	-1.3613 [a]	-0.8966 [a]	-0.9920 [a]	-1.7246 [a]	-1.6029 [a]
	(0.2417)	(0.2147)	(0.0957)	(0.3960)	(0.0895)
Household size	0.0212	0.1039 [a]	-0.0412 [a]	0.0727 [a]	0.0438 [a]
	(0.0195)	(0.0285)	(0.0136)	(0.0172)	(0.0121)
Non-rice income	0.0046 [a]	-0.0054 [a]	0.0052 [a]	0.0035 [a]	0.0045 [a]
	(0.0008)	(0.0016)	(0.0006)	(0.0012)	(0.0005)
Land ownership	-2.4563 [a]	-0.2303 [b]	0.0033	0.0677	-0.6144 [a]
	(0.1395)	(0.1072)	(0.0806)	(0.0649)	(0.0400)
Machine ownership	-1.6245 [a]	-1.4406 [a]	-2.1153 [a]	-1.2265 [a]	-1.9849 [a]
	(0.1120)	(0.3418)	(0.1232)	(0.3359)	(0.1127)
Farm to market distance	-0.0295 [a]	0.0389 [a]	-0.0046	0.0556 [a]	-0.0038 [c]
	(0.0034)	(0.0093)	(0.0047)	(0.0127)	(0.0024
Year 2 (2001/2002)	-1.4912 [a]	-0.9750 [a]	-3.1314 [a]	-0.6717 [a]	-2.1653 [a]
	(0.1178)	(0.2468)	(0.1778)	(0.1488)	(0.0743)
Year 3 (2006/2007)	-1.0404 [a]	0.2381	-0.7014 [a]	0.0742	-0.6971 [a]
	(0.1355)	(0.1867)	(0.1138)	(0.1156)	(0.0720)

Standard errors are in parenthesis.
[a] denotes significance at the 1% level, [b] denotes significance at the 5% level, [c] denotes significance at the 10% level

Table 10 shows the estimated partial elasticities of output relative to production inputs. To reiterate, the first-order coefficients can be interpreted as elasticities of output with respect to inputs because the translog variables in logarithm form were mean corrected to zero. Results indicate that area planted is the highest contributor to rice production with an elasticity of output ranging from 0.40 to 0.60 among climatic zones. The estimated output elasticity for the machinery input is also high, ranging from 0.30 to 0.50 across groups and averaging 0.35 in all groups.

Table 10. Output elasticity estimates for inputs in the stochastic frontier production

Input	Stochastic frontier production				
	Climate zone 1	Climate zone 2	Climate zone 3	Climate zone 4	Pooled
Area	0.6113	0.4266	0.5427	0.4973	0.5230
	(0.0202)	(0.0314)	(0.0199)	(0.0193)	(0.0108)
Seed quantity	0.0152	0.0469	0.0447	0.0800	0.0570
	(0.0119)	(0.0249)	(0.0133)	(0.0124)	(0.0069)
Fertiliser	0.0908	0.0397	0.0943	0.1229	0.0979
	(0.0089)	(0.0109)	(0.0087)	(0.0087)	(0.0044)
Pesticide	0.0183	0.0220	0.0160	0.0031	0.0138
	(0.0051)	(0.0085)	(0.0054)	(0.0059)	(0.0029)
Labour	0.0305	-0.0408	-0.0029	-0.0272	0.0010
	(0.0129)	(0.0271)	(0.0131)	(0.0141)	(0.0075)
Machine cost	0.2924	0.4872	0.3412	0.3604	0.3542
	(0.0160)	(0.0274)	(0.0152)	(0.0164)	(0.0088)
Returns to scale	1.0586	0.9816	1.0360	1.0364	1.0468

Standard errors are in parenthesis.

The estimated returns-to-scale parameters are obtained by aggregating the output elasticities of all inputs at their mean values. Except for climatic zone 2, it can be observed that all other models have a returns-to-scale parameter greater than one. Nevertheless, these values are very close to one which implies that diseconomies of scale are unlikely to exist on the frontier.

4.2 Farm-level performance indexes

The technical efficiency estimates for the individual climatic zones and pooled dataset with respect to the group frontier and metafrontier are presented in Table 11. The average technical efficiency in the pooled data set is 0.75, which suggests that on average farmers produce only 75% of the maximum attainable output for given input levels. Across climatic zones, the estimated efficiency scores are fairly uniform. Farms in climatic zone 4 have the highest mean technical efficiency of 0.76 with a standard deviation of 0.15. The technical efficiency of those farms in climatic zone 1 (0.75) is almost the same with that of group 4 (0.76). Farms in zones 2 and 3 have a slightly lower technical efficiency of 0.74.

The estimated ETGR estimates presented in Table 11 are also similar across climatic zones but are higher and more dispersed. Farms in climatic zone 3 achieved the highest estimated ETGR of 0.88 followed by those in zones 1 (0.86), 2 (0.84) and 3 (0.83). The group that has the highest variation in TGRs is in climatic zone 4. The mean ETGR across all climatic zones is 0.85. These ETGR values can be regarded as the technology gap faced by farmers in each climatic zone when their performances are compared at the national level or to the whole country. A notable feature of the estimates is that all climatic zones have at least one farmer operating on the metafrontier.

Table 11. Technical efficiencies and environmental-technology gap ratios by climatic zone

Pooled year	Climatic zone			
	Type 1	Type 2	Type 3	Type 4
Number of observations	3021	1285	3160	3611
Technical efficiency with respect to group frontier (TE_G)				
Mean	0.7520	0.7355	0.7376	0.7582
Standard deviation	0.1679	0.1716	0.1797	0.1496
Variance	0.0282	0.0294	0.0323	0.0224
Minimum	0.0054	0.0695	0.0188	0.0781
Maximum	0.9689	0.9550	0.9627	0.9639
Environment-technology gap ratio (ETGR)				
Mean	0.8558	0.8439	0.8706	0.8330
Standard deviation	0.0727	0.0843	0.0756	0.1098
Variance	0.0053	0.0071	0.0057	0.0121
Minimum	0.2357	0.4152	0.2927	0.3201
Maximum	1.0000	1.0000	1.0000	1.0000
Technical efficiency with respect to metafrontier (TE_M)				
Mean	0.6437	0.6216	0.6445	0.6333
Standard deviation	0.1537	0.1595	0.1693	0.1542
Variance	0.0236	0.0255	0.0287	0.0238
Minimum	0.0013	0.0559	0.0159	0.0613
Maximum	0.9400	0.8891	0.9283	0.9233

Estimates of technical efficiencies with respect to the metafrontier are also quite uniform across climatic zones, with an average across all groups of 0.64. Climatic zones 1 and 3 farms have an estimated mean technical efficiency similar to that of the average while group 4 has an estimated mean technical efficiency of 0.63 and climatic zone 2 has the lowest estimate of 0.62. The standard deviations of the estimated technical efficiencies in each climatic zone are similar, ranging from 0.15 to 0.17.

The results above suggest that technology diffusion and information transmission seems to suit different agroclimatic conditions. The variation in production technology and ecological conditions has been successfully managed by rice scientists to develop and disseminate appropriate technology and knowledge products.

The annual trend in mean technical efficiencies obtained from the group and metafrontiers are presented in Table 12 for the period. Overall, the technical efficiency score with respect to the group frontier in the base year 1996/1997 was 0.75, which indicates that farmers were producing 75% of the potential output given the current state of technology. As expected, the mean efficiency score relative to the metafrontier is lower at 0.60. One interesting observation is that the technical efficiency of farmers with respect to the group frontier and metaproduction frontier had improved in the second year by 2.72% (TE_G=0.77) and 7.78% (TE_M=0.65), respectively. It is worth noting that the output produced declined during the crop year 2001/2002 as indicated by the significant negative coefficient of the year 2 dummy variable in the production function. Such results imply that farmers became more efficient despite the decrease in output. Unfortunately, the technical efficiencies of farmers did not improve in 2006/2007. The estimated ETGR also increased from 1996/1997 to 2001/2002 but stagnated in the last year of the study period.

Table 12. Changes in technical efficiencies and ETGRs from 1996 to 2007

All climatic zones	Crop year			Growth rate (base year 1996)		
	1996/97	2001/02	2006/07	1996/97-2001/02	1996/97-2006/07	Geometric mean
Climatic zone 1						
N	1011	1023	987			
TE (Group frontier)	0.7493	0.7745	0.7723	3.35%	3.07%	3.21%
TE (Metafrontier)	0.6052	0.6595	0.6458	8.97%	6.72%	7.77%
ETGR	0.8075	0.8489	0.8366	5.12%	3.60%	4.29%
Climatic zone 2						
N	377	544	364			
TE (Group frontier)	0.7521	0.7827	0.7548	4.06%	0.36%	1.21%
TE (Metafrontier)	0.5756	0.6322	0.6218	9.83%	8.03%	8.88%
ETGR	0.7693	0.8058	0.8213	4.74%	6.76%	5.66%
Climatic zone 3						
N	1141	1181	838			
TE (Group frontier)	0.7320	0.7797	0.7333	6.52%	0.17%	1.07%
TE (Metafrontier)	0.6115	0.6591	0.6453	7.78%	5.53%	6.56%
ETGR	0.8301	0.8438	0.8797	1.66%	5.97%	3.15%
Climatic zone 4						
N	1241	1395	975			
TE (Group frontier)	0.7675	0.7557	0.7571	-1.54%	-1.36%	……
TE (Metafrontier)	0.6065	0.6502	0.6394	7.19%	5.42%	6.24%
ETGR	0.7886	0.8593	0.8438	8.96%	7.00%	7.92%
All climatic zones						
N	3770	4143	3164			
TE (Group frontier)	0.7504	0.7707	0.7553	2.72%	0.66%	1.33%
TE (Metafrontier)	0.6046	0.6527	0.6410	7.95%	6.02%	6.92%
ETGR	0.8043	0.8453	0.8485	5.10%	5.49%	5.29%

Across climatic zones, farmers in climatic zone 3 achieved the highest ETGR in crop year 1996/1997 and 2006/2007. This group of farmers achieved continuous improvement in ETGR over time. Climatic zone 2 also had positive growth over the period while climatic zones 1 and 4 had positive ETGR growth in 2001/2002 but a slight decline in 2006/2007. The pattern in interzonal TE scores with respect to the group and metafrontiers has the same trend with that of the pooled data where TE scores improved in the second year and declined in the third year.

5. Implications of results

The level of productivity gains vary across different climatic zones due to variations in environmental constraints faced by farmers. Results of this study imply that the performance of farmers operating in one climatic zone is virtually at par with farmers operating in other climatic zones. The fairly uniform technical efficiencies relative to the metafrontier signifies that farmers are able to adapt their farming practices to their environmental conditions and use technologies that are suitable to their place. The maximum ETGR of one in all climatic zones suggest that closing the environment-technology gap is possible. Closing and/or substantially narrowing the technology gap largely depends on the ability of farmers to exploit the productivity-enhancing technologies available.

It was found out that technical efficiencies within individual group frontiers are lower than the metafrontier TE scores. This implies that there is a potential scope to reach the highest attainable output in the metafrontier by moving up the productivity of those farmers below the frontier within each climatic zone. Effective extension services are then needed to make farmers take advantage of the available technology. It is imperative for the government to strategically disseminate suitable technologies in a particular area coupled with training and information services. As indicated by the estimated regression coefficients, the size of area cultivated and mechanisation are two important factors that significantly and substantially contribute to production output. The government should then invest in regions with larger farms because these areas are likely to better adopt improved technologies.

Specifically, on-farm technology demonstrations and intensive training of farmers on Integrated Crop Management (ICM) practices like the PalayCheck system should be conducted. The PalayCheck system showcase a package of technology on seeds, soil and water as well as the mitigation of climatic and biotic constraints, hence, its adoption can improve farmer’s productivity and increase their technical efficiency. Specific crop management technologies that were developed to achieve higher and sustainable productivity include Site-Specific Nutrient Management (SSNM), Integrated Pest Management (IPM), Controlled Irrigation (CI), high-quality seed use, and postharvest technologies. In addition, intensive mechanisation and access to irrigation infrastructure are also important drivers of farm productivity. The construction of new irrigation infrastructures, rehabilitation of existing irrigation facilities, and provision of water technologies such as of shallow tube wells (STWs) and water pumps especially in rainfed areas will increase cropping intensity. Furthermore,, farm productivity and efficiency within climatic zones can be further improved through the development of localised rice plans. With this strategy, location-specific constraints in rice production especially those associated with unfavourable environments could be easily identified and addressed.

The farm-level efficiency indexes across periods suggest that the productivity performance of farmers have been stable over the years. Shifting the production frontier requires more technological advancement in rice production. The role of R&D on new rice technologies is essential to expand the current production frontier. Science-based technologies that cater key production constraints at the farm level are still one of the most effective sources of improving productivity. Hence, it is important that the national R&D institute through Philippine Rice Research Institute (PhilRice) must align its R&D program thrusts especially in technology advancement with the present and anticipated needs of rice farmers. PhilRice in collaboration with the International Rice Research Institute (IRRI) should continue developing high yielding rice varieties and hybrids to push the yield frontier into a higher level.

6. Concluding remarks

In this paper, we measured technical efficiencies and environmental-technology gaps in rice production for farmers in four agroclimatic zones in which farmers may employ different production technologies according to environmental conditions. A stochastic metafrontier function is used to compare mean technical efficiency and ETGR estimates across climatic zones. A farm-level panel data set was used in assessing the performance of farmers in three cropping periods (1996WS/1997DS, 2001WS/2002DS and 2006WS/2007DS). We estimated four regional stochastic frontiers using the standard stochastic frontier model based on a translog functional form. A deterministic metafrontier production function was then fitted to the regional frontiers.

The estimated output elasticities of conventional inputs which include area, seeds, fertiliser, pesticides, labour and machine cost were all found to be highly significant. Farm-specific variables such as age, education, experience, training, household size, non-rice income, resource ownership and distance from farm to market have varied effects on farm-level efficiencies. Mean technical efficiencies and ETGRs were reasonably similar across climatic zones which suggest that farmers are able to adapt their management practices according to the environmental constraints they face. Such a result could also mean that the government is currently on the right track in its national rice program, specifically on the development and provision of location-specific technologies. Nevertheless, technological progress has been stagnant over the years. The advancement of rice technologies is then the next challenge for rice scientists to shift the rice metaproduction frontier outwards.

Finally, temporal measurement of technical efficiencies by season and ecosystem is to be considered for future analysis. This will determine the shifts in the metafrontier over time in irrigated and rainfed ecosystems.

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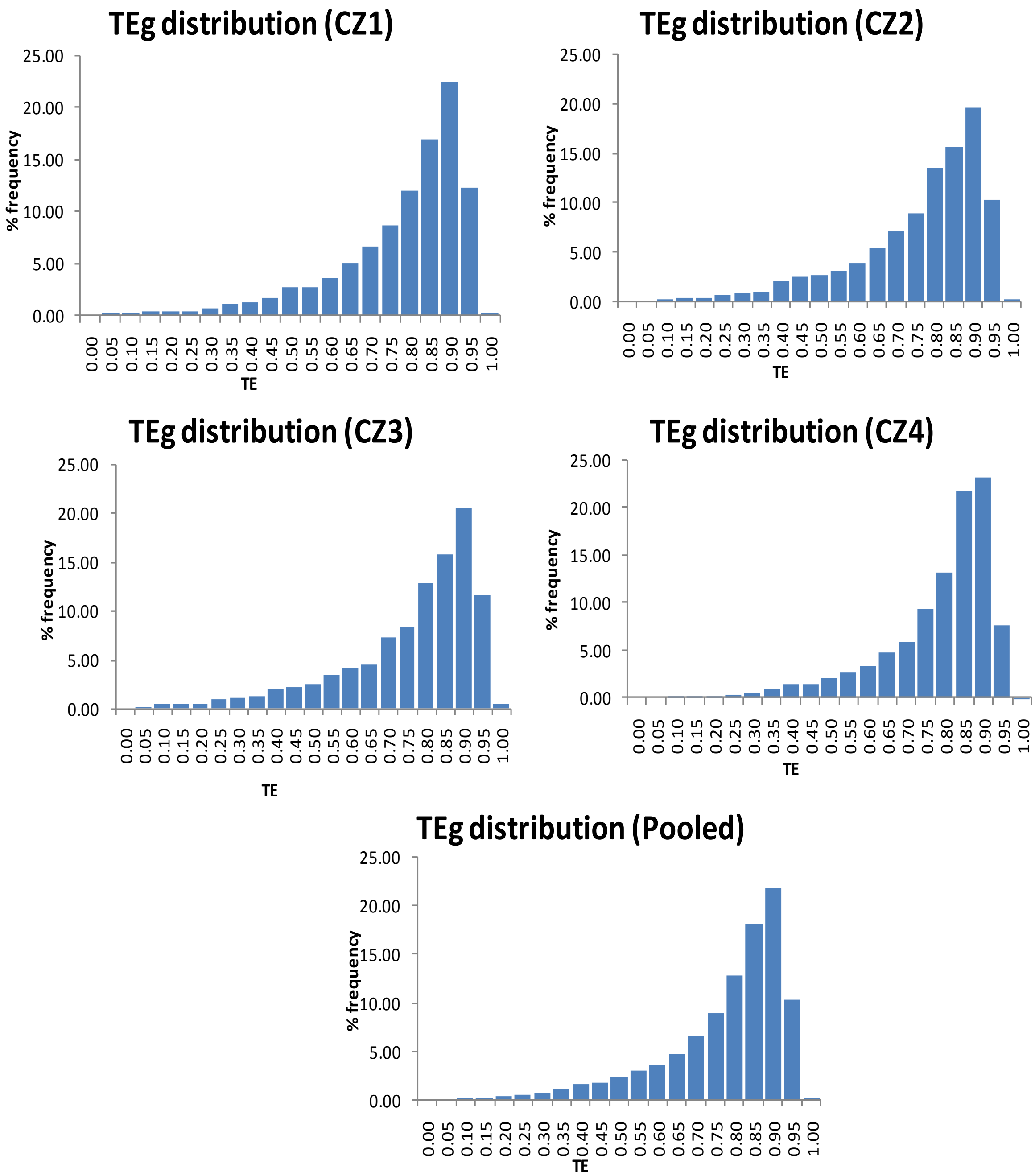
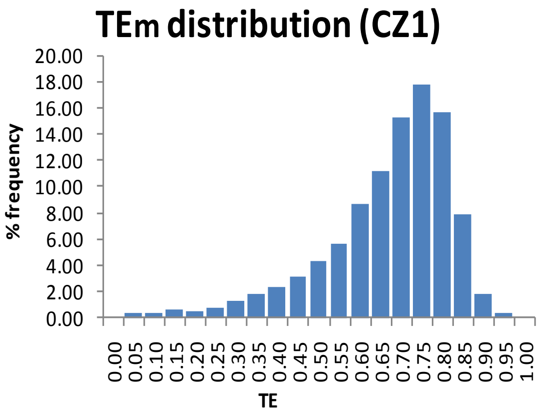
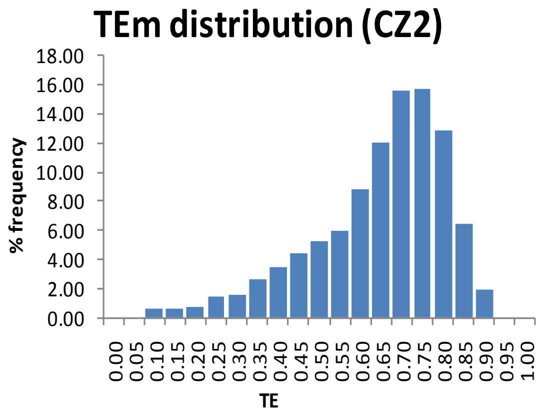
Appendices

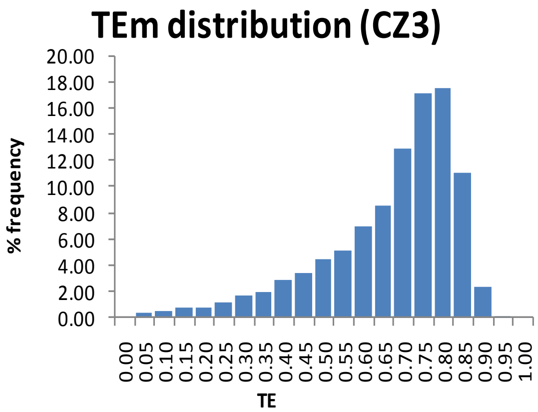
Appendix 1. Percentage distribution of Farm-level technical efficiencies with respect to the group frontier

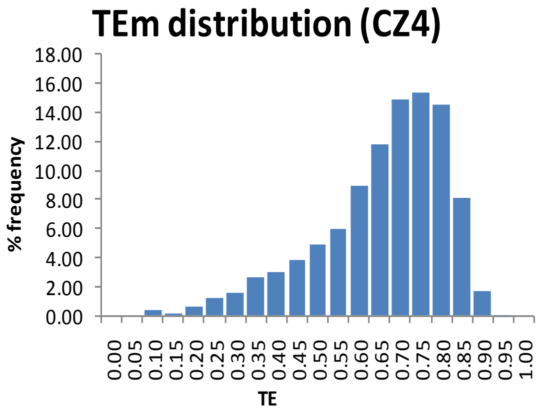


Appendix 2. Percentage distribution of Farm-level technical efficiencies with respect to the meta-frontier









Appendix 3. Percentage distribution of Environment-technology gap ratios (ETGR)