An Analysis of Scope Economies and Technical Efficiency in Intensive Rainfed Lowland Rice-based Cropping Systems in Northwest Luzon, Philippines

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Abstract

Farming in the rainfed lowlands of northwest Luzon, Philippines, is highly intensive, diversified, and commercialised. The cropping-system is predominantly rice-based in the wet season and high-value cash crops are grown during the dry season. Using panel data from 100 randomly selected farmers, a stochastic input distance function is used to investigate scope economies in this environment. Results show that significant scope economies exist between rice and the major dry-season crops of garlic and mungbean. Scope diseconomies exist between rice and maize.

Key words: stochastic input distance function, technical efficiency, rice

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1. Introduction

Farming in the rainfed lowlands of northwest Luzon, Philippines, is highly intensive, diversified and commercialised (Lucas et al. 2000). Rice is the most common crop in the lowlands during the wet season from May to October. Cropping in the dry season is more diversified. Farmers grow a range of cash crops, including garlic, mungbean, pepper, tomato and tobacco, and partly subsistence crops, such as maize These dry-season crops are supported by groundwater irrigation. A well developed marketing system has facilitated the evolution of the highly intensified rice-cash crop production system (Lucas et al. 1999).

The profitability of cash crops has encouraged most rainfed farmers to diversify and maximise land use intensity by growing two or three cash crops. In some cases, diversification can also be classified as a strategy of farmers in dealing with risk. Through crop diversification, farmers are able to reduce the effects of production risk on the variability of household income. It can also be hypothesised that diversification can have an impact on the technical efficiency of rainfed lowland farmers. The dynamics between sub-systems can influence the scope for complementarity between, and technical efficiency of, their operations, especially in light of the seasonality of demand for household labour and management inputs within the farming system (Coelli and Fleming 2004).

The objective of this paper is to analyse economies of scope in the intensive rainfed lowland rice-based cropping system. While scope economies have been studied in a wide range of industries, few studies have produced empirical evidence of scope economies in agricultural production (e.g. Chavas and Aliber 1993, Coelli and Fleming 2004). This study provides evidence on scope economies in rice-based crop production using survey data in the northwest Luzon, Philippines.

The rest of the paper is organised as follows. In the next section we discuss the study location and the data set. The third section presents the method of analysis, which includes the empirical model. The results of the econometric analysis are presented in the fourth section, with discussion focusing on the estimated model parameters, technical inefficiency and scope economies. Finally, we present a brief conclusion to the study.

2. Study Area

This paper is based on a panel data set collected to examine the economics of intensive cropping systems in Ilocos Norte, northwest Luzon, Philippines. The rainfed lowland of Ilocos Norte demonstrates a case of high cropping intensity and can serve as a model for other areas that are being intensified. Panel data from 100 randomly selected farmers were collected over the cropping seasons from 1994/95 to 1997/98. Sampling design and sample selection have been discussed by Lucas et al. (1999). Farms are small, with the average size of the sampled farmers only 1.1 hectares. Almost 58 per cent of the area is cultivated by tenants. Land holdings are fragmented, and each farm household has an average of three parcels that have an average size of 0.4 hectares.

The usual cropping pattern for this environment is depicted in Figure 1. Almost all land is planted to rice during the rainy season, except for some upland fields that are not suitable for rice. A range of upland crops is grown in these fields such as beans, eggplant, and tomato. Most of the farmers plant modern rice varieties. Land preparation activities begin immediately after rain occurs. They are mostly done using hand tractors and water buffaloes. The average annual rainfall is 2267 mm, with most of this rainfall occurring during the months of June to October.

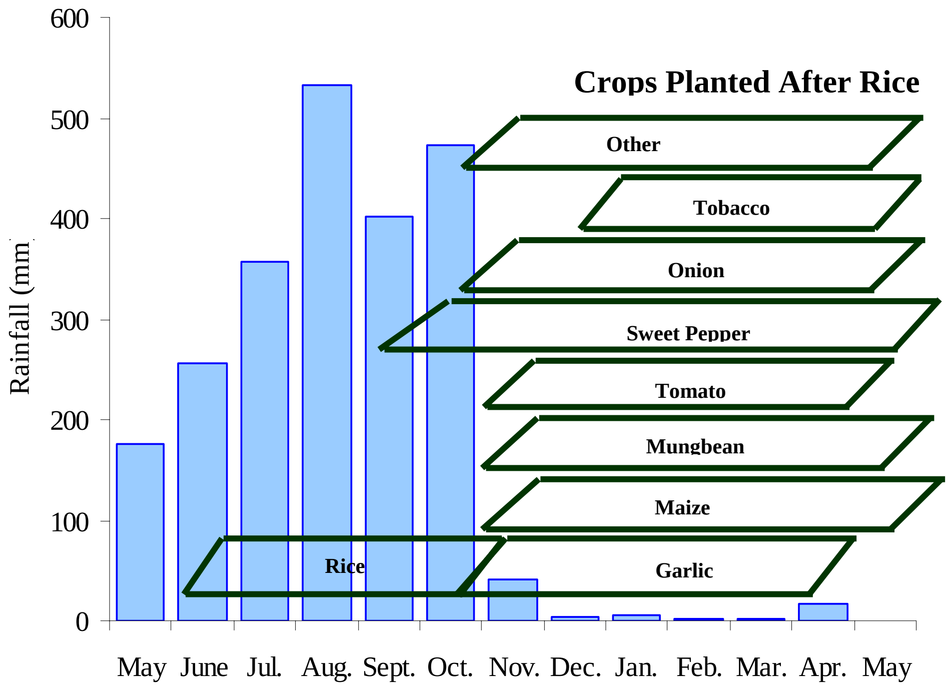

Figure 1. Cropping calendar and average monthly rainfall in Ilocos Norte, Philippines
Source: Lucas et al. 2000, p. 392

Table 1 summarises the average material and labour inputs and costs for rice in Ilocos Norte. Rice plants are established by transplanting, with an average seeding rate of 101 kilograms per hectare. Chemical fertilisers are applied at a rate of 129-31-21 kilograms of NPK per hectare. Fertilisers are applied twice, the first application being made two weeks after transplanting and the second about five weeks after transplanting. The rate of chemical application was low. Overall, rice production is based mainly on the use of hired labour, with family labour contributing only about 20 per cent of the total labour requirement. Labour inputs accounts for 56 per cent of the total cost of rice production. Average labour usage in rice production over the four-year period was 85 person-days per hectare. The four-year average of rice output was 3.1 tonnes per hectare.

Table 1. Average inputs and costs for rice (1994-97), Ilocos Norte, Philippines[a].

Categories	**1994**	**1995**	**1996**	**1997**	**All years**
Inputs					
Seed (kg ha $^{-1}$)	111	107	103	93	101
	(76)	(68)	(53)	(42)	(57)
Nitrogen (kg ha $^{-1}$)	155	143	121	116	129
	(87)	(99)	(41)	(39)	(64)
Phosphorus (kg ha $^{-1}$)	30	39	30	30	31
	(25)	(38)	(22)	(19)	(25)
Potassium (kg ha $^{-1}$)	19	22	19	25	21
	(15)	(20)	(18)	(19)	(18)
Chemicals (kgai ha $^{-1}$)	0.05	0.12	0.20	0.05	0.11
	(0.12)	(0.21)	(0.34)	(0.12)	(0.24)
Total labour	73	103	87	88	85
	(46)	(56)	(58)	(50)	(82)
Costs					
Material costs (US$ ha $^{-1}$) [b]	174	198	131	147	155
	(95)	(78)	(45)	(46)	(66)
Labour costs (US$ ha $^{-1}$)	206	179	243	177	197
	(122)	(123)	(110)	(98)	(114)
Total costs (US$ ha $^{-1}$)	380	377	352	324	351
	(190)	(137)	(127)	(120)	(140)
Yield (t ha $^{-1}$)	3.95	3.56	3.3	2.88	3.31
	(2.4)	(1.4)	(1.3)	(1.2)	(1.5)

[a]Figures in parentheses are standard deviations, [b] 1US$=P25.

In the dry season, maize, garlic, mungbean and tomato are the four major crops occupying almost 75 per cent of the area planted. Other crops planted during the dry season are tobacco, onion, pepper and vegetables. Dry-season crops are entirely dependent on irrigation from tube wells. Overall, input usage in dry-season crops is high except for mungbean (Table 2). Farmers apply over 500 kilograms of NPK per hectare, and chemicals are also applied at a higher rate. Material inputs account for 40 to 50 per cent of the total production cost. The high profitability of sweet pepper, tomato and garlic may have encouraged farmers to apply higher doses of inputs (Lucas et al. 2000, p. 399).

Table 2. Average input use and costs of major dry-season crops (1994-98), Ilocos Norte, Philippines [a].

Categories	Maize	Garlic	Mungbean	Sweet Pepper	Tomato
No. of fields	184	233	135	54	89
Inputs					
Seed (kg ha^{-1})	21	264	31	1.3	0.70
	(15)	(119)	(20)	(1)	(0.59)
Nitrogen (kg ha^{-1})	102	136	6	305	126
	(73)	(71)	(30)	(138)	(51)
Phosphorus (kg ha^{-1})	23	49	2	85	67
	(25)	(35)	(9)	(69)	(42)
Potassium (kg ha^{-1})	27	41	1.3	78	111
	(30)	(40)	(8)	(69)	(73)
Chemicals (kg a.i. ha^{-1})[b]	0.11	1.09	0.28	3.63	2.28
	(0.28)	(1.71)	(0.28)	(3.26)	(2.31)
Fuel (l ha^{-1})[a]	16	32	16	81	32
	(20)	(32)	(19)	(52)	(23)
Total labour	40	63	32	105	73
	(35)	(39)	(37)	(65)	(50)
Costs					
Material costs (US $)	156	786	80	547	383
	(77)	(404)	(58)	(236)	(181)
Labour costs (US $)	133	200	118	429	272
	(95)	(156)	(105)	(211)	(411)
Total Costs (US $)	289	986	198	976	655
	(124)	(450)	(134)	(343)	(504)
Yield (t ha^{-1})	3.15	0.84	0.41	6.0	33
	(2.9)	(0.73)	(0.37)	(4.8)	(19.5)

[a] Figures in parentheses are standard deviations, [b] includes insecticides, fungicides and herbicides.

3. Method of Analysis

3.1 Economies of Scope

By definition, economies of scope (EOS) refer to the economies associated with the composition of output. They are traditionally defined relative to a cost function. Consider the case where a firm produces two outputs, y_1 and y_2. Following Baumol et al. (1982), we can measure the economies of scope between two crops by the following definition:

$$EOS_{1,2} = [C(y_1,y_2) - C(y_1, 0) - C(0, y_2)]/C(y_1,y_2) \qquad (1)$$

where $C(y_1,y_2)$ is the multiple output cost function of joint production of y_1 and y_2; $C(y_1,0)$ is a cost function when only y_1 is produced; $C(0, y_2)$ is a cost function when only y_2 is produced. In our case, y_1 and y_2 can be defined as the outputs of crops 1 and 2, respectively. Economies of scope are said to exist if $EOS_{1,2} < 0$, and diseconomies of scope exist if $EOS_{1,2} > 0$. Intuitively, economies of scope between crop 1 and crop 2 imply that the cost of producing y_1 and y_2 jointly is less than the cost of producing them separately.

Empirically, $EOS_{1,2}$ can be calculated and evaluated by using the predicted values of $C(y_1,y_2)$, $C(y_1,0)$ and $C(0,y_2)$. However, because of the limited data on costs and individual prices of inputs received by farmers, the estimation of cost functions was not possible. As an alternative, an input-distance function is estimated. Following Coelli and Fleming (2004), the input distance function is used on the basis that the estimation of cost functions is not possible and on the premise that the assumption of cost minimisation is unlikely to be applicable to rainfed lowland rice farmers. As indicated in the use of level of inputs, farmers in this area are applying inputs more than the recommended rate. In the same context, the cropping system in Ilocos Norte is profit-driven, which makes the farmers grow two or more crops in the same parcel of land. The use of an input distance function is appropriate for this problem and the model allows for the possibility of inefficiency in our production model.

Coelli, Rao and Battese (1998 p. 64) defined the input distance function as:

$$d(x,y) = \left\{ D : \left(\frac{x}{D} \right) \in L(y) \right\} \tag{2}$$

where $L(y)$ represents the set of all input vectors, x, which includes all fixed and variable inputs, that can produce the output vector, y. The properties of input distance function can be easily derived using the assumptions of production technology. The expression $d(x,y)$, is non-decreasing in x and increasing in y, and linearly homogeneous and concave in x. The value of the distance function is equal to or greater than one if x is an element of the feasible set, $L(y)$. That is, $d(x,y) \geq 1$ if $x \in L(y)$. It is equal to one if x is located on the inner boundary of the input set. That is, it equals 1 if the firm is technically efficient and exceeds 1 is the firm is technically inefficient (Coelli and Fleming 2004, p. 232). This measure is the inverse of the traditional input-orientated technical efficiency measure defined by Farrell (1957), which lies between 0 and 1.

Following Coelli and Fleming (2004), economies of scope can be computed using the derivative of the input distance function. The first partial derivative of the input distance with respect to the *i*th output is generally negative. This indicates that the addition of an extra unit of output, with all variables held constant, reduces the amount by which we need to deflate the input vector to put the observation onto the efficient frontier. The second cross-partial derivative would need to be positive to provide evidence of scope economies (Coelli and Fleming, 2004). From equation (2), economies of scope exist between outputs i and j if:

$$\frac{\partial^2 D}{\partial Y_i \partial Y_j} > 0, \quad i \neq j, \quad i, j, = 1, \ldots, m. \tag{3}$$

Equation (3) provides the basis for computing the economies of scope between the different rice-based cropping systems in the rainfed lowlands in Ilocos Norte, Philippines. There are potentials for the existence of scope economies in this area. For example, in the case of rice-mungbean cropping pattern, we would expect that this cropping pattern would have significant scope economies because mungbean is a nitrogen-fixing crop thereby reducing the amount of fertiliser applied on the following wet season. Among the dry-season crops, complementarities in organising farm work, input use such as labour management, water management and pest and insect control can result in scope economies in the production system.

There are also potentials for diseconomies of scope, caused by on-site externalities between the different crops. On-site effects include adverse changes in the physical, chemical and biological properties of the soil-water-plant complex that reduce farm productivity. For example, reduced availability of nutrients to plants in the intensified irrigated rice systems of tropical Asia could make these systems unsustainable because of changes in soil properties (Cassman and Pingali 1995). Scope diseconomies may also exist as a result of off-site externalities that are not normally valued in the market place, such as groundwater contamination, damage to irrigation infrastructures due to soil erosion.

These on-site and off-site effects may be present in the case of the intensive cropping systems in Ilocos Norte. The high-input intensive systems may be unsustainable in the long run. Scope diseconomies may exist between rice and maize cropping pattern because maize is a nitrogen-depleting crop and therefore parcels planted to maize would need to have more fertiliser applied for a sustainable system. Excess nitrogen has been found to move to deeper soil layers (Tripathi et al. 1997), where it is prone to loss through leaching of nitrate into groundwater (Gumtang et al. 1998) and/or emission of nitrous oxide into the atmosphere.

3.2 Variables and Data

The data on the multiple outputs and multiple inputs used in this study are based on aggregate values for each farm. Before the data were aggregated, they were converted from values on a per hectare basis into actual values. This allows us to include land (area) planted to crops as an additional variable in our analysis.

The input variables considered are land, seeds used, fertiliser, chemicals, labour and power used. Land was defined as the total area planted to rice and non-rice crops during the given cropping season per farm. To capture the amount of seed used, we calculated the deflated total value of seed costs as the sum of all values of seed costs for all crops planted during the cropping year. Fertiliser is the total value of active ingredients of nitrogen, phosphorus and potassium. Chemicals include the total amount of active ingredients of insecticides, pesticides, fungicides and herbicides used for all crops. Labour is the total number of days of labour used in all cropping practices for all crops per year. Power is composed of the cost of power used for land preparation, such as the tractor and fuel inputs, and the fuel costs used for supplementary irrigation.

For the purpose of the analysis, we have limited the output variable into four categories, rice output plus the values of respective outputs of garlic, maize, mungbean and other crops. Because of the multiplicity of outputs derived from different crops during the dry season, we focus on the top three major crops grown during the dry season. This classification is based on the number of fields or parcels planted to maize (184), garlic (233) and mungbean (135) during the four-year periods. These crops are planted almost always on the same parcels over time. For the remaining parcel of land, there are different crops planted that are not necessarily planted on the same land over time. Garlic and mungbean are considered as cash crops while maize is predominantly for home consumption. We have summed the values of these other outputs into one additional category called other crops. The most important crop in the other crops category is sweet pepper.

We have considered the data for 50 farmers during the 1994-95 and 1995-96 cropping seasons and the data for 100 farmers during the 1996-97 and 1997-98 cropping seasons. The reason for this unbalanced number of observations is that data were initially collected for 50 farmers and the sample size was only increased to 100 in 1996.

Evidence of economies of scope in rainfed lowland rice environment can be derived from by using equation (3). We note that, although rice and other crops are grown in different seasons, farmers are still faced with the decision of which combination is best and more efficient. For this purpose, we examine whether economies of scope exist between the different cropping patterns and between the different crops grown in the dry season. The different cropping patterns considered are: rice-garlic, rice-maize, rice-mungbean and rice-other crops. Because farmers diversify and plant several crops during the dry season, the different combinations of crops are also examined, namely garlic-maize, garlic-mungbean, garlic-other crops, maize-mungbean, maize-other crops and mungbean-other crops.

3.3 Empirical Model

We make use of the methodology proposed by Coelli and Fleming (2004), Coelli and Perelman (1996) and Battese and Coelli (1992). A multi-output multi-input stochastic input distance function was estimated, and the results were used to evaluate the economies of scope. This function is also used to calculate the technical efficiency index for each sampled farmer in each year, and the mean technical efficiency by year and for the whole period. The model is based on a translog functional form that takes into account the interactions between outputs and input variables. The means of the logged variables were adjusted to zero so that the coefficients of the first-order terms may be interpreted as elasticities, evaluated at the sample means.

Following Coelli and Perelman (1996), the translog stochastic input distance function can be specified as:

$$\begin{aligned}\ln d_{it} = \beta_0 + \sum_{i=1}^{6}\beta_i \ln X_{it} + \sum_{j=1}^{5}\alpha_j \ln Y_{jt} + 0.5\sum_{i=1}^{6}\sum_{i'=1}^{6}\beta_{ii'} \ln X_{it} \ln X_{i't} \\ +0.5\sum_{j=1}^{5}\sum_{j'=1}^{5}\alpha_{jj'} \ln Y_{jt} \ln Y_{j't} + \sum_{i=1}^{6}\sum_{j=1}^{5}\varphi_{ij} \ln X_{it} \ln Y_{jt} + \sum_{d=1}^{5}\phi D_{it} + \delta_1 T + \delta_2 T^2\end{aligned} \tag{4}$$

where Y_{it} is the i-th input in period t and X_{jt} is the j-th output in period t, and $\beta, \alpha, \phi, \varphi$ and δ are parameters to be estimated. As mentioned earlier, the five inputs variables in the model are area, seeds, fertiliser, power, labour and chemicals. The outputs are the rice outputs and the value of the outputs of garlic, maize, mungbean and other crops. The dummy variables to take into account the zero values of Y_js and X_i were also included. This implies that the logarithms of these variables are taken only if they are positive, otherwise they will have a value of zero (Battese 1997). The variables T and T^2 are included to take technical change into account.

In order to obtain the estimating form of the stochastic input distance function, we set $-ln\ d_{it} = v_{it}-u_{it}$ and impose the restriction that $\Sigma\beta_i = 1$ (Coelli and Perelman 1996, Coelli and Fleming 2004). The translog stochastic input distance function can now be re-written as:

$$-\ln A_{it} = \beta_0 + \sum_{i=1}^{5}\beta_i \ln\left(\frac{X_{it}}{A_{it}}\right) + \sum_{j=1}^{5}\alpha_j \ln Y_{jt} + 0.5\sum_{i=1}^{5}\sum_{i'=1}^{5}\beta_{ii'} \ln\left(\frac{X_{it}}{A_{it}}\right)\ln\left(\frac{X_{i't}}{A_{it}}\right)X_{i't}$$
$$+0.5\sum_{j=1}^{5}\sum_{j'=1}^{5}\alpha_{jj'} \ln Y_{jt} \ln Y_{j't} + \sum_{i=1}^{5}\sum_{j=1}^{5}\varphi_{ij} \ln\left(\frac{X_{it}}{A_{it}}\right)\ln Y_{jt} \qquad (5)$$
$$+\sum_{d=1}^{5}\phi D_{it} + \delta_1 T + \delta_2 T^2 + v_{it} - u_{it}$$

where

A_{it} is the total area planted to rice and non-rice crops in period *t*, in hectares;

X_1 the total cost of seeds used, in pesos;

X_2 the total amount of fertiliser used in all crops, in kilograms of NPK;

X_3 the total cost of power used, including cost of tractor and fuel cost, in pesos;

X_4 is the total labour used in all crop production, in person-days;

X_5 is the total amount of chemicals used, including insecticide, pesticides and fungicides, in pesos;

Y_1 the total output of rice, in kilograms;

Y_2 the total value of output of garlic, in pesos;

Y_3 the total value of output of maize, in pesos;

Y_4 the total value of output of mungbean, in pesos;

Y_5 the total value of output of other crops, in pesos.

D_1 is the dummy variable for garlic, with a value of 1 if $Y_2>0$ and 0 if $Y_2 = 0$;

D_2 is the dummy variable for maize, with a value of 1 if $Y_3>0$ and 0 if $Y_3 = 0$;

D_3 is the dummy variable for mungbean, with a value of 1 if $Y_4>0$ and 0 if $Y_4=0$;

D_4 is the dummy variable for other crops, with a value of 1 if $Y_5>0$ and 0 if $Y_5=0$;

D_5 is the dummy variable for chemicals, with a value of 1 if $X_5> 0$ and 0 if $X_5=0$.

v_{it}s are assumed to be independent and identically distributed with mean zero and variance σ_v^2;

$u_{it} = \{\exp[-\eta(t-T)]\}u_i$, where u_is are assumed to be independent and identically distributed non-negative truncations of the $N(\mu, \sigma^2)$ and η is an unknown parameter to be estimated.

Following Coelli and Perelman (1996) and Coelli and Fleming (2004), the input distances are predicted as:

$$d_i=E[\exp(u_i)|e_i] \text{ where } e_i = v_i-u_i. \tag{6}$$

The parameters of the model are estimated using the maximum likelihood estimation procedures in running the FRONTIER 4.1 program (Coelli 1996). Various hypothesis testing are carried out using the likelihood ratio test.

4. Results

4.1 Partial elasticities of inputs and outputs

The maximum likelihood estimates of the parameters of the translog stochastic input distance function given by equation (5) are presented in Appendix 1. Because the values of the explanatory variables were mean-corrected to zero, the first-order parameters are estimates of input and output elasticities. A summary of the estimates of input and output elasticities is presented in Table 3. Because of the restriction required for homogeneity of degree +1 in inputs, the estimated partial output elasticity for land (total area planted to crops) is 0.516. This estimate is plausible and consistent with the output elasticities estimated for other rainfed lowland areas in the Philippines. For example, Villano (2004) applied a translog stochastic frontier model in the rainfed lowland of Tarlac, Central Luzon, Philippines and obtained an output elasticity for land of 0.510.

Except for chemicals, all the elasticity estimates for inputs are significant at the one per cent level. All estimated coefficients fall between zero and one, which satisfies the monotonicity condition at the mean of inputs – all marginal products are positive and diminishing. Among the inputs other than land, fertiliser and labour showed the highest elasticity estimates at 0.181 and 0.161, respectively. This underlines the importance of these two inputs in the cropping systems. Farmers in Ilocos Norte use high levels of fertiliser because of the economic benefits derived from its application to high-value crops. High-value crop cultivation is very labour-intensive and large quantities of fertiliser, pesticide and irrigation are required.

The estimated partial output elasticity of seeds was found to be significant. We note that this variable is the total costs of seeds used in all crops grown. This variable is particularly important in the dry-season crops. Unlike in the case of rice, where farmers can collect seeds from their previous harvests, costs of seeds for dry-season crops are relatively expensive. For garlic, and sweet pepper, the best quality seed materials are selected from the farmer's harvest. Farmers who do not have sufficient seed materials for garlic and sweet pepper before the onset of the dry-season usually buy from the market where the cost is more than double the regular selling price.

Maize and tomato seeds are bought from seed companies. The elasticity implies that farmers would increase their output from seed input with the assurance of good quality seed materials, despite the high costs. Usually, farmers sow more seeds than what is needed for replanting purposes particularly, for sweet pepper, tomato and tobacco but also for rice.

The estimated output elasticity of power is low, but significant. Likewise, the estimated output elasticity for chemicals was found to be low but it was insignificant. Even without the threat of pest and disease infestation, farmers generally apply chemicals indiscriminately because they believe it is a protection mechanism. Ideally, we should have included a variable that captures the incidence of insects, pests and diseases infestation in addition to including the actual amount of chemical used. This is evidenced by the fact that the coefficient of the dummy variable for chemicals, ϕ_5, is significant.

Table 3. Estimates of input and output elasticities

Variable	**Estimated elasticity**	**Standard error**	***t*-value**
Inputs:			
Seeds	0.089	0.027	3.26
Fertiliser	0.181	0.041	4.45
Power [a]	0.051	0.020	2.54
Labour	0.161	0.035	4.62
Chemicals [b]	0.002	0.011	0.18
Outputs:			
Rice	- 0.317	0.030	-10.61
Garlic	-0.214	0.097	-2.22
Maize	0.138	0.070	1.96
Mungbean	-0.339	0.162	-2.09
Others [c]	-0.075	0.013	-5.59

[a] includes the cost of hiring tractor and animals, and fuel cost for land preparation and irrigation; [b] includes the active ingredients of insecticides, fungicides and herbicides; [c] include other crops such as tomato, sweet pepper, tobacco and vegetables.

The estimated partial elasticities of input for rice, garlic, mungbean and other crops are of expected sign and magnitude, and highly significant at one per cent level (Table 3). Because of our formulation of the input distance function in equation (5), we would expect the signs of the input elasticities for outputs to be negative. A negative elasticity estimate denotes a positive output response to a proportional increase in all inputs. These values show the impact of a proportional change of inputs to the outputs of rice, garlic, mungbean and other crops. For example, a 10 per cent increase in all inputs would increase rice output by approximately 3.2 per cent. The values of output of garlic, mungbean and other crops would increase by approximately, 2.1, 3.3 and 0.75 per cent, respectively. The result for maize was positive and significant at 10 per cent level. This is not expected, because it implies that the set of inputs as a whole would have a negative impact on the value of the output of maize. Two explanations are proffered for this unexpected result.

One explanation is that maize is grown partly as a subsistence crop and does not receive the attention that the other commercial crops receive when inputs are allocated. Another explanation concerns a decline in the yield of maize over the four-year study period. Maize output in 1997-98 was almost 14 per cent below the 5 million tonnes output in 1993-94 according to a Bureau of Agricultural Statistics (BAS) report. This decline may be attributed to pest infestation that is not captured in the specification of the model due to data constraints. Maize borer is a major pest in Philippine maize farmers, as attested by Teng, Fernandez, and Hofer (1992) and Logroño (1998). BAS data on the impact of maize borer on maize supply in the Philippines show that a high incidence of maize borer infestation could cause maize supply losses ranging from 74,000 tonnes to 164,000 tonnes over the 1980-1981 to 1997-1998 dry seasons. At a low incidence of maize borer infestation, maize supply losses could range from 26,000 tonnes to 64,000 tonnes.

The inverse of the sum of the output elasticities, α_1, α_2, α_3, α_4 and α_5 provides a measure of ray scale economies at the sample means (Coelli and Fleming 2004). The sum is 0.807, and the inverse is 1.24, suggesting increasing returns to scale. This implies that an increase in all inputs in the same proportion, *k*, leads to an increase of output of a proportion greater than *k*, a result that reflects the small scale of commercial operations on the surveyed farms, particularly on the individual parcels.

4.2 Technical efficiency estimates

Two sets of hypothesis tests on the technical efficiency estimates were undertaken using likelihood ratio tests. First, the null hypothesis of no technical inefficiencies in production (H_0: γ=0) was tested. The value of the log-likelihood ratio test statistic was 46.92 and this was found to be greater than the critical value of 8.54 obtained from Table 1 of Kodde and Palm (1986) for three restrictions. This implies that the technical inefficiency term (u_{it}) is a significant addition to the model. The value of γ=0.6988, suggests that almost 70 per cent of the disturbances are due to inefficiency and about 30 per cent due to stochastic events. Second, we tested if the technical inefficiency varies over time (H_0: η=0). The value of log-likelihood ratio test statistic was 4.4, which is greater than the critical value of 3.841. This result provides evidence of a change in the level of inefficiency over time, reflected in the significant negative value of η reported in Appendix 1.

The average technical efficiency over the four-year crop production is 0.68, with a minimum of 0.43 and a maximum of 0.94. These figures suggest that there is an opportunity to expand crop output without using more inputs or introducing new production technologies. The average annual technical efficiency estimates are 0.77, 0.73, 0.67 and 0.63 for the cropping years 1994-95, 1995-96, 1996-97 and 1997-98, respectively.

A plausible explanation for this decline in technical efficiency is that inefficient farmers were unable to attain the benefits of the technical progress that is evident from the positive coefficient for time trend, δ_1, of 0.085 (standard error 0.031). The more progressive farmers were shifting the frontier outwards over time, but some (possibly most) farmers were maintaining their current practices, making the latter group more inefficient in relative terms. That is, their farm performance was static while progressive farmers were improving their performance. We expect that technical inefficiency is enduring over time. Anecdotal evidence from extension officers suggests that farmers who use today's technology more efficiently are likely to use tomorrow's technology more efficiently too, and be quicker to adopt improved technologies that shift out the production frontier. Many technically inefficient farmers are also constrained by the inadequacy of the basic infrastructure and support services that could enhance the efficiency of both their production and distribution activities (Gonzales, Oliva and Leynes 1995).

A plot of the distribution of technical efficiency indices is presented in Figure 2. Thirty-one per cent of farmers fall within the 61-70 per cent range. There are only about 12 per cent of farmers who obtained an average technical efficiency of more than 80 per cent.

These variations in technical efficiency estimates can be attributed to several factors such as the demographic characteristics of farmers and tenurial status. Extension of this analysis, using the Battese and Coelli (1995) model to estimate an input distance stochastic frontier function with technical inefficiency effects, will be considered in the future.

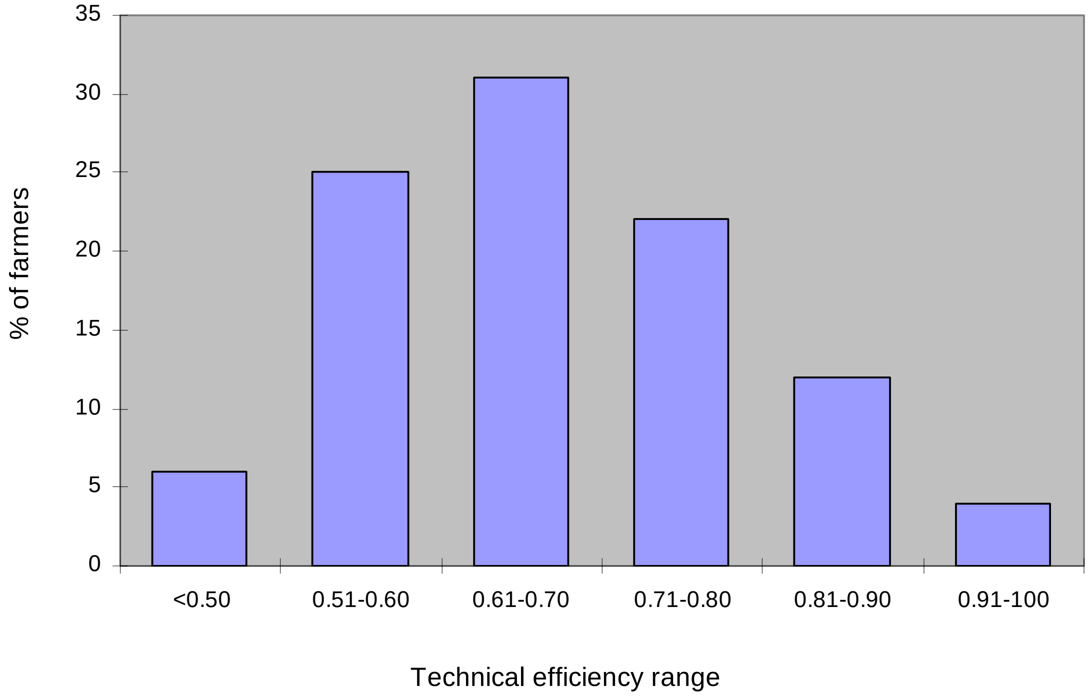

Figure 2. Distribution of technical efficiency indices of rainfed lowland farmers in Ilocos, Norte, Philippines.

4.3 Economies of scope estimates

The coefficient estimates of economies of scope with different crop combinations are presented in Table 4. These scope economies are obtained using equation (3) for each pair of outputs at the means of the sample data. Positive values of the estimated coefficients indicate scope economies and negative values indicate scope diseconomies. The corresponding standard errors of the estimates of scope economies computed using the Taylor series expansion are also reported in Table 4.

Table 4. Estimates of economies of scope in the rainfed lowlands of Ilocos Norte, Philippines

Output combinations	Estimated Coefficient	Standard error	*t*-value
Rice-Garlic	0.095	0.24	3.891
Rice-Maize	-0.032	0.015	-2.140
Rice-Mungbean	0.115	0.054	2.137
Rice-Other Crops	0.035	0.009	3.667
Garlic-Maize	-0.030	0.020	-1.499
Garlic-Mungbean	0.070	0.057	1.221
Garlic-Other Crops	0.015	0.021	0.725
Maize-Mungbean	-0.046	0.056	-0.828
Maize-Other Crops	-0.009	0.009	-0.917
Mungbean-Other Crops	0.025	0.055	0.462

Evidence of significant scope economies exists between rice and garlic, rice and mungbean, and rice and other crops. Garlic cultivation requires mulching, and the farmers use rice straw as mulching material. This mulching material is left on the field after the rice is harvested, and dug into the soil to improve it for garlic cultivation. Mungbean is a nitrogen-enhancing crop and its residue is also returned to the soil to improve soil fertility. The result of both mulching practices and nitrogen fixation is improved productivity and reduced costs to farmers engaged in these cropping patterns. There is weak evidence that scope economies exist between some crops grown in the dry season, such as between garlic, mungbean and other crops.

The estimated coefficient for rice and maize is negative and significant. As mentioned earlier, maize is a nitrogen-depleting crop with heavy fertiliser requirements. More fertiliser is applied to rice crops on parcels of land previously under maize, which increases cost. The combinations of maize with other dry-season crops also indicate (weakly) scope diseconomies, for the same reason.

In summary, our estimated coefficients provide some evidence that scope economies and diseconomies can occur in intensive rice-based mixed cropping systems.

5. Conclusions

This paper investigates economies of scope and technical inefficiency in a rainfed lowland mixed cropping system in the Philippines. An input distance stochastic frontier function was estimated using panel data collected from 100 randomly selected farmers. Evidence is provided of economies and diseconomies of scope and the extent of inefficiency in the production system. Significant scope economies exist between rice and mungbean, rice and garlic, and rice and other crops. Scope diseconomies were observed between maize and all other crops.

Significant technical inefficiency is observed in these highly intensive and commercialised cropping systems and it appears to have been increasing over the study period as the production frontier moved outwards. The average technical efficiency was 0.68, which suggests that there is an opportunity to expand crop output without using more inputs or introducing new production technologies.

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Appendix 1. Estimates of the Stochastic Distance Function

Variable	Coefficient	Estimated Coefficient	Standard error	*t*-value
Constant	β_0	1.262	0.480	2.630 [a]
Rice	α_1	-0.317	0.030	-10.608 [a]
Garlic	α_2	-0.214	0.097	-2.222 [a]
Maize	α_3	0.138	0.070	1.965 [b]
Mungbean	α_4	-0.339	0.162	-2.087 [a]
Other crops	α_5	-0.075	0.013	-5.592 [a]
Seed	β_1	0.089	0.027	3.255 [a]
Fertiliser	β_2	0.181	0.041	4.450 [a]
Power	β_3	0.051	0.020	2.544 [a]
Labour	β_4	0.161	0.035	4.624 [a]
Chemicals	β_5	0.002	0.011	0.183
Rice^2	α_{11}	-0.118	0.060	-1.980 [b]
Rice x Garlic	φ_{12}	0.027	0.010	2.812 [a]
Rice x Maize	φ_{13}	0.012	0.006	1.884 [b]
Rice x Mungbean	φ_{14}	0.007	0.008	0.884
Rice x Other crops	φ_{15}	0.011	0.006	1.922 [b]
Rice x Seed	φ^1_1	-0.103	0.043	-2.367 [a]
Rice x Fertiliser	φ^1_2	-0.012	0.063	-0.197
Rice x Power	φ^1_3	0.085	0.022	3.781 [a]
Rice x Labour	φ^1_4	-0.131	0.052	-2.527 [a]
Rice x Chemicals	φ^1_4	0.019	0.013	1.506
Garlic^2	α_{22}	0.037	0.025	1.508
Garlic x Maize	φ_{23}	0.000	0.001	-0.346
Garlic x Mungbean	φ_{24}	-0.003	0.002	-1.361
Garlic x Other crops	φ_{25}	-0.001	0.001	-0.835
Garlic x Seed	φ^2_1	0.015	0.012	1.283
Garlic x Fertiliser	φ^2_2	-0.015	0.016	-0.954
Garlic x Power	φ^2_3	0.002	0.006	0.276
Garlic x Labour	φ^2_4	0.019	0.010	1.884
Garlic x Chemicals	φ^2_5	0.009	0.004	2.400
Maize^2	α_{33}	-0.055	0.018	-3.069 [a]
Maize x Mungbean	φ_{34}	0.000	0.001	0.427
Maize x Other crops	φ_{35}	0.002	0.001	1.673 [c]
Maize x Seed	φ^3_1	0.002	0.006	0.293
Maize x Fertiliser	φ^3_2	-0.013	0.010	-1.314
Maize x Power	φ^3_3	-0.004	0.004	-1.033
Maize x Labour	φ^3_4	0.004	0.007	0.536
Maize x Chemicals	φ^3_5	0.001	0.002	0.456
Mungbean2	α_{44}	0.047	0.032	1.492
Mungbean x Other crops	φ_{45}	0.000	0.001	-0.201
Mungbean x Seed	φ^4_1	0.021	0.009	2.352 [a]
Mungbean x Fertiliser	φ^4_2	0.019	0.014	1.336
Mungbean x Power	φ^4_3	-0.003	0.005	-0.594
Mungbean x Labour	φ^4_4	-0.018	0.009	-1.968 [a]
Mungbean x Chemicals	φ^4_5	0.007	0.003	2.591 [a]
Other^2	α_{55}	-0.006	0.001	-5.760 [a]
Other crops x Seed	φ^5_1	0.009	0.006	1.441
Other crops x Fertiliser	φ^5_2	0.031	0.009	3.296 [a]
Other crops x Power	φ^5_3	-0.002	0.004	-0.434

Other crops x Labour	φ^5_4	-0.001	0.007	-0.115
Other crops x Chemicals	φ^5_5	-0.002	0.002	-0.861
Seed^2	β_{11}	-0.154	0.064	-2.393 [a]
Seed x Fertiliser	β_{12}	0.188	0.075	2.495 [a]
Seed x Power	β_{13}	-0.043	0.028	-1.516
Seed x Labour	β_{14}	-0.065	0.050	-1.309
Seed x Chemicals	β_{15}	-0.025	0.016	-1.628
Fertiliser^2	β_{22}	-0.018	0.147	-0.126
Fertiliser x Power	β_{23}	-0.115	0.039	-2.980 [a]
Fertiliser x Labour	β_{24}	0.057	0.088	0.649
Fertiliser x Chemicals	β_{25}	0.011	0.018	0.612
Power^2	β_{33}	0.052	0.012	4.151 [a]
Power x Labour	β_{34}	0.027	0.022	1.242
Power x Chemicals	β_{35}	0.018	0.006	2.922 [a]
Labour^2	β_{44}	-0.293	0.074	-3.963 [a]
Labour x Chemicals	β_{45}	-0.032	0.018	-1.808
Chemicals2	β_{55}	0.021	0.010	2.144 [a]
Year	δ_1	0.085	0.031	2.717 [a]
Year^2	δ_{11}	0.071	0.014	5.109 [a]
Dummy - Garlic	ϕ_1	-1.817	0.948	-1.917 [b]
Dummy - Maize	ϕ_2	1.384	0.579	2.392 [a]
Dummy - Mungbean	ϕ_3	-1.958	0.939	-2.084 [a]
Dummy - Other	ϕ_4	-0.460	0.121	-3.800 [a]
Dummy - Chemicals	ϕ_5	-0.356	0.143	-2.483 [a]
σ^2		0.079	0.015	5.172 [a]
γ		0.699	0.064	10.876 [a]
μ		0.468	0.102	4.583 [a]
η		-0.164	0.078	-2.108 [a]
Likelihood ratio test of the one-sided error		46.92		

φ^j_i *j* denotes output and *i* denotes inputs.[a,b,c]denotes significance at 1, 5 and 10 per cent levels, respectively.