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TECHNICAL EFFICIENCY AND FUTURE PRODUCTION GAINS IN INDONESIAN AGRICULTURE

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I. INTRODUCTION

During the 1970s and early 1980s, Indonesia experienced a "green revolution" in rice production. The combination of an attractive incentives environment, heavy infrastructural and institutional investment, and a readily adaptable biochemical technology package contributed to a dramatic expansion in rice production. After a period as the world's largest rice importer in the early 1980s, Indonesia has been largely self-sufficient in rice since 1985.

Despite the major successes in rice production, the current rice strategy cannot be sustained. The economy faces a period of fiscal austerity due to falling petroleum prices, the dollar's devaluation, rising interest rates, and a sizable foreign debt burden. Agricultural subsidies for fertilizer, irrigation water, and credit, established during a period of expanding petroleum revenues, have come under strong pressure as government searches for ways to increase microeconomic efficiency. Agricultural trade protection and public provision of agricultural marketing services have also come under question as government attempts to shift from an inward-oriented to a more neutral trade regime. These very subsidies and market controls, which accelerated adoption of the green revolution technology, now form a fiscal burden and face retrenchment.[1]

Hence, in an era of fiscal austerity and a liberal trade orientation, and with the major technological gains from the green revolution largely exhausted, Indonesian agriculture must search for new sources of growth and employment. In the medium term, one of the primary sources of future production gains will be consolidation of existing investments and more efficient use of resources within the current technological framework. In turn, improving this technical efficiency will require identification of efficiency gaps and the subsequent design and provision of services such as agricultural education and extension to raise farmers to the best practice frontier.

Other sources of future growth include diversification of production into commodities other than rice, since these commodities have largely untapped prospects

Senior authorship is not assigned. The results are not necessarily those of the World Bank or those of the National Marine Fisheries Service.

[1] See Damaradjata, Tabor, Oka, and David [3], Dixon [4], Hart [7], Hedley and Tabor [8], and Tabor [23].

for production gains and market expansion.[2] Unlike rice, the dryland or secondary food commodities (known in Indonesia as *palawija*), such as cassava, maize, mung beans, and peanuts, have experienced relatively little technological transformation, but continue to play an important role in the Indonesian food system. Improvements in *palawija* crop productivity and technical efficiency are another means of maintaining the agricultural sector's growth momentum.

The purpose of this paper is to assess the possibilities for future production gains in the Indonesian food economy by raising the technical efficiency of farmers. We examine the technical efficiency of a sample of Indonesian farms growing wet rice and the *palawija* crops, cassava, peanuts, and mung beans. In addition, we evaluate the relationship between technical efficiency, farm size, and location.

The paper is organized as follows. The next section discusses the possible relationship of technical efficiency and farm size in Indonesia. The third section develops the analytical approach and methodology. The fourth section provides the empirical results and the implications for policy formulation. The final section contains concluding remarks.

II. TECHNICAL EFFICIENCY, YIELDS, AND FARM SIZE

Empirical studies have often found that small farmers are as technically efficient as larger farmers if not more so [9] [15] [24]. This is surprising since other research results show that large farmers typically have higher educational levels, better access to credit, extension services, and other public services. Various reasons have been advanced to explain the greater technical efficiency of small farmers. It has been argued that small farmers might pay closer attention to their tasks, could utilize a more ecologically fine-tuned pattern of land cultivation and input application, could face fewer labor shortages, and might even use less sophisticated technology which has already "settled in." Smaller farms may also have less fragmented holdings, allowing more sustained management over a given resource base. To the extent that smaller farmers utilize family rather than hired labor, technical efficiency may be enjoyed through greater X-efficiency, lower supervision costs, or more individually tailored choice of technique.

In the case of Indonesia, where more than 50 per cent of the farmers cultivate holdings below a quarter of a hectare, an important question is whether the evolutionary process of land fragmentation has pushed holdings below the point where technical efficiency gains, through the processes cited above, are of any importance compared to the forces guiding resource allocation of plots too small to support normal household subsistence requirements. Little is known about the difference in technical efficiency between the small and very-small farm households.

In some studies, yields are used as a proxy for technical efficiency. Under this framework, Hart [7] and Keuning [14] identified an inverse relationship between

[2] Fiscal austerity limits capital formation and increased usage of purchased inputs, wet rice expansion on and off Java is limited, and increased labor usage faces strong diminishing returns, particularly in densely populated Java. Hence, expanded input usage, while important, has limits as a source of growth in the near future.

rice yields and farm size for rice. Both authors found that the small farms used, on a per hectare basis, relatively more labor and intermediate inputs than did the larger farmers. Other factors cited as possibly playing a role in the productivity difference included differences in land type, climate, and cultivation technique.[3]

Whether or not different size categories of farms have different technical efficiency characteristics is an important matter for policy formation. To the extent that the technical efficiency gap is primarily a problem of the larger farms, government could target extension services specifically to these groups. To the extent that technical efficiency problems are more broadly based, little gain would be made from targeting such services.

III. APPROACH AND METHODOLOGY

In this section, we discuss procedures for econometric assessment of technical efficiency. The distribution of technical efficiency measures is an indicator of the degree to which agricultural productivity and output can be raised by a process of guiding farmers toward the best practice frontier. The measures of technical efficiency are associated with scale and location measures to assess whether socioeconomic and geographical targeting would provide a useful means of allocating investment in agricultural extension, education, and adaptive research of existing varieties.

A. *Technical Efficiency*

A farmer's technical efficiency measures the ability to produce the maximum output possible from a given set of inputs and production technology. Technical efficiency is a relative concept since each farm's production performance is compared to a best-practice input-output relationship. Herdt and Mandac [9] measured farm efficiency relative to best-practice techniques determined by a researcher's performance in a farmer's field. Usually, however, the best-practice performance, or production frontier, is established by the practices of the most efficient farmers. Technical efficiency is then measured as the deviation of individual farmers from this best-practice frontier.

This best-practice frontier is assumed to be stochastic, with a corresponding two-sided error term, in order to capture exogenous shocks beyond the control of firms. Since all farms are not able to produce the frontier output, an additional one-sided error term is introduced to represent technical inefficiency. This approach contrasts with the production function usually estimated, which provides an average relationship between output and inputs over the entire sample, and in which a single, two-sided error term captures the stochastic influences and unobserved input usage.

[3] Verma and Bromley [24] review the argument that land quality declines as the size of the holding increases.

B. *Stochastic Production Frontier*

We estimate the production frontier by the stochastic frontier approach, which may be written [1]:[4]

$$Y_i = h(X_1, X_2, \ldots, X_N, A)e^{\Phi i}, \qquad i = 1, \ldots, M, \tag{1}$$

where Y_i is the output of the ith of M farmers, X_j is the jth of N inputs, A represents a vector of parameters, e is the exponential operator, and Φ_i is a farm-specific error term.

The error term Φ_i is composed of two independent components: $\Phi_i = V_i - U_i$, $i = 1, \ldots, M$. The symmetric component, V_i, represents random variation in output due to factors outside the farm's control (such as weather and disease), measurement error, and statistical noise. It allows the deterministic frontier production frontier to be stochastic. The technical efficiency relative to the stochastic frontier, $e^{-Ui} = Y_i / [h(X_1, \ldots, X_N, A)e^{Vi}]$, is captured by the one-sided error component $U_i \geq 0$. When $U_i = 0$, production lies on the stochastic frontier and is technically efficient, and when $U_i > 0$, production lies below the frontier and is technically inefficient.

It is assumed that the symmetric error V_i is independently and identically distributed as $N(0, \sigma_V{}^2)$, and that the non-negative error U_i is distributed as the absolute value of a normal distribution, $|N(0, \sigma_U{}^2)|$, i.e., half-normal, and that $\sigma^2 = \sigma_V{}^2 + \sigma_U{}^2$. Define $\delta = \sigma_U{}^2/\sigma_V{}^2$. The more δ is greater than one, the more production is dominated by technical inefficiency, while the closer it is to zero, the more the discrepancy between the observed and frontier output is dominated by random factors beyond the control of the farmer.

Technical efficiency for the individual farmer, e^{-Ui}, requires estimation of the non-negative error term U_i, decomposing Φ_i into the individual components U_i and V_i. Jondrow, Lovell, Materov, and Schmidt [12] suggested a decomposition method from the conditional distribution of U_i given Φ_i. Given the normal distribution of V_i and the half-normal distribution of U_i, the conditional mean of U_i given Φ_i is:

$$E[U_i \mid \Phi_i] = \frac{\sigma_U \sigma_V}{\sigma}\left[\frac{f(\Phi_i\delta/\sigma)}{1 - F(\Phi_i\delta/\sigma)} - \frac{\Phi_i\delta}{\sigma}\right], \tag{2}$$

where $f(\cdot)$ and $F(\cdot)$ are the values of the standard normal density function and the standard normal distribution function estimated at $\Phi_i\delta/\sigma$ and $\delta = \sigma_U{}^2/\sigma_V{}^2$. The measure of individual technical efficiency is then calculated as $TE_i = e(-E[U_i|\Phi_i])$, $i = 1, \ldots, M$, where Φ_i is replaced by its estimate and $0 \leq TE_i \leq 1$. This measure represents the technical efficiency of farmer i relative to the practices of the

[4] While a number of alternative approaches are available to analyze technical efficiency, the stochastic frontier approach is often recommended because it is the only one which allows deviation of an observation from the frontier due to both technical inefficiency and random noise. Without such accommodation, statistical noise is counted as inefficiency. For a recent survey, see Lovell and Schmidt [17].

best farmers: the closer TE_i lies to 1 (0), the closer (further) the technical efficiency of farmer i to the best-practice production frontier.

C. *Model Specification and Estimation*

A farm-level translog stochastic production frontier is estimated for wet rice in Java, wet rice off Java, and cassava, mung beans, and peanuts throughout Indonesia for 1983.[5] The translog stochastic frontier is specified for each commodity as:

$$\ln Y = A_0 + \sum_{j\in 3} A_j \ln X_j + \sum_{j\in 3}\sum_{k\in 3} A_{jk} \ln X_j \ln X_k + \Phi. \tag{3}$$

The output Y is defined as kilograms of the commodity per farm, except for mung beans, where total value in rupiah is used. The inputs per farm X_j are defined as: (1) Land = area in square meters per farm; (2) Labor = total number of labor-days per farm; and (3) Other = a Divisia index of intermediate inputs per farm in kilograms of seeds and the fertilizers, TSP (trisodium phosphate), KCL (potassium chloride), urea, and organic. Labor is a Divisia index of family and hired labor for the following categories of labor: land preparation, planting fertilizing, weeding, irrigation, harvest and post-harvest, and tractor rental and animal hire.[6]

D. *Data*

The data are primary farm management survey records collected routinely by extension agents of the Ministry of Agriculture. Each farm management survey includes information on farm size, cost of cultivation, production, sales price, and marketing arrangements. Every month, field level extension agents complete between five to ten surveys of farm enterprises in randomly selected farm households. Since the distribution of extension agents is approximately proportional to the distribution of agricultural households (far more in Java, very few in Irian Jaya), the sampling frame is approximately proportional to the distribution of farm households. On average, nearly 5,000 questionnaires are collected each year and tabulated at the Ministry of Agriculture in Jakarta.

For this investigation, a random selection of 1,800 questionnaires was taken from the 1983 sample. The year 1983 was selected because the government specially invested project resources to supervise the collection of this farm management data and because of the lack of any major production disturbance. Of the 1,800 questionnaires, approximately 40 per cent were eliminated because observations were incomplete, the values recorded were outside technically feasible limits, or the values were illegible. Of the remaining questionnaires, those for wet rice,

[5] The areas include: West, Central, and East Java; Yogyakarta; Aceh; North, West, and South Sumatra; Bengkulu; Riau; Lampung; South, West, and Central Kalimantan; South, North, and Central Sulawesi; Bali; Maluku; Nusa Tenggara Barat; and Irian Jaya.

[6] Through separability testing with the translog form, Squires and Tabor [22] found that family and hired labor are separable from the other inputs, and hence an aggregate labor index exists.

TABLE I
PARAMETER ESTIMATES OF STOCHASTIC PRODUCTION FRONTIER

Variable	Wet Rice Java	Wet Rice off Java	Cassava	Peanuts	Mung Beans
Intercept	8.868*	−24.675*	−3.739	−12.078	15.773*
	(2.879)	(3.831)	(6.815)	(10.570)	(4.228)
Labor	0.416	−0.659*	−1.846	−1.466	−0.934
	(0.403)	(0.342)	(1.362)	(1.315)	(1.101)
Other	−0.128	−1.502*	0.212	−1.184	1.035
	(0.323)	(0.425)	(0.542)	(1.340)	(0.638)
Land	−0.944	7.446*	2.862	4.499	−1.594
	(0.610)	(0.906)	(1.690)	(2.833)	(1.287)
Labor squared	0.034	−0.019*	0.042	0.033	−0.141
	(0.032)	(0.008)	(0.104)	(0.088)	(0.191)
Other squared	0.030	−0.029	0.028*	0.039	0.110*
	(0.022)	(0.028)	(0.014)	(0.071)	(0.037)
Land squared	0.088*	−0.438*	−0.158	−0.286	0.135
	(0.034)	(0.053)	(0.110)	(0.203)	(0.101)
Labor•Other	−0.085*	−0.088*	0.027	−0.114	0.034
	(0.034)	(0.023)	(0.047)	(0.136)	(0.076)
Labor•Land	−0.020	0.115*	0.209	0.222	0.208
	(0.042)	(0.040)	(0.175)	(0.206)	(0.208)
Other•Land	0.031	0.231*	−0.054	0.153	−0.198*
	(0.036)	(0.049)	(0.067)	(0.189)	(0.103)
δ	1.338*	1.850*	1.685*	0.839	3.017
	(0.111)	(0.334)	(0.550)	(0.739)	(1.963)
$\sigma^2=\sigma_U^2+\sigma_V^2$	0.661*	0.535*	0.885*	0.749*	0.911*
	(0.019)	(0.036)	(0.096)	(0.146)	(0.143)
Number of observations	489	323	161	177	69

Notes: 1. Translog functional form.
2. Standard errors are in parentheses.
3. Maximum likelihood estimates assuming half-normal error term.
4. Total revenue is used as dependent variable for mung beans equation.

* Statistically significant at the 5 per cent level.

cassava, mung beans, and peanuts were analyzed. The staff of the Ministry of Agriculture coded, cleaned, and computerized the data.

IV. EMPIRICAL RESULTS

To examine technical efficiency, the translog production frontier (3) is estimated for each commodity by maximum likelihood assuming a half-normal distribution for U_i. The parameter estimates are reported in Table I.[7]

[7] Parameter estimates from flexible functional forms such as the translog have little meaning in themselves. Hence, caution must be exercised in their interpretation.

The ratio δ of the standard error of U_i to that of V_i given in Table I is statistically significant at 5 per cent and greater than one for wet rice on and off Java and for cassava throughout Indonesia. The discrepancy between the observed and frontier output for these commodities as a whole is dominated by technical inefficiency rather than by random factors beyond the farmer's control.[8] These findings suggest that there is considerable scope for expanding production and raising efficiency by improving farmers' technical management abilities.

It is not surprising that there is ample opportunity to raise technical efficiency in the production system for high yielding rice varieties. In contrast to traditional rice varieties, modern rice technology increases the importance of such activities as water control, fertilizer and pesticide application, and weeding. Hence, considerable time may elapse before farmers learn to most efficiently produce under the green revolution technology. To the extent that incremental technical change, such as introduction of more disease or pest resistant varieties, is an on-going process, the production frontier continually expands and technical efficiency lags behind.

For rice and cassava, there are clear opportunities to realize important production gains without introducing new technological regimes or even incremental technical change; considerable production gains can still be enjoyed simply by utilizing the existing inputs and technology more efficiently.

The ratio δ is statistically insignificant at the 5 per cent level of significance for mung beans and peanuts, suggesting that for each of these commodities as a whole, the statistical noise dominates the technical inefficiency. The discrepancy between the observed and frontier output appears to be due primarily to random factors beyond the control of individual farmers.[9] Nonetheless, as indicated below, technical inefficiency does appear to exist for some individual mung bean and peanut farmers. Hence, judiciously allocated public assistance would help increase their output.

It is not surprising that differences in technical efficiency for mung beans and peanuts appear related to random factors. These foodcrops are relatively unimportant by government of Indonesia standards, and the great majority of producers rely on varieties produced within their immediate surroundings [11]. Hence, there is little apparent gain from advancing technical efficiency for these two crops as a whole, since the predominant technology is rudimentary to begin with and this technology is well settled in. Development of new technologies offers the best source of future production gains, while encouraging marginal managerial changes to attain best practices is a lesser priority.

[8] In contrast, using a linear production function, Esparon and Sturgess [6] found technical efficiency for wet rice production in West Java. Similar to our finding, Siregar [20], using a Cobb-Douglas form, found technical inefficiency for wet rice in West Java, and Soekartawi and MacAulay [21] found technical inefficiency in wet rice production in East Java.

[9] Because mung beans and peanuts are secondary food crops of lesser importance than wet rice and even cassava, we would expect a wide distribution of technical efficiency. However, because these secondary crops are of lesser importance, measurement error is also possible, so that the apparent white noise may include measurement error. The large apparent white noise could then provide a misleading result. Because of this possibility, we continue to evaluate the technical efficiency of these two crops.

TABLE II

FREQUENCY DISTRIBUTION OF TECHNICAL EFFICIENCY BY CROP

Efficiency Interval	Wet Rice Java	Wet Rice off Java	Cassava	Peanuts	Mung Beans
0.95–	0	0	0	0	0
0.90–0.94	3 (0.61)	4 (1.24)	0	0	0
0.85–0.89	8 (1.64)	26 (8.05)	1 (0.62)	0	3 (4.35)
0.80–0.84	31 (6.34)	64 (19.81)	8 (4.97)	12 (6.78)	4 (5.80)
0.75–0.79	108 (22.09)	50 (15.48)	9 (5.59)	32 (18.08)	5 (7.25)
0.70–0.74	132 (26.99)	50 (15.48)	13 (8.07)	45 (25.42)	8 (11.59)
0.65–0.69	98 (20.04)	39 (12.07)	26 (16.15)	37 (20.09)	6 (8.70)
0.60–0.64	59 (12.07)	30 (9.29)	27 (16.77)	27 (15.25)	6 (8.70)
0.55–0.59	18 (3.68)	13 (4.02)	15 (9.32)	12 (7.91)	5 (7.25)
0.50–0.54	11 (2.25)	15 (4.64)	20 (12.42)	6 (3.39)	7 (10.14)
0.40–0.49	9 (1.84)	20 (6.19)	18 (11.18)	5 (2.82)	7 (10.14)
0.30–0.39	3 (0.61)	10 (3.10)	12 (7.45)	6 (3.39)	7 (10.14)
0.10–0.29	9 (1.84)	2 (0.62)	12 (7.45)	0	11 (15.94)
Mean	0.697	0.704	0.575	0.687	0.552
Median	0.715	0.734	0.608	0.700	0.591
Minimum	0.146	0.246	0.134	0.332	0.119
Maximum	0.949	0.946	0.883	0.847	0.893
Std. Dev.	0.108	0.134	0.158	0.086	0.204

Note: Percentages are in parentheses.

The frequency distributions of technical efficiency for each farm by crop are reported in Table II, where class frequency percentages are given in parentheses. The arithmetic sample means, medians, minimum and maximum values, and standard deviations for each crop are also reported. Production of irrigated rice, both on and off Java, displays both the highest individual and mean efficiency measures, and generally a greater proportion of farmers with higher efficiency measures. This result undoubtedly reflects the greater attention wet rice farmers have received by the public sector and the importance of wet rice to the Indonesian agricultural economy. Similarly, reflecting the lesser attention and economic importance of the *palawija* crops, the mean technical efficiency measures are lower,

TABLE III

MEDIAN TECHNICAL EFFICIENCY BY FARM SIZE AND CROP

Farm Size (ha)	Wet Rice Java	Wet Rice off Java	Cassava	Peanuts	Mung Beans
0.00–0.19	0.893	—	0.539	0.755	0.402
0.20–0.39	0.695	0.704	0.609	0.698	0.569
0.40–0.59	0.718	0.751	0.583	0.705	0.627
0.60–0.79	0.713	0.778	0.642	0.690	0.546
0.80–0.99	0.711	0.848	0.614	0.766	—
1.00–1.49	0.727	0.713	0.651	0.700	0.566
1.50–1.99	0.708	0.807	0.746	—	0.580
2.00–	0.743	0.697	0.364	0.665	—

and generally a larger proportion of farmers operate in the lower efficiency ranges. Cassava and mung beans display the lowest mean technical efficiency measures. This suggests significant scope for expanded production of rice and the *palawija* crops by using the existing technology more efficiently, although as noted above, efforts to promote rapid technological change in mung bean and peanut production may offer larger production gains.

A. *Technical Efficiency and Farm Size*

Table III reports the median measures of technical efficiency by crop and farm size (measured in hectares). The distributions of the technical efficiency measures appear fairly constant across farm size for each crop.

To statistically test whether individual farmer technical efficiency measures varied by farm size and region, we applied covariance analysis. Ekayanake [5] noted that by definition technical efficiency (*TE*) is bounded between zero and one, and therefore cannot be assumed as normally distributed. We follow his approach, and use as a dependent variable the transformation $T = \ln[TE/1 - TE]$, which varies between $-\infty$ and $+\infty$. This transformation of the technical efficiency measure was regressed upon an intercept, dummy variables for areas, and the continuous farm size measure. When appropriate, we applied White's [25] procedure to correct for a general, unknown form of heteroscedasticity.

Table IV reports these regression results for wet rice on and og Java. The regression equations were statistically insignificant at 5 per cent for mung beans, peanuts, and cassava, and are consequently not reported. The *t*-ratios for wet rice farm size both on and off Java are statistically insignificant at the significance level of 5 per cent.

The regression results for all commodities (including those that are not statistically significant) indicate that technical efficiency is not significantly related to farm size. The empirical evidence indicates that higher yields on smaller farms are not due to greater technical efficiency, and that the more intensive labor utilization on smaller farms is not applied with more technical efficiency than labor application on the larger farms. In other words, the internal structure of farm firms as it affects technical efficiency does not vary significantly by farm size,

TABLE IV

COVARIANCE ANALYSIS OF TECHNICAL EFFICIENCY DIFFERENCES BY FARM SIZE AND REGION

Variable	Coefficients	
	Wet Rice Java	Wet Rice off Java
Intercept	0.891* (0.036)	1.017* (0.101)
Farm size (ha)	−0.002 (0.028)	−0.069 (0.071)
Regional dummy variables:		
Yogyakarta	−0.351* (0.091)	
Central Java	0.008 (0.040)	
East Java	−0.059 (0.055)	
Kalimantan		−0.491* (0.109)
Sulawesi		0.191* (0.098)
Bali		0.084 (0.151)
Nusa Tenggara Barat		0.108 (0.195)
R^2	0.033	0.178

Notes: 1. Standard errors are in parentheses.
2. Heteroscedastic covariance consistent estimates.

* Statistically significant at the 5 per cent level.

after controlling for regional variation. This result is similar to those of Huang and Bagi [10] and Sidhu [19] for the Punjab, Esparon and Sturgess [6] in West Java, and Kalirajan [13] in India, but contradicts those of Lau and Yotopoulos [15] for India and Herdt and Mandac [9] for the Philippines.

While considerable scope exists for improved production relative to best practice techniques, efforts to improve existing management practices, extension services, education, and the like cannot be readily improved simply by targeting interventions to different sized farms. There is also no compelling reason to promote consolidation of smaller farms into large farms to improve technical efficiency. Conversely, land ceilings are not required for technical efficiency purposes.

B. *Technical Efficiency and Regions*

Technical efficiency might also vary by region. Keuning [14] noted marked regional differences throughout Indonesia for all food crops of cropping intensities, land productivity, and labor input; technical efficiency could similarly have wide spatial variability. As indicated by F-tests for regional dummy variables as a group, technical efficiency does not vary by region for wet rice on Java but does off Java.[10] The individual t-ratios for the different regions in Java indicate that technical efficiency is lower for wet rice in Yogyakarta than in West Java, but that the technical efficiency in Central or East Java equals that of West Java. The individual t-ratios for the individual islands off Java indicate that technical efficiency is lower in Kalimantan than for Sumatra, but that technical efficiency in Bali, Sulawesi, or Nusa Tenggara Barat equals that of Sumatra at the 5 per cent level of significance. Thus, after controlling for farm size, technical efficiency has surprisingly little area variation in Indonesia. Along similar lines, Booth [2] noted that any important regional disparities in yields on Java for wet rice and secondary food crops appears to have evened out. Should priorities be established for allocation of scarce public resources to improve technical efficiency, Yogyakarta and Kalimantan might receive some of the first attention, but on the whole, such public resources can be evenly applied.

The low R^2 values for the regression equations indicate that a number of factors other than farm size and location explain differences in technical efficiency. Unfortunately, data limitations preclude further investigation along these lines. Nonetheless, experience would suggest that extension and education, or more generally, information and investment in human capital, make substantial contributions to improving farm efficiency by shifting farmers toward the production frontier.[11]

Several possibilities exist for improving technical efficiency in Indonesian agriculture. The special extension program, Insus, introduced in 1979, has evolved to become the super-special intensification program, Supra-Insus, unveiled in 1988. Under these intensification programs, farmers are encouraged to apply improved chemical input packages, carefully manage water resources, synchronize planting, rotate varieties, utilize modern post harvest equipment, and manage production and product sales on a cooperative basis. These programs have yet to reach more than a minority of rice farmers and, for all practical purposes, do not function for the *palawija* farmers. In the case of both rice and cassava, improving the coverage of these programs would appear to hold important promise as a means of guiding farmers toward the best practice frontier. Mass media outreach efforts may also contribute to raising technical efficiency levels, given Indonesia's vast distances and broad-based national radio and telecommunications system.

V. CONCLUDING REMARKS

The policies designed to enhance technical efficiency differ from those designed to promote rapid and qualitatively different technological change. With the general

[10] Against the null hypothesis of no differences in technical efficiency between regions, the F-test statistics, with numerator and denominator degrees of freedom in parentheses, are $F(3, 484) = 0.874$ for wet rice on Java, indicating non-rejection at 5 per cent, and $F(4, 317) = 6.242$ for wet rice off Java, indicating rejection at the 5 per cent level of significance.

[11] See Ekayanake [5], Herdt and Mandac [9], Lockheed, Jamison, and Lau [16], and Shapiro and Muller [18].

diffusion of the green revolution wet rice technology largely completed, and with limited prospects for the introduction of comparable technological change for *palawija* crops, further technological advance for production of wet rice and *palawija* crops is likely to be incremental and more slowly paced. Such technical change will most likely come through further refinements in varieties and their adaptation to local conditions.

Indonesian policymakers will be struggling with the challenge of continuing economic growth while maintaining food security and generating new productive employment opportunities for a rapidly growing labor force. While Indonesia has successfully stimulated agricultural growth through a process of technological transformation, principally in wet rice, coupled with an active price policy and generous subsidies, the opportunities for further agricultural growth based on significant technological change have largely been exhausted. Moreover, the tight fiscal situation caused by declining petroleum rents limits the resources available to promote growth based on different technological regimes, rapid technological change, and sizable increases in input usage.

In an era of budgetary austerity and limited new technological opportunities, more efficient resource allocation that raises farmers' technical skills and managerial abilities offers an important opportunity for gains in production, incomes, and employment. Enhancing technical efficiency would also help consolidate past extensive investments in research, extension, irrigation, and infrastructure supporting the green revolution.

The results from this study indicate that raising farmers' technical efficiency can be an important source of production gains, particularly for irrigated rice and cassava, and less so for the secondary food crops. In one sense, raising production by encouraging greater technical efficiency is a way of completing the process of technical change which began with the use of new high yielding rice varieties. In another sense, raising technical efficiency levels of Indonesian farmers, by augmenting management and skills, provides the basis for future technological change and, by advancing competitive abilities, more efficient allocation of existing resources.

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