ECONOMIC EFFICIENCY OF SMALL FARMERS IN A CHANGING WORLD: A SURVEY OF RECENT EVIDENCE

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Abstract: The growing literature on economic efficiency of farmers in Third World agriculture is reviewed with emphasis on conceptual and methodological issues, and empirical results of studies aimed at measuring technical efficiency. While substantial methodological progress has been made in measuring inefficiency, important conceptual problems remain. Results from regions undergoing rapid technological change suggest substantial technical inefficiencies, of the order of 30 per cent, as well as allocative inefficiencies on the use of purchased inputs. Most studies are able to relate levels of inefficiency to farmers’ information and skills, and input supply problems. The results suggest that further improvements in productivity in Green Revolution areas will need to give more emphasis to exploiting the technical efficiency gap through adaptive research, extension, farmer education, and improved input supply.

1 INTRODUCTION

One of the enduring themes in development thought over the past two decades has been Schultz’s (1964) ‘poor-but-efficient’ hypothesis — that is, that small farmers in traditional agricultural settings are reasonably efficient in allocating their resources and respond positively to price incentives. Although Schultz’s thesis has been challenged from some fronts (e.g., Adams, 1986; Nair, 1979; Lipton, 1968), it has been widely accepted by both economists and policy makers.

The level of efficiency of small farmers has important implications for development strategy. If farmers are reasonably efficient, then increases in productivity require new inputs and technology to shift the production function upward. Hence Schultz’s hypothesis provided the theoretical justification for the ‘high payoff’ or ‘science-based’ strategy of agricultural development as exemplified by the Green Revolution. On the other hand, if there are significant opportunities to increase productivity through more efficient use of farmers’ resources and inputs with current technology, a stronger case can be made for institutional investments in input delivery, infrastructure,
extension systems, farm management services, and farmers' skills in order to promote efficiency of resource use at the farm level.

In fact, agricultural development strategies over the past three decades have alternated between these divergent views. In the 1950s, the community development model, which emphasized extension, was in vogue (Staatz and Eicher, 1984). The failure of the community development model was widely attributed to the lack of useful technology to extend to farmers. In the 1960s, the pendulum swung toward investment in agricultural research, which eventually produced the new wheat and rice varieties that were widely adopted during the Green Revolution in Asia. The emphasis on research continued through the 1970s when expenditures on agricultural research in Asia tripled while expenditures in extension declined in real terms (Table 1). Preliminary evidence from the 1980s suggests that growth in research expenditures has slowed considerably while extension may be getting more emphasis, especially through the Training and Visit system sponsored by the World Bank (Byerlee, 1987).

In practice, the two approaches — technology development and transfer versus more efficient use of available technology and resources at the farm level — are likely to be a continuum in the development process, as Shultz (1975) himself argued a decade after the publication of his 'poor-but-efficient' hypothesis. A major rationale for assuming efficiency of small farm agriculture is that farmers in a traditional agriculture depend largely on their own resources and have had a long period to adjust and fine-tune their management to the most efficient use of these resources in their environment. However, in a dynamic agriculture, characterized by a continually changing technical and economic environment, farmers find it more difficult to adjust allocative decisions to keep pace with changes in their environment and, at the same time, maintain an efficient allocation of resources. Farmers in this situation are likely to be in a continual state of disequilibrium, and there will be high returns to improving their information and skills to help them to adjust more rapidly and reduce technical and allocative errors. Since farmers in a technically dynamic agriculture depend much more on use of purchased inputs, hired labour, and machinery services, farm support systems such as input delivery, infrastructure and its management, and extension and credit services must also adjust continuously to new demands. Much of

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1 In fact, this argument was made, albeit less forcefully, in later chapters of *Transforming Traditional Agriculture* (Schultz, 1964).
Third World agriculture, particularly in Asia, which was characterized two decades ago as traditional, has now entered a post-Green Revolution phase in which decisions are made in a dynamic, technical and economic environment.

This paper reviews evidence accumulated over the past decade on the economic efficiency of small farmers in the Third World, emphasizing those regions that have undergone rapid change due to introduction of new technology. Such a review is timely for a number of reasons. First, as mentioned earlier, agriculture in much of the Third World has experienced profound changes and can no longer be classified as traditional. In this new situation, the scope for inefficiencies in resource use is much greater and hence development strategy may need to be re-examined. Second, the analysis of economic efficiency in agriculture has been broadened from the earlier emphasis by Schultz (1964) and others on allocative efficiency, to consider also technical efficiency — that is, the productivity of a given mix of inputs. Also efficiency is now viewed more in terms of system performance, including farmers and farm support systems, rather than focusing narrowly on farmer rationality. Finally, in recent years there have been important methodological developments in measuring economic efficiency that may provide improved empirical estimates of the level of inefficiency.

This survey is organized in four parts. First, we briefly review the conceptual basis for defining the likely conditions for the existence of economic inefficiencies and their policy relevance. Second, we summarize methodological approaches to measuring inefficiencies although no attempt is made to provide a comprehensive review. Third, we review the evidence on levels of inefficiency and the factors explaining inefficiencies in Third World agriculture, with particular reference to Asia. Finally, we conclude with a brief discussion of the implications for development strategies aimed at improving the efficiency of small farm agriculture.

2 ECONOMIC EFFICIENCY: CONCEPTUAL ISSUES

Definition of Economic Efficiency

Following the pioneering work of Farrell (1957), economic efficiency is usually disaggregated into two types: a) technical efficiency and b) price or allocative efficiency. Technical inefficiency refers to failure to operate on the production frontier (QR/OR in Figure 1, where R is the current level of inputs, X1 and X2, to produce output, Y0, and Q is the level of inputs needed to produce Y0 on the production frontier). The production frontier may be defined in terms of the highest production achieved from a given level of inputs in a population of farmers, or it may be defined by reference to a potential frontier based on experimental data.

Allocative inefficiency generally refers to failure to meet the marginal conditions for profit maximization. The usual test for allocative efficiency is to compare the MVP of an input to its normalized price. A more constraining case is to define allocative inefficiency only in terms of factor-factor space — that is failure to operate on the expansion path. By this definition, allocative errors would be measured by PQ/OQ in Figure 1, where C0 is the budget constraint, to give total economic efficiency of PR/
Figure 1. Definition of technical inefficiency (QR/OR) and allocative inefficiency (PQ/OQ) following Farrell (1957).

OR. If there are fixed factors or economies of scale, further allocative gains might be made by movement along the expansion path to the profit maximization point, S in Figure 1. These we will refer to as scale errors. In a multiproduct firm, allocative errors may also arise in output-output space due to the choice of enterprise mix. In this survey, we will focus on the conceptually simpler case of single-product firms.

The definition and measurement of economic inefficiency is very dependent on the specification of the production process. Assume the following generalized production function:

\[ Y = f(X, E) \]  

(1)

where X is the matrix of inputs (both variable and fixed) controlled by farmers and E is the matrix of environmental variables such as soil type and rainfall that are not controlled by the farmer and may only be known with a certain probability distribution at the time of making the decision on X. The estimation of technical and economic inefficiency is conditional on four important decisions in the specification of this production function:

1. If E variables are not included in the function, then firm-specific variation in productivity due to environmental factors may wrongly be attributed to inefficiency. In agriculture, microclimatic variation in soils and rainfall are particularly important and omission of E variables is likely to lead to serious misspecification and overestimation of technical efficiency.

2. The X variables may be specified at various levels of aggregation.
Consider the following three levels:

(a) All inputs that are not perfect substitutes are specified individually (e.g., nitrogen, phosphorus, harvesting labour, transplanting labour, weeding labour, etc.) and the timing and method of application of each of these inputs, as well as their levels, are also included in the specification.

(b) All inputs that are not perfect substitutes are specified individually in terms of their levels but no variables for timing and method of application are included.

(c) Inputs are specified in aggregate categories such as land, labour, capital, and purchased inputs.

In the first case, there would be no technical inefficiency and only allocative inefficiency is measured (Stigler, 1976). In the third specification, on the other hand, the estimated technical inefficiency includes both technical inefficiency plus allocative errors between individual inputs within the aggregate categories of inputs. This can be seen in Figure 2 where farmers purchase two types of fertilizer, nitrogen and phosphorus. If the farmer is operating at Q in Figure 2a, only allocative inefficiency, \(\frac{PQ}{OQ}\), is present. (That is, too much nitrogen relative to phosphorus is applied). If, however, only aggregate fertilizer expenditure is entered into the production function, these allocative errors are represented as technical inefficiency, \(\frac{RS}{MS} = \frac{PQ}{OQ}\) in Figure 2b. Hence, although total economic inefficiency may be similar in each specification, the partitioning of this inefficiency between technical and allocative may be quite sensitive to the level of aggregation. Clearly the preferred specification of the frontier function is that which includes the level, but not the timing and method, of each input that is not a perfect substitute for another. Variation from the frontier can then be explained in terms of the timing and method of using inputs, which is consistent with Farrell’s (1957) original definition of technical inefficiency.

Similar problems of delineating technical and allocative efficiency arise in output-output space in multicommodity firms when a whole farm production function is estimated. However, whole farm production functions are not well suited to represent complex farming systems characterized by several enterprises with strong interactions between them (Upton, 1979), and hence we focus our survey on the analysis of single-commodity production processes.

3. Some of the input variables (X) are likely to be fixed factors in the short run. Treatment of these fixed factors as variable inputs will tend to bias the measure of technical inefficiency upwards (Grosskopf, 1986; Russell and Young, 1983).

4. Technical efficiency is usually assumed to be independent of prices. However, if we assume firm-specific prices and technology (Yotopoulos et al., 1970), technical inefficiency can only be defined in terms of prices. Hence a broader definition of technical efficiency is the ability of a firm to select an appropriate technology given the prices it faces.

**Causes of Economic Inefficiencies**

The early interest in economic efficiency centred on the question of whether small farmers of the Third World were economically rational and price responsive. This
question is no longer seriously debated. Rather, economic efficiency should be viewed only as a standard by which to judge resource productivity against its potential. As such, interest now centres on system inefficiencies that cause resource productivity to fall below its potential. These system inefficiencies, which may be both internal and external to the farmer, and their relationship to the different categories of inefficiencies are shown in Table 2.

Technical inefficiency due to inappropriate timing and method of using an input is likely to reflect inadequate information and technical skills on the part of farmers, although factors external to farmers, such as untimely input supply, may be important.
Table 2. Classification of economic inefficiencies and their policy relevance.

<table>
<thead>
<tr>
<th>Type of inefficiency</th>
<th>Likely cause of inefficiency</th>
</tr>
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<tbody>
<tr>
<td><strong>1. Technical inefficiency</strong></td>
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</table>
| Failure to operate on the production frontier due to errors in the timing or method of application of inputs | a. Inadequate information  
b. Insufficient technical skills  
c. Untimely input supply |
| **2. Constrained allocative errors** |                             |
| Errors in allocating input within existing expenditure levels — movement to the expansion path | a. Inadequate information  
b. Market failure in input supply  
c. Differential risk effects of inputs  
d. Institutions (e.g., tenancy) |
| **3. Scale errors** |                             |
| Failure to use profit maximizing levels of inputs | a. Capital constraint  
b. Risk aversion  
c. Inadequate information  
d. Institutions (e.g., tenancy) |

in some cases. Allocative errors may also reflect inadequate information and skills especially for the constrained case, but other factors such as risk aversion, capital constraints, institutional constraints (e.g., tenancy), interdependence of production and consumption decisions in farm households, and failures in input markets are also expected to play an important role, especially in determining scale errors. Many of these factors, such as input market failures, are exogenous to the farmer. Even the failure to use the most efficient technique of production due to inadequate information suggests that the cost to the individual farmer of acquiring better information is greater than the benefits because of failure in information markets. Therefore, the presence of inefficiency in resource use at the farm level is not inconsistent with the hypothesis of the rationality of small farmers.

Economic efficiency must also be considered in a dynamic context. With the introduction of a new input \((X^P)\) (e.g., a new variety), farmers may experience initial inefficiency as they learn about the new input. This inefficiency may include technical inefficiency as farmers acquire skills in applying the input and allocative errors as they adjust the level of use of the new input to their own specific circumstances. This is especially true if the \(E\) variables in Equation 1 are farmer-specific and there are strong interactions between \(X^p\) and \(E\).

If the introduction of a new input is a one-time change to the system, farmers will eventually adjust to a reasonably efficient use of the input through learning by doing. In practice, much of Third World agriculture in the past two decades has undergone continuous changes in both the technical and economic environment. Changes in the technical environment arise through two major sources. First, new inputs, \(X^P\), become available and alter the production function. For example, new wheat varieties are released almost every year to maintain rust resistance against evolving pathogens.  

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\(1\) In fact, it may be rational for decision makers in the short run to deliberately introduce inefficiencies in order to learn about the response to the new input (Welch, 1978).
Second, the environmental variables, $E$, are subject to change over time. In particular, $E_t = g(X_{t-1}, X_{t-2}, \ldots)$, where $X_{t-j}$ is input use in period $t-j$. A common example of this change in the technical environment is the carryover of residual soil phosphorus levels as phosphatic fertilizer is applied over seasons. On the other hand, higher yields and more intensive cropping often deplete the levels of other soil nutrients, especially micronutrients. Likewise, use of pesticides will often change the composition of pest populations in future seasons.

Changes in the technical environment are often accompanied by changes in the economic environment. The development of better transportation and marketing infrastructure encourages crop specialization. At the same time, input–output price relationships are subject to sharp changes, especially with the policy reforms in many countries in the 1980s, which have reduced subsidies on inputs such as fertilizers. The combination of an evolving technical and economic environment means that the equilibrium required for economic efficiency is a constantly moving target.

The complexity of decision making in a dynamic environment is compounded by several other sources of complexity in a modernizing agriculture. These sources of complexity are caused by:

1. A wide array of purchased inputs, $X^p$, which can potentially be applied.
2. Strong interaction (i.e., high $dY/(dX^p dE_k)$) between some purchased inputs and environmental variables (e.g., between fertilizer and soil type or rainfall).
3. Interaction between $X^p$ and the time and method of application (i.e., a potentially wide variation in $dY/dX^p$).
4. Interactions between management of preceding and succeeding crops in a multiple cropping sequence (multiple cropping is the norm in much of Asia).

In a dynamic agriculture where decision making is a complex process, it is hypothesized that in the short run the managerial skills and information available to farmers may be more important in causing inefficiencies than institutional variables, such as tenancy.

3 METHODOLOGICAL ISSUES IN MEASURING INEFFICIENCY

The major methodological developments have focused on measuring technical efficiency and the factors causing technical inefficiency. A number of approaches have also been used to jointly estimate technical and allocative efficiency.

Measurement of Technical Efficiency

Two major approaches, the frontier and the ‘direct’ approaches, have been used to identify technical inefficiency and its causes in agricultural production processes. In the frontier approach, the production frontier is estimated as the most efficient set of points in input–output space. Deviation from this frontier is used as the measure of technical inefficiency. Farm-specific inefficiency can then also be related to characteristics of the farm and farmer to test hypotheses about the causes of inefficiency. These variables may measure information status and managerial skills, such as education, technical knowledge, and extension contacts, as well as system effects exogenous to
the farm, such as access to credit, input markets, or tenancy. Hence a two-stage process is used.

\[
Y_n = f(X/E) + u_n \\
u_n = h(M),
\]

where \( Y_n, X, \) and \( E \) are as defined above, \( u_n \) is a firm-specific measure of inefficiency, and \( M \) is nonconventional inputs (e.g., farmer education) or external factors likely to relate to inefficiency (e.g., a credit constraint).

In the second approach, which we will call the 'direct' or nonfrontier approach, human capital, managerial information, and system variables are included directly in the production function as 'nonconventional' inputs — that is, \( Y = f(X, M, E) \). This approach enables the effect of the nonconventional variables on relative technical efficiency to be tested but it does not provide a measure of absolute inefficiency. Some authors (e.g., Muller, 1974) have argued that this indirect approach is preferable since it provides for interaction effects between 'nonconventional' and conventional inputs. However, we prefer the specification of equation (2) which clearly separates inputs that directly affect production and management variables that influence how those inputs are used, and avoids the simultaneity problem of including both conventional and nonconventional inputs in the production function.\(^4\)

A number of frontier approaches have been used to estimate the production frontier and have been extensively reviewed by Forsund et al. (1980). We have summarized these approaches in Figure 3. Following Farrell (1957), the early work on estimating production frontiers was based on nonstatistical methods. Farrell used linear programming to estimate an isoquant frontier in input–input space. This approach has been refined by specifying a particular form of the production frontier, usually the Cobb-Douglas, and then requiring all observations to be on or beneath the frontier (Aigner and Chu, 1968). This frontier can be estimated by linear or quadratic programming. The advantage of using a particular specification of the frontier is that production techniques can be conditional on the firm-specific environment (e.g., fixed factors) rather than having a unique isoquant frontier for all firms. However, the choice of the functional form will clearly affect the estimate of inefficiency.

In the nonstatistical approaches, the frontier function, and hence the estimate of inefficiency, is particularly sensitive to outlier observations (Forsund et al., 1980). Since outliers are likely to arise because of random effects and measurement errors, technical inefficiency will be overestimated. To reduce this problem, Timmer (1971) proposed a probabilistic frontier in which some outliers are deleted or allowed to lie above the frontier. The decision on how many observations to delete is essentially arbitrary (Aigner et al., 1977), although in practice the rate of change in parameter estimates usually diminishes rapidly with successive deletion of outliers.

A second major approach to frontier estimation, based on statistical estimates of parameters of the frontier, has been applied widely in recent years. Afriat (1972) proposed a production frontier:

\[
Y = f(X/E) e^u \quad 0 < e^u < 1,
\]

\(^4\) We are aware of only one effort to compare the results of the frontier and nonfrontier approaches. Phillips and Marble (1986) using the frontier approach found that education had a significant effect in explaining firm-specific differences in technical efficiency. Using the same data set, Phillips and Marble found that education had no significant effect when included in the production function as a nonconventional input.
where a parametric one-sided Beta distribution was assumed for the deviation from the frontier, \( u \). This function can be estimated by Maximum Likelihood Estimation (MLE), although Schmidt (1976) has shown that if the distribution of \( u \) is exponential or half normal the MLE estimate is equivalent to the linear or quadratic programming solution, respectively (Forsund et al., 1980). Alternatively, the error term can be transformed to enable the application of OLS by correcting for known bias in the intercept term. This approach is usually referred to as Corrected Ordinary Least Squares (COLS).

Like the nonstatistical approaches, the early application of statistical approaches were deterministic and assumed that all deviation from the frontier was due to technical inefficiency. The stochastic frontier model (sometimes called the pseudo-frontier model) suggested by Aigner et al. (1977) and Battese and Corra (1977) relaxes this assumption. In the stochastic specification the error term is decomposed into two parts as follows:

\[
Y = f(X)e^{\nu u}
\]

where \( \nu \) is a symmetric, normally distributed component representing the random effect of measurement error and stochastic events (e.g., weather) outside the firm's
control, and $u$ is a one-sided component representing technical inefficiency. Parameters of the stochastic model may be estimated by MLE or COLS if the distribution of $u$ is specified. (The results may, however, be quite sensitive to the choice of distribution).

The stochastic formulation of the frontier parallels the probabilistic approach employed by Timmer (1971) using nonstatistical methods. The estimate of inefficiency may be drastically reduced in the stochastic formulation as shown by Taylor and Shonkwiler (1986) where estimated inefficiency was over 70 per cent for the deterministic formulation but only about 20 per cent for the stochastic formulation.\footnote{Ekanayake and Jayasuriya (1987) also found large differences in estimated technical inefficiency when they compared the deterministic and stochastic approaches using farm-level data from Sri Lanka.}

Initial applications of the stochastic frontier model allowed average technical inefficiency to be estimated for the sample but not for individual firms since individual residuals could not be decomposed into the two components, $v_i$ and $u_i$. Recently, however, Jondrow et al. (1982) and Kalirajan and Flinn (1983) have developed a specification for the expected firm-specific inefficiency, $E(u)$, conditional on the random disturbance, $v$. All of the approaches reviewed above estimate the production frontier from cross-sectional sample data. If time series data are available for a sample of farms, the cross-sectional and time series data can be pooled by analysis of covariance with firm-specific dummies to estimate a production frontier and firm-specific inefficiency. Time series data on individual farms are rarely available in the Third World and Lingard et al. (1983) and Baidya (1986) are the only applications of this type.

Finally, in some cases it may be possible to estimate the production frontier from experimental data (i.e. an engineering production function). The difference between output estimated by this function and actual output of a farmer, at farmers' current input level, can be attributed to technical inefficiency. The main drawbacks to this approach are, first, ensuring that the 'engineering' frontier is representative of farmers' conditions, and second, the cost of conducting an extensive on-farm experimental programme over several years. Nonetheless, the approach has been successfully applied by Herdt and Mandac (1981).

**Estimation of Allocative Efficiency**

The publication of Schultz's (1964) book stimulated a number of studies to test allocative efficiency by comparing the MVP of each input to the price of the input. However even if farmers are on average allocating resources efficiently, there may be large firm-specific allocative errors. Indeed, the successful estimation of a production function from cross-sectional data requires substantial allocative errors in the sample of farmers (Doll, 1974), unless there are differences between firms in input–output price ratios, fixed factors, or environmental factors.

Most recent studies of allocative efficiency have attempted to jointly test technical and allocative efficiency based on the estimation of the profit function (Yotopoulos and Lau, 1973), in which normalized prices of variable inputs and the levels of fixed factors are the arguments. Both technical and allocative efficiency can be tested and nonconventional inputs can also be included to test the effects of managerial variables.
Nonetheless, the approach has a number of problems. High standard errors of coefficients of the profit function make it unlikely that the null-hypothesis of profit maximization will be rejected (Quiggin and Ahn, 1984). Furthermore, successful application of the profit function approach requires cross-sectional variability in the prices of variable inputs. Finally, the profit function does not allow estimation of the absolute level of inefficiency relative to a frontier, but does allow estimation of the relative inefficiency of different groups of farmers.

Recently, the profit function has been extended by estimating a profit frontier analogous to the production frontier. In the stochastic frontier model, deviation from the profit frontier is decomposed into a component due to random error and a component due to economic inefficiency, (both technical and allocative) (Ali, 1986; Huang et al., 1986; Kalirajan, 1986). Economic inefficiency in this case includes both technical and allocative inefficiency, and Ali (1986) and Kalirajan (1986) provide a method to disaggregate the estimated inefficiency, into these two components. This approach also enables technical efficiency to be defined in terms of the appropriate technology given the firm-specific prices for variable inputs and outputs.

Finally an indirect method has been proposed to isolate the separate effects of nonconventional inputs (e.g., education) included in the production function, on technical and allocative efficiency (Welch, 1970). Welch called these the ‘worker’ effect and the ‘allocation’ effect. The production function is specified in terms of output, gross revenues, and value added. The MVP of the nonconventional input (e.g., education) in the production function is due to the effect of that variable on technical efficiency. The difference between the MVP in the value-added function and the gross-sales function measures the effects of allocative errors.

4 EMPIRICAL EVIDENCE ON TECHNICAL AND ALLOCATIVE INEFFICIENCY IN THIRD WORLD AGRICULTURE

Technical Inefficiency

Frontier Approaches
The results of 12 frontier studies that have estimated technical inefficiency are summarized in Table 3. These studies have applied the full range of estimation techniques discussed previously. The most frequently used technique in recent years has been the stochastic frontier approach.

The average level of technical inefficiency in these studies is about 30 per cent but varies substantially from about 10 per cent to over 50 per cent. Most studies are from areas of Asia that experienced rapid change following the Green Revolution. Because only two of these studies, Mijindadi and Norman (1984) for Nigeria and Belbase and Grabowski (1985) from Nepal, were conducted in traditional agricultural settings, it is not possible to compare technical inefficiency for traditional and modernizing settings. Nonetheless, it is worth noting that the two estimates from traditional settings indicate substantially lower technical inefficiency than the average.

Somewhat over half of these studies have taken the next step and related firm-specific estimates of technical inefficiency to characteristics of farmers and their environment. The variables selected differ substantially between studies but usually include some variables relating to farmers’ human capital, technical knowledge, and
information contacts, as well as ‘institutional’ variables such as tenancy, access to credit, and irrigation water constraints. Very few studies have included specific management practices related to the timing and method of using inputs that are believed to be the sources of technical inefficiency. Exceptions are Ali and Flinn (1989) and Hussain (1989), who were able to relate inefficiency to timing of some operations, as well as to agronomic variables such as plant stand or weeds.

Although it is difficult to compare absolute levels of technical efficiency in these studies because of different levels of input aggregation (shown by the number of independent variables in Table 3), exclusion of environmental variables (E) in many studies, and use of whole farm data in other studies, a particularly important finding in all studies that analysed causes of technical inefficiency is that one or more variables relating to information source, technical knowledge, and human capital were significant in explaining variation in technical efficiency between farmers. This finding supports the earlier argument that in post-Green Revolution agriculture, both technical and allocative inefficiencies are likely to arise from deficiencies in technical and managerial skills of farmers who are striving to adjust to a new, science-based agriculture.

Beyond this group of management variables, no generalization can be made about the causes of technical inefficiency. Farm size, for example, has no consistent effect on technical inefficiency, a finding that is in agreement with the recent voluminous literature from South Asia on this subject (Singh, 1988).

Non Frontier Approaches
Lockheed et al. (1980) summarized 20 studies using the nonfrontier approach in which nonconventional inputs, mostly education, are included in the production function. Most of these studies found that education had a positive and significant effect on productivity. More important, the average increase in productivity due to completion of basic education (four to six years) was 9.5 per cent in a modernizing environment versus 1.3 per cent in a traditional environment. The Asian studies found that the effect of education was particularly strong and consistent (Phillips, 1987), as would be expected in a post-Green Revolution setting. These findings are supported further by more recent studies from Asia and Latin America which were not included in the Lockheed et al. survey (Table 4).

These studies offer little evidence of how schooling affects productivity. Recently, Jamison and Moock (1984) attempted to establish the intermediate outputs (literacy, numeracy, cognitive skills, technical information) of formal education in Nepal that have a bearing on efficiency. They found that numeracy had a large and significant effect on efficiency in wheat production, although their results were inconclusive for other types of educational inputs and other crops. Fuller (1983) concluded that literacy, in this case adult education, increased economic efficiency of Bangladeshi rice farmers. To date we still have a very incomplete understanding of which educational products are most important in small farmer management at different stages of development.

A number of studies, especially Bhati (1973), Bernsten (1977), Shapiro and Muller (1977), and Salam (1976) have included an index of farmers' technical knowledge in the production function and in almost all cases the effect is positive and highly significant. For example, Bernsten (1977) found that differences in technical knowledge between farmers accounted for differences in rice yields of up to 1t/ha.
<table>
<thead>
<tr>
<th>Source and location and year of study</th>
<th>Crop</th>
<th>Sample size</th>
<th>Method of estimation¹</th>
<th>Number of inputs specified</th>
<th>Environmental variables included</th>
<th>Average inefficiency</th>
<th>Factors influencing inefficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shapiro, 1983 (Tanzania, 1977)</td>
<td>Cotton</td>
<td>35</td>
<td>Probabilistic, LP Frontier (CD)</td>
<td>2</td>
<td>No</td>
<td>34%</td>
<td>na</td>
</tr>
<tr>
<td>Mijindadi and Norman, 1984 (Northern Nigeria, 1966-68)</td>
<td>Whole farm</td>
<td>340</td>
<td>Probabilistic, LP Frontier (CD)</td>
<td>7</td>
<td>Yes</td>
<td>8%</td>
<td>na</td>
</tr>
<tr>
<td>Belbase and Grabowski, (Nepal, 1974–75)</td>
<td>a) Rice</td>
<td>537</td>
<td>Probabilistic, COLS (CD)</td>
<td>6</td>
<td>No</td>
<td>a) 16%</td>
<td>Income (–)** Nutrition(–)** Education (–)** Experience (–)</td>
</tr>
<tr>
<td></td>
<td>b) Maize</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>b) 33%</td>
<td></td>
</tr>
<tr>
<td>Phillips and Marble, 1986 (Guatemala)</td>
<td>Maize</td>
<td>1,548</td>
<td>COLS (CD)</td>
<td>6</td>
<td>No</td>
<td>53%</td>
<td>Education (–)**</td>
</tr>
<tr>
<td>Taylor and Shonkwiler, 1986 (Brazil, 1981–82)</td>
<td>Whole farm</td>
<td>433</td>
<td>Stochastic frontier with MLE (CD)</td>
<td>3</td>
<td>No</td>
<td>30%</td>
<td>na</td>
</tr>
<tr>
<td>Kalirajan, 1981 (Tamil Nadu, India, 1978)</td>
<td>Rice</td>
<td>70</td>
<td>Stochastic frontier with MLE (CD)</td>
<td>5</td>
<td>No</td>
<td>53%</td>
<td>Experience (–)** Education (–) Knowledge (–)** Extension contact (–)** Share tenant (+)</td>
</tr>
<tr>
<td>Huang and Bagi, 1984 (Haryana, India 1969–70)</td>
<td>Whole farm</td>
<td>151</td>
<td>Stochastic frontier with MLE (TL)</td>
<td>7</td>
<td>No</td>
<td>11%</td>
<td>Farm size (no effect)</td>
</tr>
<tr>
<td>Source and location and year of study</td>
<td>Crop</td>
<td>Sample size</td>
<td>Method of estimation</td>
<td>Number of inputs specified</td>
<td>Environmental variables included</td>
<td>Average inefficiency</td>
<td>Factors influencing inefficiency</td>
</tr>
<tr>
<td>--------------------------------------</td>
<td>-----------</td>
<td>-------------</td>
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<td>---------------------------</td>
<td>---------------------------------</td>
<td>----------------------</td>
<td>----------------------------------</td>
</tr>
<tr>
<td>Kalirajan and Flinn, 1981 (Bulcan, Philippines, 1980)</td>
<td>Rice</td>
<td>54</td>
<td>Stochastic frontier with MLE (CD)</td>
<td>7</td>
<td>Yes</td>
<td>20%</td>
<td>Age (-) Education (-) Tenant (-) Extension contact (-)** Planting method**</td>
</tr>
<tr>
<td>Kalirajan and Flinn, 1983 (Bicol. Philippines, 1980)</td>
<td>Rice</td>
<td>79</td>
<td>Stochastic frontier with MLE (TL)</td>
<td>5</td>
<td>No</td>
<td>50%</td>
<td>Age (-) Experience (-)** Extension contact (-)** Planting method**</td>
</tr>
<tr>
<td>Lingard et al., 1983 (Central Luzon, Philippines, 1970-79)</td>
<td>Rice</td>
<td>32 by 4 years</td>
<td>Analysis of covariance with firm-specific dummies (CD)</td>
<td>5</td>
<td>Yes</td>
<td>50%</td>
<td>Age (-) Education (-)** Credit access (-)** Share tenant (+)** Land title</td>
</tr>
<tr>
<td>Flinn and Ali, 1986 (Punjab, Pakistan, 1982)</td>
<td>Rice</td>
<td>120</td>
<td>Stochastic frontier with MLE (CD)</td>
<td>4</td>
<td>Yes</td>
<td>21%</td>
<td>Education (-)** Own tenancy (-) Farm size (+) Crop establishment (+)* Late fertilizer (+)** Water problem (+)*</td>
</tr>
<tr>
<td>Hussain, 1989 (NWFP, Pakistan, 1989)</td>
<td>Wheat</td>
<td>105</td>
<td>Stochastic frontier with MLE (TL)</td>
<td>12</td>
<td>Yes</td>
<td>31%</td>
<td>New Seed (-)* Seed treatment (-)** Density (-)* Weeds (+) Sowing date (-) Knowledge score (-)*</td>
</tr>
</tbody>
</table>

a LP = Linear Programming, COLS = Corrected Least Squares, MLE = Maximum Likelihood Estimation; abbreviation for functional form included in parentheses: CD = Cobb-Doublas, TL = Translog.
b Soil type was an independent variable to explain differences in efficiency.
c *** denote significance at 5% and 10% level, respectively.
d Knowledge score was positively related to use of new seed and density.
Table 4. Summary of studies using nonfrontier approaches to estimate the effects of non-conventional inputs on technical efficiency.

<table>
<thead>
<tr>
<th>Study and location</th>
<th>Sample size</th>
<th>Survey year</th>
<th>Crop</th>
<th>Main finding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bhati, 1973 <em>(Malaysia)</em></td>
<td>42</td>
<td>1969</td>
<td>Rice</td>
<td>Highly significant and strong effect of farmers' technical knowledge on farm income and productivity.</td>
</tr>
<tr>
<td>Bernsten, 1977 <em>(Central Luzon, Philippines)</em></td>
<td>100</td>
<td>1974</td>
<td>Rice</td>
<td>Score of technical knowledge highly significant and leads to up to 1 t/ha difference in yields. Knowledge related to years of experience using new inputs and extension contact.</td>
</tr>
<tr>
<td>Amoloza, 1983 <em>(Barangay, Philippines)</em></td>
<td>33</td>
<td>1975–1977</td>
<td>Rice</td>
<td>Three management groups based on age, education, experience, technical knowledge and attitudes, and motivation were identified. Farmers in the lowest management group achieved lower yields than farmers in highest group. Knowledge score had highly significant and positive effect on labour productivity.</td>
</tr>
<tr>
<td>Shapiro and Muller, 1977 <em>(Tanzania)</em></td>
<td>40</td>
<td>1970</td>
<td>Cotton</td>
<td>Management index based on education and farmers’ experience was highly significant and increased productivity by 6–26%, depending on region. Management variable based on farmers’ knowledge increased productivity for the main crop by 15%.</td>
</tr>
<tr>
<td>Makary and Rees, 1981 <em>(Egypt)</em></td>
<td>120</td>
<td>1975</td>
<td>Cotton</td>
<td>In most cases education had a positive and significant effect on productivity. The average effect was 9.5% in a modernizing environment and only 1.3% in a traditional setting.</td>
</tr>
<tr>
<td>Salam, 1976 <em>(Punjab, Pakistan)</em></td>
<td>172</td>
<td>1972</td>
<td>Wheat</td>
<td></td>
</tr>
<tr>
<td>Lockheed, <em>et al.</em>, 1980 <em>(Review article of 20 studies covering different countries, crops, and years)</em></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Study and location</td>
<td>Sample size</td>
<td>Survey year</td>
<td>Crop</td>
<td>Main finding</td>
</tr>
<tr>
<td>-------------------------</td>
<td>-------------</td>
<td>-------------</td>
<td>---------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Antiporta, 1978</td>
<td>2,459</td>
<td>1972</td>
<td>Rice</td>
<td>Education increased productivity by less than half a per cent. However, farming experience improved productivity up to 6%.</td>
</tr>
<tr>
<td>Butt, 1984</td>
<td>2,002</td>
<td>1977</td>
<td>Wheat, rice</td>
<td>Primary education increased productivity 7% and secondary education by 10.7%. Strong positive interaction of education and fertilizer use.</td>
</tr>
<tr>
<td>Antle, 1984</td>
<td>1,438</td>
<td>1971</td>
<td>Rice</td>
<td>Strong positive effect on productivity of 4% per year of schooling.</td>
</tr>
<tr>
<td>Jamison and Moock, 1984</td>
<td>683</td>
<td>1978</td>
<td>Wheat, rice</td>
<td>Completion of at least 7 years of schooling increased productivity in wheat by 27–31% and in rice by 13%.</td>
</tr>
<tr>
<td>Chou and Lau, 1987</td>
<td>174</td>
<td>1972–1978</td>
<td>Rice</td>
<td>Education increased productivity by 2.2–2.9% per year of schooling.</td>
</tr>
<tr>
<td>Feder et al., 1987</td>
<td>365</td>
<td>1983</td>
<td>Wheat</td>
<td>Education increased productivity by 1% per year of schooling. T &amp; V extension system also increased productivity by 9%.</td>
</tr>
<tr>
<td>Cotlear, 1987</td>
<td>555</td>
<td>1983</td>
<td>Potato</td>
<td>Primary schooling increased productivity by up to 30% in modernizing agriculture with complex technology. Little effect of either education or extension in a traditional setting.</td>
</tr>
</tbody>
</table>
Bernsten was also able to relate farmers' technical knowledge to such socioeconomic characteristics as age, experience, and extension contact, although education did not emerge as a significant determinant of farmers' technical knowledge.

These studies and others also point out that farmers' level of technical knowledge is relatively low, given the complexity of managing the new, science-based agriculture (Byerlee, 1987). Bernsten (1977) measured farmers' knowledge of management practices judged to be 'critical for the farmer to achieve maximum input efficiency' in growing modern rice varieties; practices included, among others, age of transplanting and application of the appropriate insecticide for a given pest. Out of a maximum score of 12, farmers averaged 5.7, suggesting substantial scope for increasing their technical knowledge. Similar evidence is available for Pakistan, where farmers have had nearly two decades of experience with modern wheat varieties (Heisey, 1990; Hussain, 1989).

Allocative Efficiency

The publication of Schultz's (1964) poor-but-efficient thesis stimulated a number of pioneering studies to test the hypothesis of allocative efficiency by comparing the MVP of inputs to their prices (Hopper, 1965; Chennareddy, 1967; Sahota, 1968). These studies tended to be highly conservative in rejecting the null-hypothesis that farmers were efficient in allocating their resources even when they found large differences between the MVP and the normalized price. For example, the early studies all concluded that farmers were profit maximizing even though K, the ratio of MVP of an input to its price, varied from 0.6 to 3.6 (Shapiro, 1983). Similar studies in the 1970s and 1980s also show a wide range in variation in K (Table 5). Some efforts have been made to explain high values of K in terms of risk aversion of farmers (Dillon and Anderson, 1971; McPherson, 1986). In general, the value of K tends to be higher for modern inputs such as fertilizer, suggesting that farmers are still in the stage of adjustment to the optimal level.

Further evidence that farmers in many Third World settings are slow to adjust to equilibrium fertilizer levels is given by the comparison of the Coefficient of Variation (CV) in per-hectare use of fertilizer (a modern input) to the CV of traditional input use in relatively homogeneous areas where most farmers had adopted fertilizer (Table 6). The CV is always higher for the modern input than for the traditional input. After nearly 20 years of using new varieties and fertilizer, farmers in Pakistan's irrigated areas still exhibit wide variation in fertilizer doses in a given area. Calculated from cross-sectional data, the CV has fallen from over 100 per cent in an area where fertilizer was only recently introduced, to 50–60 per cent in the irrigated Punjab where fertilizer has been used for the past 20 years. By contrast, the CVs for fertilizer use on wheat in three counties of Michigan were 30–40 per cent in 1959–61, less than 10 years after widespread adoption (calculated from Hoffnar and Johnson, 1966).

Farm-specific price variation allows the use of a profit function to test allocative efficiency. Although this approach is also likely to be conservative in rejecting the null-hypothesis of allocative efficiency (Quiggin and Ahn, 1984), Junakar (1980a, 1980b) rejects the hypothesis that Indian farmers in two separate samples (wheat and rice, respectively) are allocatively efficient. Yotopoulos and Lau (1979) and Jamison and Lau (1982), on the other hand, accept the hypothesis in other Asian settings. When
Table 5. Summary of recent studies giving estimates of $K$, the ratio of MVP of input to its normalized price.

<table>
<thead>
<tr>
<th>Study, location, year</th>
<th>Crop</th>
<th>Sample size</th>
<th>K for input</th>
</tr>
</thead>
<tbody>
<tr>
<td>Miglani and Sidhu, 1982 (Punjab, India, 1984)</td>
<td>Whole farm</td>
<td>144</td>
<td>1.71</td>
</tr>
<tr>
<td>Bagi, 1982 (Haryana, India, 1970)</td>
<td>Whole farm</td>
<td>34</td>
<td>1.0</td>
</tr>
<tr>
<td>Khan and Young, 1979 (Pakistan, 1977)</td>
<td>Whole farm</td>
<td>222</td>
<td>-</td>
</tr>
<tr>
<td>Hussain and Young, 1985 (Visayas, Philippines)</td>
<td>Wheat</td>
<td>140</td>
<td>-</td>
</tr>
<tr>
<td>Armenia, 1983</td>
<td>Rice</td>
<td>289</td>
<td>2.0</td>
</tr>
<tr>
<td>Barnum and Squire, 1978 (U.P., India 1972)</td>
<td>Rice</td>
<td>386</td>
<td>1-7-1.8</td>
</tr>
<tr>
<td>Bliss and Stem, 1982</td>
<td>Wheat</td>
<td>47</td>
<td>-</td>
</tr>
</tbody>
</table>
Table 6. Coefficient of variation of traditional and modern inputs for farmers, 5–10 and 15–20
years after introduction of modern varieties.

<table>
<thead>
<tr>
<th>Number of years since initial adoption of variety and fertilizera</th>
<th>Kenya (Vihiga)</th>
<th>Pakistan (Gilgit)</th>
<th>India (Palanpur)</th>
<th>Pakistan (Gujranwala)</th>
<th>Pakistan (Multan)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5-10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15-20</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coefficient of variation (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Traditional inputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seed/ha</td>
<td></td>
<td></td>
<td>29</td>
<td>11</td>
<td>14</td>
</tr>
<tr>
<td>Number of ploughings</td>
<td></td>
<td></td>
<td>28</td>
<td>33</td>
<td>43</td>
</tr>
<tr>
<td>Organic manure/ha</td>
<td></td>
<td></td>
<td>70</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Labour/ha</td>
<td>35</td>
<td></td>
<td>-</td>
<td>46</td>
<td>-</td>
</tr>
<tr>
<td>Modern inputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nitrogen/ha</td>
<td>98</td>
<td>100</td>
<td>61b</td>
<td>52</td>
<td>53</td>
</tr>
<tr>
<td>Phosphorus/ha</td>
<td>85</td>
<td>131</td>
<td>-</td>
<td>60</td>
<td>66</td>
</tr>
</tbody>
</table>

a All inputs were used by over 80% of farmers in the year of the survey, except phosphorus in Gilgit (47%).
b Total fertilizer applied.

education has been included as a variable in the profit function (Sidhu and Baanate, 1981; Pudasaini, 1983; Jamison and Lau, 1982) it has had a positive and usually significant effect on profits, indicating the existence of management-related inefficiency.

The measurement of allocative inefficiency also depends on whether a constrained case (i.e., at farmers’ existing expenditure level) or profit maximization is assumed. Van der Veen (1975) in a study of rice in the Philippines failed to reject the hypothesis of cost minimization for most farmers (constrained case) but did reject the hypothesis of profit maximization (unconstrained case) for 36 out of 78 farmers in his sample.

With so much controversy over whether farmers are allocatively efficient it is not surprising that very few studies have attempted to quantify the magnitude of allocative errors, if they exist. Baidya (1986) in the Philippines and Taylor and Shonkwiler (1986) estimated losses due to allocative errors of about 25 per cent. Baidya (1986) was also able to show that farmers’ education was a major determinant of farm-specific losses arising from allocative errors.

Three studies have estimated technical and allocative efficiency jointly using an engineering frontier (Herdt and Mandac, 1981) or a profit frontier (Ali, 1986; Kalirajan, 1986) (Table 7). All three show that technical inefficiency is considerably higher than allocative inefficiency. To some extent this finding reflects the fact that profits are relatively insensitive to input levels for a wide margin around the economic optimum (Anderson, 1975). Also, given the problems of input aggregation discussed earlier, estimates of the relative magnitude of technical and allocative inefficiencies may not be very meaningful even though in some cases the distinction may be important from a policy standpoint.

The approach developed by Welch (1970) to isolate the effects of education on technical and allocative efficiency was also applied by Pudasaini (1983) in two regions of Nepal. Although education positively affected both technical and allocative efficiency in each region, the allocative effect was more important than the effect on technical efficiency.
Major factors determining inefficiency are:

For Herdt and Mandac, 1981: farm size (−)**, information (+)** (for TE only), age (−), education (+), off-farm work (+)**, rainfed (−)**, risk experience (+ for AE only).

For Ali and Flinn, 1988: education (+)**, late planting (−)*, late fertilizer application (−)*, irrigation water problems (−)*. *, ** denote significance at 5% and 10% level, respectively.

Table 7. Summary of studies analysing both technical and allocative efficiency.

<table>
<thead>
<tr>
<th>Study, location, and year</th>
<th>Crop</th>
<th>Sample size</th>
<th>Estimation method</th>
<th>Number of independent variables</th>
<th>Environmental variables included</th>
<th>Estimated inefficiency (%)</th>
<th>Technical (TE)</th>
<th>Allocative (AE)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Herdt and Mandac, 1981 (Nueva Ecija, Philippines, 1974–77)</td>
<td>Rice, wet season; Rice, dry season</td>
<td>76</td>
<td>Engineering frontier</td>
<td>10</td>
<td>Yes</td>
<td>17</td>
<td>8</td>
<td>25</td>
<td></td>
</tr>
<tr>
<td>Ali and Flinn, 1989 (Punjab, Pakistan, 1982)</td>
<td>Rice</td>
<td>120</td>
<td>Stochastic profit frontier with MLE</td>
<td>5</td>
<td>Yes</td>
<td>23</td>
<td>5</td>
<td>28</td>
<td></td>
</tr>
<tr>
<td>Kalirajan, 1986 (Laguna, Philippines)</td>
<td>Rice</td>
<td>103</td>
<td>Stochastic profit frontier with MLE</td>
<td>5</td>
<td>No</td>
<td>25</td>
<td>10</td>
<td>35</td>
<td></td>
</tr>
</tbody>
</table>

*Major factors determining inefficiency are:

For Herdt and Mandac, 1981: farm size (−)**, information (+)** (for TE only), age (−), education (+), off-farm work (+)**, rainfed (−)**, risk experience (+ for AE only).

For Ali and Flinn, 1988: education (+)**, late planting (−)*, late fertilizer application (−)*, irrigation water problems (−)*. *, ** denote significance at 5% and 10% level, respectively.
5 CONCLUSION

This survey of the rapidly increasing volume of literature on efficiency in small farmer agriculture has pointed out a number of conceptual and methodological problems with this research. First, emphasis should be placed on analysing the efficiency of the total system in which farmers operate, rather than on the rationality or efficiency of farmers themselves. Research with this broader perspective should be more useful in designing appropriate development strategies that focus on the major constraints to improving efficiency of resource use at the farm level, whether those constraints are inadequate technical knowledge on the part of small farmers or imperfections in input or factor markets.

Second, the distinction between technical and allocative efficiency that is often drawn by economists may not be very meaningful. The partitioning of inefficiencies between the two is sensitive to the level of aggregation of inputs. From a policy perspective we would suggest that the most useful specification of the production function for measuring economic inefficiency is: \( Y = f(X^h, X^p, E) \), where \( X^h \) are household resources of land, labour, and capital; \( X^p \) is an aggregate category for all purchased inputs; and \( E \) is a set of environmental variables defined in equation (1). The estimation of 'technical efficiency', using a production frontier in this case, would include technical efficiency for all inputs as conventionally defined (i.e., in terms of timing and method of application of inputs), as well as allocative efficiency within the aggregate category of purchased inputs (constrained by the total cash outlay on purchased inputs). Economic inefficiency (technical and allocative) estimated by this specification is likely to arise from managerial variables such as education and technical knowledge. Causes of inefficiency may be identified by analysing the residuals in terms of timing and method of application of inputs, the relative levels of purchased inputs, and system constraints.

We also conclude that in agriculture, technical inefficiency is likely to be overestimated by inadequate specification of environmental variables. This problem can be reduced by greater attention to soil type, rainfall, and pest problems in farm-level surveys, which have traditionally reflected economists' biases of gathering data on inputs and outputs only. Likewise, studies aimed at estimating inefficiency should be confined to small, relatively homogeneous areas to reduce environmental variability. Though economists have tried to overcome these problems by employing increasingly sophisticated statistical methods (e.g., the use of stochastic specifications of the frontier), this is unlikely to be an adequate substitute for a well-specified function and careful measurement of environmental variables.

Nonetheless, a synthesis of the results of many recent studies, especially from Asia, strongly suggests the existence of sizeable inefficiencies, which in most cases can be traced to human capital and management variables. This result should not be surprising for the post-Green Revolution stage of agricultural development, given that similar evidence is also available from industrial countries (e.g., Pingali and Carlson, 1985; Welch, 1978; Huffman, 1977). Deficiencies in information and technical skills are likely to be even more serious in post-Green Revolution areas where a single generation of farmers has switched from a largely traditional agriculture to a science-based agriculture. Moreover, in some regions, levels of formal schooling are still very low. For example, only one-third of the farmers in Pakistan's irrigated Punjab are literate (Heisey, 1990). These farmers use, or are expected to use, a wide array of
purchased inputs and machinery in increasingly complex multiple cropping systems.

The evidence surveyed in this paper also indicates that some rethinking of recent development strategies is in order. Most of the recent growth of Asian agriculture over the past two decades can be attributed to Green Revolution inputs — short-statured wheat and rice varieties, increasing doses of fertilizer, and improved supplies of irrigation water (CIMMYT, 1989; Scandizzo, 1984). There is evidence that returns to these inputs have now fallen sharply (CIMMYT, 1989; Levine et al., 1988) and that no major technological breakthroughs are expected before the early years of the next century (Byerlee 1990). Hence alternatives sources of growth are needed to maintain increased food production for the next 10–20 years. One such source of growth suggested by the evidence presented in this paper is measures to increase the efficiency of resource use, such as adaptive research to generate location-specific technical information, upgrading extension services, giving more attention to basic education (including adult education), and seeking ways to increase the efficiency of input markets and irrigation systems.

ACKNOWLEDGEMENT

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REFERENCES


Economic Efficiency of Small Farmers in a Changing World


26 M. Ali and D. Byerlee


