

Is Environmentally-Friendly Agriculture Less Profitable for Farmers?
Evidence on Integrated Pest Management in Bangladesh

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World Bank Policy Research Working Paper 3417, September 2004

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Abstract

Concerns about the sustainability of conventional agriculture have prompted widespread introduction of integrated pest management (IPM), an ecologically-based approach to control of harmful insects and weeds. IPM is intended to reduce ecological and health damage from chemical pesticides by using natural parasites and predators to control pest populations. Since chemical pesticides are expensive for poor farmers, IPM offers the prospect of lower production costs and higher profitability. However, adoption of IPM may reduce profitability if it also lowers overall productivity, or induces more intensive use of other production factors. On the other hand, IPM may actually promote more productive farming by encouraging more skillful use of available resources. Data scarcity has hindered a full accounting of IPM's impact on profitability, health and local ecosystems.

Using new survey data, this paper attempts such an accounting for rice farmers in Bangladesh. We compare outcomes for farming with IPM and conventional techniques, using input-use accounting, conventional production functions and frontier production estimation. All of our results suggest that the productivity of IPM rice farming is not significantly different from the productivity of conventional farming. Since IPM reduces pesticide costs with no countervailing loss in production, it appears to be more profitable than conventional rice farming. Our interview results also suggest substantial health and ecological benefits. However, externality problems make it difficult for farmers to adopt IPM individually. Without collective adoption, neighbors' continued reliance on chemicals to kill pests will also kill helpful parasites and predators, as well as exposing IPM farmers and local ecosystems to chemical spillovers from adjoining fields. Successful IPM adoption may therefore depend on institutional support for collective action.

1. Introduction

Approximately 84% of Bangladesh's people are directly or indirectly dependent on agriculture for their livelihood, and agriculture contributes about 24% of gross domestic product (Bangladesh Bureau of Statistics, 2001). Rice is the major staple crop, accounting for 76% of the cultivated area, 78% of the irrigated area, 52% of agricultural GDP, and 71% of caloric intake (Bangladesh Bureau of Statistics, 2001). Plant, animal and insect pests pose a constant threat to rice production, inflicting losses conservatively estimated at 10-15% annually (FAO, 2001). Farmers have used toxic chemicals extensively for pest control, because of their reputation for speed and effectiveness. However, rising use of chemical pesticides has also posed serious health risks, as well as threatening widespread ecological damage. These problems will undoubtedly increase if Bangladeshi farmers respond to rapidly-rising food demand by intensifying their use of chemicals for pest control.

In response to rising concern about the sustainability of conventional agriculture, the government has collaborated with international assistance agencies to promote Integrated Pest Management (IPM). IPM has no standard definition, but comprises approaches that range from carefully-targeted use of chemical pesticides to biological techniques that use natural parasites and predators to control pests (Sorby et al., 2003). Since chemical pesticides are expensive for poor farmers, IPM also offers the prospect of lower production costs and higher profitability. Of course, adoption of IPM may reduce overall profitability if it also lowers productivity, or induces more intensive use of other production factors. However, application of IPM techniques may also raise overall productivity, by encouraging more effective use of other inputs. Data scarcity has hindered a full accounting of IPM's impact on profitability, health and local ecosystems.

Using new survey data, this paper attempts such an accounting for farmers in Bangladesh. We compare outcomes for farming with IPM and conventional techniques, using simple input-use accounting and estimation of conventional and frontier production functions, along with farmers' assessments of their own health status and local ecological conditions.

The remainder of the paper is organized as follows. Section 2 describes recent trends in pesticide use, the associated problems, and the current status of IPM programs

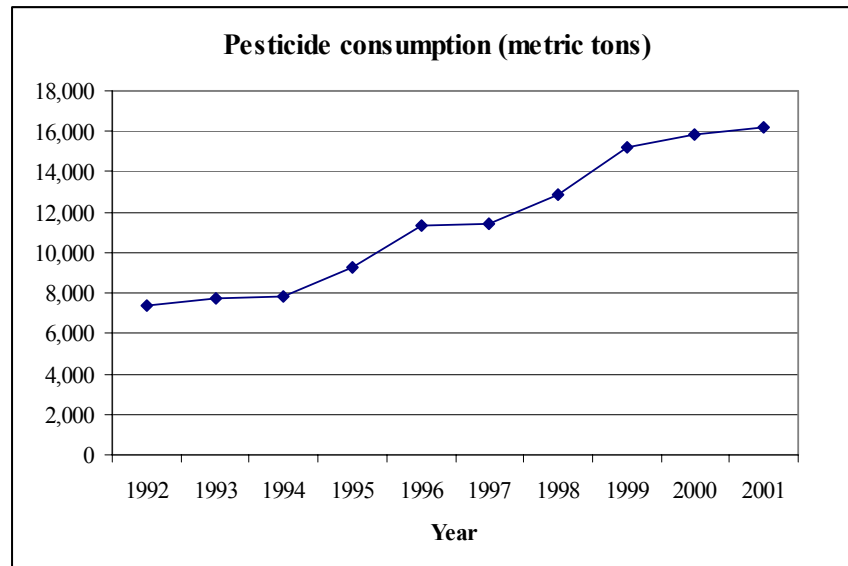
in Bangladesh. In Section 3, we introduce our survey and provide a summary description of the farmers who are currently using IPM techniques. Section 4 examines the determinants of IPM adoption, while Section 5 presents our productivity comparisons for IPM and conventional rice farming. In Sections 6 and 7, we summarize our survey results on farmers' health status and local ecological conditions. Section 8 concludes the paper and discusses some implications of our results.

2. Agriculture and Environment in Bangladesh

2.1 Pesticide Use

Like many developing countries, Bangladesh has promoted the use of pesticides to expand agricultural land and increase output per acre. Promotional activities have included extension services and significant subsidies (Rasul and Thapa, 2003; Hossain 1988). Figure 1 shows that pesticide use has more than doubled since 1992, rising from 7,350 metric tons to 16,200 metric tons in 2001. An FAO analysis of pesticide composition in Bangladesh has revealed high shares of toxic chemicals that epidemiological studies have found to cause cancer, genetic damage, fetal damage, and

Figure 1: Trends in Pesticide Use, 1992-2001



Source: Department of Agricultural Extension, Plant Protection Wing, Bangladesh

severe allergic responses in exposed populations (Zahm, Ward and Blair, 1997).¹

Many pesticides used in Bangladesh are banned or restricted under international agreements (NOVIB, 1993; SUNS, 1998; SOS-arsenic.net, 2004). In addition, several studies have shown that inadequate product labeling and farmers' lack of information have led to widespread overuse or misuse of dangerous pesticides. Substantial anecdotal evidence suggests that pesticide poisonings and ecological damage have become common in Bangladesh (Ramaswamy, 1992)

2.2 IPM in Bangladesh

Bangladesh's IPM activities began with rice in 1981, and the FAO played a strong catalytic role with government officials and the donor community. The program provided capacity-building for the Department of Agricultural Extension (DAE), introduced Farmer Field Schools, and trained representatives of local NGO's. Subsequently, the government and NGO's initiated several IPM projects for rice and vegetables with donor funds.² At present, the Plant Protection Wing of the DAE is responsible for the implementation of IPM activities (FAO, 2001).

3. Survey Data

The research reported in this paper is based on a large survey of Bangladeshi farmers, carried out by the World Bank in the summer of 2003. We used structured questionnaires to collect information on conventional and IPM farming techniques, pesticide use and practices, applicator precautions and damage-averting behavior, health effects and environmental impacts.³ To provide greater depth, we also interviewed 139 randomly-selected rice farmers who currently use IPM.

¹ See Appendix I for details. The FAO study has found particularly high shares for carbamates and organophosphates, which pose the health hazards noted above.

² To date, major IPM programs in Bangladesh have included the DAE-UNDP/FAO IPM Project (BGD/95/003); DAE-DANIDA Strengthening Plant Protection Services (SPPS) Project; Command Area Development Project (CAD); CARE-New Options for Pest Management; CARE-Integrated Rice and Fish Project (INTERFISH); AID-Comilla's Integrated Pest Management Project; USAID-funded IPM Collaborative Research Support Program; and FAO's Regional Cotton Project

³ The survey was designed and supervised by the World Bank team, and conducted by the Development Policy Group in Bangladesh. To minimize reporting bias, the survey was conducted under the agreement that the team would not reveal the identity of the farms surveyed or the respondents who participated.

We surveyed the IPM farmers in districts with significant IPM participation: Rajshahi and Rangpur in the Rajshahi division (Northwest) , Comilla in Chittagong division (East), Jessore in Khulna division (West), and Kishoreganj in Dhaka division (North -- see Figure 2). We also surveyed 689 farmers who use chemical pest controls. Table 1 displays the regional distribution of farmers in our sample.

Table 1: Regional Distribution of Survey Respondents

District	Conventional Farmers	IPM Farmers
Bogra	27	0
Chapainawabganj	3	0
Chittagong	56	0
Comilla	61	31
Jessore	111	54
Kishoreganj	35	20
Munshiganj	25	0
Narsingdi	82	0
Rajshahi	137	8
Rangpur	68	26
Mymensingh	84	0
Total	689	139

Among the surveyed IPM farmers, reported techniques include manual removal of pests (70% of the sample), use of natural parasites and predators (58%), light traps (14%), crop rotation (10%) and smoke (5%). All of the surveyed IPM farmers received formal training, with more than 90% identifying Agriculture Ministry officials as the providers. The farmers attributed their adoption of IPM to Ministry officials' recommendations (41%); cost-saving from reduced pesticide use (33%); environmental benefits (12%); and improved health (6%). About 52% reported increased output, and reported pesticide use fell by 67%.

4. Adoption of IPM

IPM programs have existed in our survey areas for twenty years, so it is reasonable to assume that most farmers have at least some information about them. Farmers' adoption of IPM may depend on a variety of factors, including personal characteristics

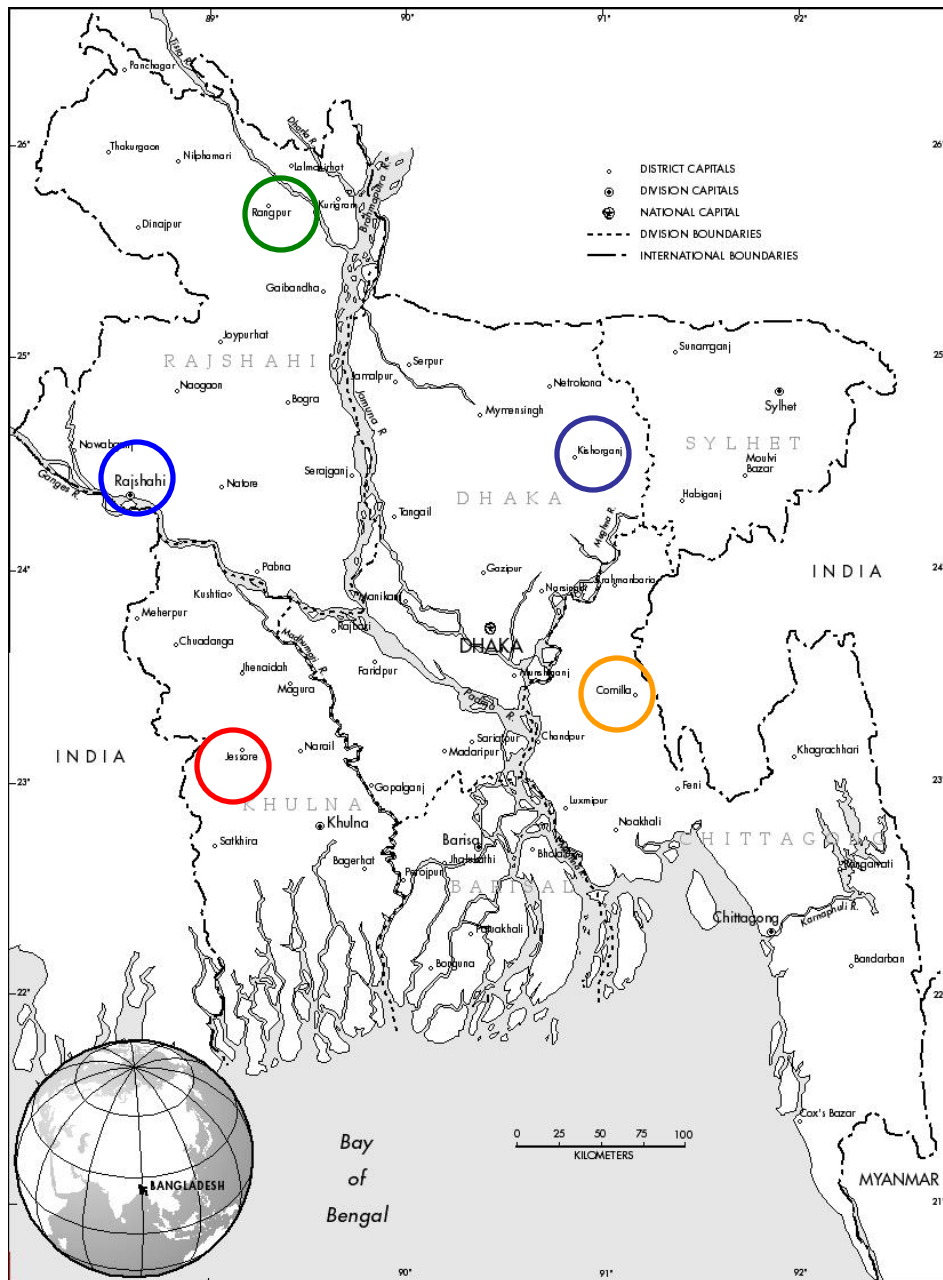
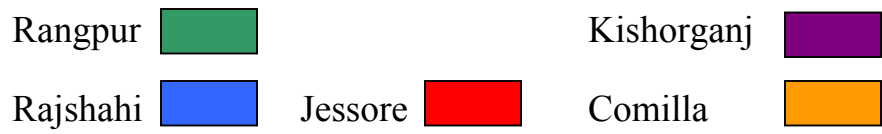


Figure 2: IPM Survey Districts in Bangladesh.

such as education and experience, farm characteristics such as production scale, and selective judgments by Agriculture Ministry official charged with promoting such programs. Some personal and farm characteristics that influence IPM adoption could also affect productivity, so it may be important to introduce controls for these variables in a comparison of IPM and conventional farming.

Using linear probability and probit models, we test for the effects of age, education, farming experience, ownership status, prior training in pesticide use, production scale and health status on IPM use.⁴ Our prior expectation is that education, farm ownership, prior training and poor health are positively related to IPM adoption, while age and farming experience may be negatively related. More educated farmers may be more receptive to new techniques; owners and unhealthy farmers may perceive greater long-run gains from adoption; prior training in pesticide handling may encourage IPM adoption, by sensitizing farmers to the hazards of pesticide use; older farmers and those with long experience in conventional farming may resist new approaches. We are agnostic about production scale.

Our estimation results (Table 2) confirm some of our prior expectations but contradict others. Education, ownership, prior training, experience and poor health all have the expected signs, and the first three variables are highly significant by the conventional criteria.⁵ However, age has an unexpected, positive effect on adoption probability. Production scale is insignificant, suggesting (*ceteris paribus*) that farmers do not perceive greater scale economies in IPM than in conventional rice production. We conclude that personal and farm characteristics are significant determinants of IPM adoption, and we control for these characteristics in our production function estimation because they may affect farming efficiency as well.

⁴ We recognize the risk of simultaneity bias for health status, so we have estimated the probability models with and without this variable. Farmers with lower health status may be more likely to adopt IPM, since it reduces exposure to dangerous pesticides. However, farmers using IPM may already have realized significant health improvement. In an IPM adoption equation that does not account for simultaneity, the measured health status effect could therefore be negative, zero or positive. We cannot account for simultaneity here, because all available instruments such as age and education are also variables in the IPM adoption equation. In any case, results for other variables are not affected by the inclusion or exclusion of health status.

⁵ Rejection of the null hypothesis (“no effect”) with 95% confidence or greater.

Table 2: Determinants of IPM Adoption in Rice Production

	Linear Probability	Probit
Age	0.008 (3.41)**	0.029 (3.34)**
Education	0.089 (5.37)**	0.296 (5.11)**
Ownership	0.129 (2.42)*	0.570 (2.55)*
Training	0.375 (4.27)**	1.057 (3.69)**
Experience	-0.003 (1.27)	-0.012 (1.36)
Farm Scale	0.001 (0.11)	0.003 (0.13)
Poor Health	-0.063 (1.70)	-0.205 (1.53)
Constant	-0.232 (2.62)**	-2.504 (7.19)**
Observations	551	551
R-squared	0.13	

Absolute value of t statistics in parentheses

* significant at 5%; ** significant at 1%

5. Comparative Input Use, Productivity and Profits

We use two quantitative techniques for assessing IPM and conventional techniques in rice production: Comparative estimates of input-output relationships, and production function estimation. In both cases, we control for farmers' characteristics (age, education, farming experience, ownership status, prior training, production scale, health status) that may affect both productivity and the propensity to adopt IPM.

5.1 Input-Output Results

For each farm in the sample, we calculate input-output (IO) coefficients for land, family labor, hired labor, capital, irrigation, seed, fertilizer and pesticide. We test for significant differences between mean coefficients for conventional and IPM farming by regressing the IO coefficients on a dummy variable for IPM use. Since all distributions of IO coefficients are highly skewed, we guard against outlier effects by estimating log

regressions as well as linear regressions.⁶ The results, reported in Table 3, are similar for both specifications. Family and hired labor inputs per unit of output are generally lower for IPM production, suggesting that time savings from reduced pesticide applications more than compensate for reallocation of some labor to IPM-related activities. Seed inputs are also significantly lower per unit of output. As expected, pesticide inputs per unit of output are significantly lower for IPM production in both the linear and log models. However, IO coefficients for land, capital, irrigation and fertilizer are not significantly different in the two modes of production.

Table 3: Impact of IPM on Input-Output Ratios for Rice Production

		Linear Estimates						
	(1)	(2)	(3)	(4)	(5)	(7)	(8)	(9)
	Land	Family Labor	Hired Labor	Capital	Irrigation	Seed	Fertilizer	Pesticide
IPM	0.000 (0.25)	-0.006 (3.01)**	-0.005 (1.85)	-0.054 (1.21)	0.143 (1.68)	-0.049 (2.28)*	0.000 (0.09)	-0.001 (6.02)**
Constant	0.001 (45.65)**	0.018 (23.81)**	0.022 (18.76)**	0.662 (35.76)**	1.077 (30.81)**	0.303 (34.61)**	0.088 (40.88)**	0.001 (21.89)**
Obs	829	829	829	829	829	829	829	829
R ²	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.04
		Log Estimates						
IPM	0.049 (1.33)	-0.237 (2.48)*	-0.213 (3.01)**	-0.056 (0.98)	-0.056 (0.87)	-0.130 (2.16)*	0.009 (0.16)	-0.662 (3.75)**
Constant	-7.669 (512.47)**	-4.474 (115.18)**	-4.058 (139.82)**	-0.611 (25.92)**	-0.014 (0.50)	-1.418 (57.40)**	-2.571 (112.49)**	-7.243 (132.87)**
Obs	829	807	798	828	753	829	812	659
R ²	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.02

Absolute value of t statistics in parentheses
significant at 5%; ** significant at 1%

Our results suggest that IPM may be more profitable than conventional farming, since no IO coefficient is significantly higher for IPM and several are significantly lower. For pesticides, the savings are clear: Conventional farmers use an average of 2.33 kg of

⁶ We have also estimated these regressions for a sample limited to the five regions where we collected data on IPM farmers, and for specifications that include the IPM determinants in Table 2. The results are indistinguishable from the full-sample estimates in Table 3.

pesticides per acre, while IPM farmers use .77 kg/acre. Pesticide purchase shares of variable costs for non-IPM and IPM farmers are 8.1% and 2.9%, respectively.

5.2 Cobb-Douglas Results

We estimate a standard Cobb-Douglas production function with factor and material inputs: land, family labor, hired labor, capital, irrigation, seed and fertilizer. We include pesticide inputs and a dummy variable for IPM use in alternative specifications, since IPM explicitly minimizes pesticide use. In addition, we allow for Hicks-neutral efficiency differences across farms that are attributable to age, education, ownership, pesticide application training, farming experience, poor health, and production scale.

The production function is as follows:

$$\ln y_i = \beta_0 + \sum_{n=1}^6 \beta_n x_i + \sum_{j=1}^6 \alpha_j \ln z_i + u_i \quad (4)$$

where

y_i	=	rice output (in kg)
x_i	=	land (acres)
		labor (man-days)
		capital (in Taka)
		irrigation cost (Taka)
		fertilizer (kg)
		IPM (dummy variable: 1 if IPM; 0 otherwise)
		or pesticide (kg)
z_i	=	age (years)
		education (categorical: 0-4 (none, primary, middle, secondary, tertiary))
		ownership (1 if owner of farm; 0 otherwise)
		training (1 if prior training in pesticide applications; 0 otherwise)
		farming experience (years)
		poor health (1 if significant self-reported health problems; 0 otherwise)
		farm scale (log of total farm size in acres)

Table 4 presents estimates for equations that include IPM and pesticide use, with and without regional dummies and efficiency variables. All inputs except labor and pesticides are significant in all or most of the models. Our results suggest that the survey farmers are operating under surplus labor (zero marginal productivity) conditions for both

Table 4: Cobb-Douglas Production Function Results

	(1)	(2)	(3)	(4)	(5)	(6)
Land	0.646 (19.52)**	0.643 (21.11)**	0.596 (17.06)**	0.597 (19.05)**	0.602 (14.91)**	0.590 (16.26)**
Family Labor	-0.025 (1.46)	-0.019 (1.23)	-0.014 (0.85)	-0.005 (0.32)	-0.013 (0.77)	-0.003 (0.17)
Hired Labor	0.022 (1.18)	0.024 (1.39)	0.025 (1.29)	0.026 (1.56)	0.026 (1.35)	0.028 (1.64)
Capital	0.083 (3.80)**	0.087 (4.26)**	0.064 (2.88)**	0.070 (3.43)**	0.067 (2.99)**	0.070 (3.35)**
Irrigation	0.115 (5.56)**	0.094 (4.97)**	0.130 (6.16)**	0.106 (5.56)**	0.131 (6.10)**	0.107 (5.45)**
Seed	0.040 (1.87)	0.048 (2.40)*	0.036 (1.68)	0.043 (2.14)*	0.038 (1.77)	0.044 (2.16)*
Fertilizer	0.088 (3.66)**	0.074 (3.29)**	0.100 (3.99)**	0.098 (4.25)**	0.095 (3.77)**	0.092 (3.94)**
Pesticide	-0.008 (0.80)		0.008 (0.75)		0.011 (1.03)	
IPM		-0.024 (0.79)		-0.028 (0.90)		-0.028 (0.84)
<u>Regions</u>						
Bogra			-0.246 (3.12)**	-0.224 (3.20)**	-0.236 (2.84)**	-0.230 (3.11)**
Chapainawabganj			-0.059 (0.28)	-0.052 (0.25)	-0.059 (0.28)	-0.074 (0.35)
Chittagong			0.111 (1.10)	0.110 (1.09)	0.116 (1.13)	0.125 (1.22)
Comilla			-0.191 (3.54)**	-0.166 (3.42)**	-0.186 (3.39)**	-0.156 (3.14)**
Jessore			-0.199 (4.09)**	-0.201 (4.73)**	-0.200 (4.00)**	-0.201 (4.61)**
Kishoreganj			-0.131 (2.17)*	-0.136 (2.57)*	-0.135 (2.20)*	-0.134 (2.48)*
Munshiganj			0.171 (1.70)	0.154 (1.65)	0.181 (1.76)	0.148 (1.55)
Narsingdi			-0.191 (3.50)**	-0.149 (3.04)**	-0.200 (3.57)**	-0.151 (2.98)**
Mymensingh			-0.148 (2.81)**	-0.156 (3.20)**	-0.161 (3.02)**	-0.164 (3.28)**
Rajshahi			-0.266 (5.44)**	-0.287 (6.32)**	-0.268 (5.39)**	-0.291 (6.27)**
<u>Efficiency Factors</u>						
Age					-0.000 (0.14)	-0.000 (0.25)
Education					-0.022 (1.84)	-0.011 (1.03)
Ownership					0.049 (1.29)	0.048 (1.31)
Training					0.029 (0.48)	0.009 (0.15)
Experience					-0.002 (1.04)	-0.001 (0.49)
Health					-0.020 (0.75)	-0.025 (1.03)
Farm Scale					-0.013 (0.39)	0.011 (0.36)
Constant	5.517 (25.04)**	5.664 (28.38)**	5.620 (25.76)**	5.700 (29.19)**	5.626 (24.60)**	5.717 (27.63)**
Observations	569	697	569	697	569	693
R ²	0.89	0.88	0.90	0.89	0.90	0.89

Absolute value of t statistics in parentheses
 * significant at 5%; ** significant at 1%

family and hired labor. We also find no evidence of positive productivity for pesticide use, possibly because direct benefits of pesticides are counteracted by their toxic impact on beneficial soil organisms and insects that prey on pests. We obtain functionally-equivalent results for the IPM dummy: Farmers who reduce pesticide use by adopting IPM are neither more nor less productive than conventional farmers, *ceteris paribus*. This result is not affected by the inclusion of regional dummies and efficiency-related variables. Many of the former are highly significant, suggesting important roles for local soil and weather conditions, while we find no significance for any of the variables that were hypothesized to affect efficiency as well as IPM adoption.

5.3 Stochastic Production Frontier Estimation

For a more sophisticated assessment of conventional and IPM methods, we use the stochastic production frontier methodology developed by Battese and Coelli (1993, 1995). The general stochastic production function, with inefficiency effects, is defined as:

$$y_i = f(x_i, \beta) \exp(v_i - u_i) \quad i = 1, \dots, n \quad (1)$$

where y_i denotes the output quantity of the i th farm, x_i is a $(1 \times J)$ vector of input quantities and β is a $(J \times 1)$ vector of unknown parameters to be estimated. The v_i are two-sided random variables associated with measurement errors in output and are assumed to be independently and identically distributed $N(0, \sigma_v^2)$ and independent of the u_i . In the absence of the stochastic term u_i , the model in (1) reduces to a purely deterministic (mean) production function. The u_i are defined as non-negative random variables which account for technical inefficiency effects in production and are independently distributed as truncations at zero of the $N(\mu_i, \sigma_u^2)$ distribution, where:

$$\mu_i = \delta_0 + \sum_{k=1}^K \delta_k z_{ik} + \omega_i \quad (2)$$

and z_i is a $(1 \times K)$ vector of farm characteristics that affect efficiency and δ is an $(K \times 1)$ vector of parameters to be estimated. The ω_i 's are random variables generally defined by the truncation of the normal distribution with zero mean and variance σ^2 , with the point of truncation as $\omega_i \geq -\delta z_i$.

Maximum likelihood methods are used to simultaneously estimate the stochastic frontier and technical inefficiency effects models. For the likelihood function, the

variance terms are parameterized as $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$, with $0 \leq \gamma \leq 1$ (Battese and Coelli, 1995). Technical inefficiency for the i -th farm is estimated as the expectation of u_i , conditional on the observed value of $(v_i - u_i)$:

$$TE_i = E [\exp(-u_i) | v_i - u_i] = E [\exp(-\delta_o - \sum_{k=1}^K \delta_k z_{ik} - \omega_i) | v_i - u_i] \quad (3)$$

5.4 Alternative Production Functions

For the production function in equation (1), we begin with the translog specification:

$$\ln y_i = \beta_o + \sum_{n=1}^8 \beta_n \ln x_i + \frac{1}{2} \sum_{n=1}^8 \sum_{k=1}^8 \beta_{nk} \ln x_{in} \ln x_{ik} + v_i - u_i \quad (4)$$

where

- y_i = represents the quantity of rice output (in kg)
- x_i = land (acres)
- family labor (man-days)
- hired labor (man-days)
- capital (in Taka)
- irrigation cost (Taka)
- seed cost (Taka)
- fertilizer (kg)
- pesticide (kg)
- IPM (dummy variable: 1 if IPM; 0 otherwise)

We specify the technical inefficiency model as:

$$\mu_i = \delta_o + \sum_{k=1}^K \delta_k z_{ik} + \omega_i \quad (5)$$

where

- z_i = age (years)
- education (categorical: 0-4 (none, primary, middle, secondary, tertiary))
- farm size (total acres)
- farming experience (years)
- ownership (1 if owner of farm; 0 otherwise)
- training (1 if trained in applying and safe handling of pesticides; 0 otherwise)
- health status (1 if significant health problems; 0 otherwise)

Appendix II provides more precise variable definitions and descriptive statistics.

5.5 Estimation results

We obtained maximum likelihood estimates for the parameters using the Frontier 4.1 program (Coelli, 1996), and ran several likelihood ratio (LR) tests on the functional form, the stochastic specification and inefficiency effects (Table 5).⁷ We report full results in Table 6. In row 1 of Table 5, we test the null hypothesis on the joint translog restrictions implied by the Cobb-Douglas specification. We find that the restrictions cannot be rejected at a very high confidence level, so we adopt the Cobb-Douglas form because its constant-elasticity results are more easily interpreted.

Table 5. Tests of Hypotheses

Null hypothesis	Restrictions	Log-Likelihood			# restr.	Critical value	Outcome
		(H ₀)	(H ₁)	λ			
Functional form							
Cobb-Douglas	$\beta_{nk} = 0 \quad \forall k, \forall n$	-94.274	-54.790	78.970	36	47.212	Reject H ₀ at 10%
Mean function (OLS)							
Cobb-Douglas	$\gamma = \delta_0 = \delta_1 = \dots = \delta_5 = 0$	-113.525	-94.274	38.501	12	25.549	Reject H ₀ at 1%
Accounting for inefficiency effects							
Cobb-Douglas	$\delta_1 = \dots = \delta_5 = 0$	-113.525	-94.274	38.502	11	24.725	Reject H ₀ at 1%

Row 2 tests the estimated stochastic frontier against the mean function estimated by ordinary least squares: Under H_0 the error term u is assumed to be non-stochastic and equal to zero. Failure to reject H_0 implies that deviations from the frontier are purely random, and that variables chosen to model inefficiency effects can enter directly into the production function for estimation by ordinary least squares. Our LR test rejects H_0 with high confidence, implying that deviations from the frontier are systematic in Bangladeshi farming.⁸

⁷ The likelihood ratio test is $\lambda = -2[\ln LF(H_0) - \ln LF(H_1)]$, where LF denotes the likelihood function, H_0 the null hypothesis and H_1 the alternative hypothesis. λ follows a chi-squared distribution with the number of degrees of freedom equal to the number of restrictions. Estimation results report the parameters $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$, where σ^2 corresponds to the variance of the overall model, and γ is the share of inefficiency variance to overall model variance. Since γ is the ratio of two variances, and is therefore always positive, the test statistic follows a mixed chi-square distribution, with the critical values to be found in Kodde and Palme (1996).

⁸ This result can be confirmed via the estimated value of γ (0.17 in Table 6, where $\gamma = 1$ implies no random noise) and the calculated variance-ratio parameter γ^* (0.07). This implies that only 7% of the difference between observed and frontier output is due to differences in farmer efficiency. Statistical significance for γ implies that distributional variation in u can be systematically explained by the regressors in the inefficiency model. Although γ is not significant, the likelihood ratio test above suggested a mild effect.

Row 3 tests whether the variables in our inefficiency effects model (equation 5) have joint significance in explaining farmer inefficiency. Rejection of the null at the 1% level indicates that farmer inefficiency is significantly associated with differences in farmers age, education, farm size, experience, ownership, training, health and regional conditions.

Table 6 reports estimates for the translog and Cobb-Douglas models, with and without controls for IPM use. Since we cannot reject the translog constraints implied by the Cobb-Douglas specification, we focus on results for the latter because they are easily interpreted as elasticities. Our results suggest that land is easily the most significant factor in Bangladeshi rice production. In the Cobb-Douglas estimate with a single dummy control for IPM, a 1% increase in land under production translates into a 0.57% increase in rice output. The two labor variables, family and hired, are insignificant, with a small negative elasticity in the case of family labor. The very small, insignificant elasticities for labor may imply that rice production is currently in a condition of surplus (zero-marginal-productivity) labor. Capital is also significant, although the estimate implies that a 1% increase in capital is only associated with a 0.08% increase in rice output. Irrigation appears to play a significant role, as do seed inputs, although to a lesser degree. Fertilizers also make a significant contribution to rice production, with an elasticity of 0.11. However, pesticides do not have any significant effect, suggesting that potential incremental gains are neutralized by toxic soil saturation or elimination of beneficial soil organisms and insect predators. The sum of input elasticities ($\sum \beta_n = 0.92$) suggests modestly-decreasing returns to scale, a finding similar to other results in the frontier production estimation literature (Coelli, Rahman and Thirtle, 2002; Wadud and White, 2000).

To measure the contribution of inefficiency variance to overall frontier variance, we use $\gamma^* = \bar{\gamma} [\gamma + (1 - \gamma)\pi/(\pi - 2)]$ (Coelli, Rao and Battese, 1998). For the Cobb-Douglas model, this is equal to 7%.

Table 6. Maximum-likelihood estimates of the stochastic production frontier model

Variable	Parameters	Translog		Cobb-Douglas		Cobb-Douglas + IPM	
		Coefficients	t-ratio	Coefficients	t-ratio	Coefficients	t-ratio
Constant	β_0	13.992	9.030 ***	5.592	24.266 ***	5.617	13.742 ***
Land	β_L	3.257	6.329 ***	0.570	14.935 ***	0.615	8.308 ***
Family labor	β_{FL}	-0.447	-1.490	-0.016	-0.889	-0.015	-0.628
Hired labor	β_{HL}	-0.253	-0.693	0.026	1.244	0.048	1.751 *
Capital	β_C	-1.410	-4.000 ***	0.076	3.184 ***	0.056	1.864 *
Irrigation	β_I	0.191	0.576	0.115	5.244 ***	0.124	4.306 ***
Seed	β_S	-0.201	-0.405	0.042	1.918 *	0.037	1.466
Fertilizer	β_F	-0.552	-1.154	0.111	4.173 ***	0.090	2.422 **
Pesticide	β_P	-0.142	-0.790	0.001	0.096	0.002	0.070
Land x Land	β_{LL}	0.477	4.329 ***				
Fam lab x Fam lab	β_{FLFL}	-0.011	-0.400				
Hire lab x Hire lab	β_{HLHL}	0.016	0.591				
Capital x Capital	β_{CC}	0.090	2.052 **				
Irrigation x Irrigation	β_{II}	0.037	0.923				
Seed x Seed	β_{SS}	-0.016	-0.296				
Fertilizer x Fertilizer	β_{FF}	0.125	2.188 **				
Pesticide x Pesticide	β_{PP}	0.016	1.161				
Land x Fam lab	β_{LFL}	-0.099	-2.119 **				
Land x Hire lab	β_{LHL}	-0.144	-2.672 ***				
Land x Capital	β_{LC}	-0.166	-3.034 ***				
Land x Irrigation	β_{LI}	0.039	0.851				
Land x Seed	β_{LS}	-0.100	-1.566				
Land x Fertilizer	β_{LF}	-0.074	-0.994				
Land x Pesticide	β_{LP}	-0.018	-0.689				
Fam lab x Hire lab	β_{FLHL}	-0.028	-1.135				
Fam lab x Capital	β_{FLC}	0.058	1.816 *				
Fam lab x Irrigation	β_{FLI}	-0.006	-0.221				
Fam lab x Seed	β_{FLS}	-0.015	-0.484				
Fam lab x Fertilizer	β_{FLF}	0.056	1.611				
Fam lab x Pesticide	β_{FLP}	0.007	0.536				
Hire lab x Capital	β_{HLC}	0.054	1.515				
Hire lab x Irrigation	β_{HLI}	-0.035	-1.158				
Hire lab x Seed	β_{HLS}	0.008	0.234				
Hire lab x Fertilizer	β_{HLF}	0.033	0.811				
Hire lab x Pesticide	β_{HLP}	0.018	1.325				
Capital x Irrigation	β_{CI}	0.045	1.207				
Capital x Seed	β_{CS}	0.025	0.693				
Capital x Fertilizer	β_{CF}	-0.005	-0.130				
Capital x Pesticide	β_{CP}	-0.016	-0.824				
Irrigation x Seed	β_{IS}	-0.018	-0.412				
Irrigation x Fertilizer	β_{IF}	-0.082	-2.046 **				
Irrigation x Pesticide	β_{IP}	0.029	1.711 *				
Seed x Fertilizer	β_{SF}	0.066	1.540				
Seed x Pesticide	β_{SP}	-0.006	-0.336				
Fertilizer x Pesticide	β_{FP}	-0.003	-0.149				
IPM	β_{IPM}	-0.050	-1.071	-0.039	-0.824	0.893	0.892
Land x IPM	$\beta_{L \times IPM}$					0.150	1.118
Family labor x IPM	$\beta_{FL \times IPM}$					-0.003	-0.043
Hired labor x IPM	$\beta_{HL \times IPM}$					-0.102	-1.846 *
Capital x IPM	$\beta_{C \times IPM}$					0.032	0.411
Irrigation x IPM	$\beta_{I \times IPM}$					-0.052	-0.610
Seed x IPM	$\beta_{S \times IPM}$					0.005	0.050

Fertilizer x IPM	$\beta_{F \times IPM}$					-0.078	-0.913
Pesticide x IPM	$\beta_{P \times IPM}$					0.016	0.514
<i>Inefficiency effects</i>							
Constant	δ_0	-0.780	-2.295 **	-0.175	-1.076	-0.545	-1.644
Age	δ_A	0.002	0.456	0.001	0.202	0.001	0.225
Education	δ_E	0.012	0.411	0.022	1.062	0.007	0.302
Owner	δ_O	0.012	0.142	0.041	0.607	0.034	0.279
Training	δ_T	-0.044	-0.307	-0.047	-0.432	-0.105	-0.415
Experience	δ_{Exper}	0.000	0.048	0.001	0.253	0.000	-0.306
Health	δ_{Health}	0.010	0.183	0.043	1.080	0.018	0.577
Farm scale	$\delta_{Farm\ scale}$	0.006	0.322	-0.028	-1.712 *	0.006	0.346
Bogra	δ_{Bogra}	0.934	2.087 **	0.387	2.854 ***	0.624	4.428 ***
Chapinawabganj	δ_{Chapi}	-0.247	-0.244	-0.741	-0.700	-0.157	-0.220
Chittagong	δ_{Chitta}	-0.080	-0.161	-0.102	-0.459	-0.149	-0.464
Comilla	$\delta_{Comilla}$	0.812	1.713 *	0.304	2.835 ***	0.553	4.424 ***
Jessore	$\delta_{Jessore}$	0.831	1.693 *	0.330	3.137 ***	0.549	4.877 ***
Kishoreganj	δ_{Kishor}	0.658	0.998	0.228	1.828 *	0.446	2.298 **
Munshiganj	δ_{Munsh}	-0.312	-0.538	-0.224	-1.174	-0.165	-0.842
Narshingdi	δ_{Narsh}	0.798	1.604	0.342	3.084 ***	0.537	4.484 ***
Mymensingh	δ_{Mymen}	0.794	1.600	0.332	3.019 ***	0.479	4.110 ***
Rajshahi	$\delta_{Rajshahi}$	0.948	2.415 **	0.452	4.600 ***	0.651	6.396 ***
<i>Variance parameters</i>							
Sigma-squared	$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.078	4.396 ***	0.086	9.130 ***	0.078	13.354 ***
Gamma	$\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$	0.190	0.721	0.171	1.144	0.066	0.972
Log-likelihood		-54.790		-94.274		-74.755	
Number of observations		569		569		569	

Note: *, **, *** - significant at the 10%, 5%, and 1% level, respectively.

In no case do we find significance for IPM, whether it enters as a single control (dummy variable) or interacted with each input (with the single exception of hired labor). We also find no significance for other hypothesized inefficiency factors. The overall significance of the regional dummies suggests that local environmental and geographic factors may have important effects on farmer inefficiency.⁹

Table 7 presents statistics for farm-level technical efficiency scores estimated by the model. Mean technical efficiency across farms is 83%, with variation from a minimum of 63% to over 98%. The distribution of scores is fairly central, with 65% of the farmers around 75-90% efficient and a fairly uniform distribution (20%) above and below this range of technical efficiency. Other studies of Bangladesh rice farming have yielded similar average efficiency scores (Coelli, Rahman and Thirtle, 2002; Rahman, 2003; Wadud and White, 2000). These results imply that, on average, farmers can increase rice

⁹ For example, soil quality attributes would be one area for further investigation.

output, and thus increase profits, by approximately 17% (100-83%) by improving technical, allocative and scale efficiency in production.

Table 7. Distribution and summary statistics of farm-level technical efficiency

Efficiency score	No. of farms	% of farms	Cumulative
0-25	0	0.0	0.0
25-50	0	0.0	0.0
50-75	83	14.6	14.6
75-90	371	65.2	79.8
90-95	58	10.2	90.0
95-100	57	10.0	100.0
Total	569	100.0	
Summary statistics			
Mean	83.0		
Min	62.9		
Max	98.6		
Standard deviation	7.5		
Coefficient of variation	9.1		

6. Health Effects of IPM Adoption

Our survey results suggest that farmers' exposure to toxic pesticides is quite serious in Bangladesh,¹⁰ while our productivity analysis suggests that any direct benefits from pesticide use have been offset by adverse impacts on soil organisms, natural pest predators, and farmers' health and productivity (Rola and Pingali, 1993). Exposure can produce numerous acute effects, depending on a pesticide's toxicity and the dose absorbed by the body. For pesticides with high acute toxicity, exposure can produce intoxication symptoms within minutes or hours, including headaches, flu-like symptoms, skin rashes, blurred vision, and other neurological disorders (World Resources, 1998-99). Prolonged exposure can lead to more serious cardiopulmonary, neurological and hematological symptoms, as well as skin disease (Davies, Freed, and Whitemore, 1982; Spear, 1991).

¹⁰ A distinctive feature of pesticide-related health hazards is that the magnitude of the health effect associated with pesticide use can often be reduced by averting behavior - wearing protective clothing, such as gloves or a jacket. Such measures can often reduce exposure by up to 80 or 90 percent (Cropper, 1994). However, during the study, applicators of pesticides communities were rarely found to be wearing proper protective clothing.

A detailed health examination of farmers in our survey¹¹ was beyond the scope of this study. Instead, our analysis relies on self-reported health effects. Among conventional farmers, 37% report frequent health problems such as eye irritation, headaches, dizziness, vomiting, shortness of breath, skin effects, and convulsions.¹² Among IPM farmers, 29% report similar health problems. Of these, 54% report that the health of the laborers working in their fields improved after they switched to IPM.

Although IPM farmers have a lower reported incidence of health effects, we find that the difference between the two groups is not significant at the 95% confidence level. The difference may be greater for farmers who have used IPM for an extended period, but our survey has not recorded IPM adoption dates. For more recent adopters, our result may be biased by a simultaneous relationship between IPM use and health: Adoption of IPM may well improve health, even in the short run, but farmers who attribute their poor health to pesticide use may be more likely to adopt IPM. At present, we do not have sufficient evidence to attribute strong health improvements to IPM adoption in our sample.

7. Environmental Effects

Recent evidence suggests that pesticide use in Bangladesh has damaged organisms not targeted by applications¹³, while pesticide runoff has polluted many waterways.¹⁴ Much of the damage can be attributed to the timing, frequency and dose-intensity of applications, as well as use of inappropriate products and lack of information about

¹¹ This would include a comprehensive physical examination, blood cholinesterase determination and skin patch tests.

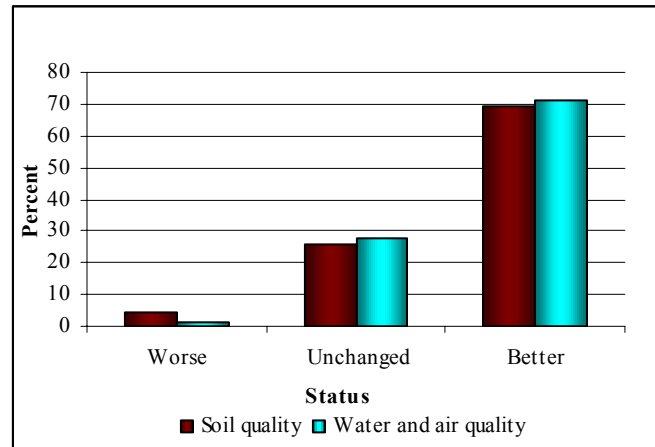
¹² Are self-reported health effects a credible measure? Suggestive evidence is provided by medical tests of the farming population in other Asian countries. Several clinical studies conducted on rice and vegetable farmers in Indonesia, Philippines, and Vietnam revealed that 58% - 99% of the farmers exposed to pesticides had at least one health effect (Xuyen *et al.*, 1998; Kishi *et al.*, 1995; Antle and Pingali, 1994; Rola and Pingali, 1993). This evidence suggests that the degree of upward bias, if any, in the self-assessment of health effects may not be large.

¹³ For example, a number of newspapers in Bangladesh (*Manab Zamin*, September 6, 1999; *Bhorer Kagaz*, September 1, 1999; *Inqilab*, September 2, 1999) reported the poisoning and death of thousands of birds in Ustad by Cypermethrin- treated eggplant fields in the Dakatia village of Jessore, a district in the Western border region of Bangladesh (UBINIG, 1999).

¹⁴ A government study conducted in 1995 found that 11% of tested water samples contained pesticide residues higher than WHO guidelines (Government of Bangladesh, 1995).

toxicity. When asked about environmental effects, nearly 70% of the IPM farmers in our survey report improvements in soil, water and air quality after adoption of IPM (Figure 3), as well as increased numbers birds, fish and soil organisms such as earthworms.

Figure 3. Observed change in soil, water and air quality after IPM adoption



8. Summary and Conclusions

In this paper, we have used new survey data on rice production to assess the net economic, health and environmental benefits of switching to Integrated Pest Management in Bangladesh. We have assessed the net economic benefits of IPM adoption in three productivity comparisons, using input ratios, standard production functions and stochastically-estimated production frontiers. In all three cases, we have found no significant difference in productivity for IPM and non-IPM rice farming. Our results hold when we control for hypothesized farm-efficiency factors that also affect the probability of IPM adoption. Our evidence suggests that IPM adoption increases profits for rice farmers, since pesticide costs are reduced with no countervailing reduction in output. The reported incidence of sickness is lower for IPM farmers, although the difference is not statistically significant in our sample. Most IPM farmers also report that environmental conditions improved after adoption of the new technique.

To summarize, our evidence suggests that further promotion of Integrated Pest Management for Bangladeshi rice farmers will yield economic, health and environmental benefits for rural communities. As we have noted, local adoption of IPM is a collective decision because farmers' pesticide applications affect their neighbors' fields as well.

Effective promotion strategies should therefore emphasize collective gains from adoption, as well as training of individual farmers in the relevant skills.

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Appendix I.

Active Ingredients Used in the Agricultural Sector, Bangladesh.

<i>Consumption (million tons)</i>	<i>Year</i>								
	1990	1991	1992	1994	1993	1995	1996	1997	1998
Insecticides									
Carbamate Insecticides	170	182	202	-	210	250	270	290	300
Chlorinated Hydrocarbons	30	24	32	-	28	35	15	1	-
Organo-Phosphates	720	751	821	-	855	810	950	980	1,020
Pyrethroids	9	9	14	-	13	14	15	5	15
Other Insecticides	26	26	33	-	18	45	50	50	30
Total Insecticides	955	992	1102	-	1124	1154	1300	1326	1365
Herbicides									
Bipiridils	-	-	-	-	-	12	20	20	19
Phenoxy Hormone Products	9	10	10	-	6	32	30	30	28
Other Herbicides	26	25	23	-	27	22	13	13	15
Total Herbicides	35	35	33	-	33	66	63	63	62
Fungicides									
Benzimidazoles	-	-	1	-	1	7	5	5	7
Diazines, Morpholines	-	-	1	-	1	5	4	4	2
Dithiocarbamates	130	125	131	-	120	132	155	170	320
Other Fungicides	4	5	3	-	6	6	5	5	23
Inorganics	142	130	175	-	200	320	375	410	350
Triazoles, Diazoles	276	260	1	-	1	5	6	4	6
Fungicide & Bacterial & Seed Treatment	276	260	312	-	329	475	550	598	708
Rodenticides									
Anticoagulants	-	-	1	-	1	2	2	1	2
Other Rodenticides	-	-	5	-	-	5	4	5	4
Total Rodenticides	-	-	6	-	1	7	6	6	6

Source: FAO

Appendix II. Variable description and statistics

Production variables:

Rice – measured in kilograms; combines the four seasonal varieties of rice, Aush, Boro, Irri and Aman;

Land – measured in acres;

Labor – measured in days; number of family and hired labor man-days;

Capital – measured in Taka; current worth of all farm machinery and equipment, depreciated at 10%, plus equipment rental costs. Equipment rental costs are reported for each crop; equipment values are imputed in proportion to crop shares in farm production.

Irrigation and seed costs (x_{IS}) – measured in Taka; stated costs per crop;

Fertilizer and pesticides – measured in kg.

Efficiency variables:

Age – measured in years;

Education – categorical variable coded as follows:

0 = can't read or write/can read, but can write

1 = Primary (≤ 5 years of schooling)

2 = Junior high school (6-10 years of schooling)

3 = Secondary or Higher Secondary (11-12 years of schooling)

4 = Above High Secondary (more than 12 years of schooling)

Experience – Years of farming experience

Training – Dummy variable (1 if trained in use of pesticide applicators; 0 otherwise)

Overall summary statistics of the sample.

Variable	Conventional				IPM			
	Mean	Min.	Max.	C.V.	Mean	Min.	Max.	C.V.
Rice production (kg)	3,469.23	200	44,000	140	4,349.29	400	27,000	110
Land (acres)	2.40	0.3	27	122	2.73	0.3	17	101
Labor (days)	229.45	11.7	1,487	140	171.81	14.1	1,224	140
Capital (Taka)	3,025.13	150	27,300	121	3,415.64	200	39,350	130
Irrigation (Taka)	4,038.16	0	41,000	113	5,066.76	0	85,000	160
Seed (Taka)	2,468.88	35	29,800	146	2,004.06	90	27,800	152
Irrigation + seed (Taka)	6,507.03	350	53,840	111	7,070.82	545	86,500	136
Pesticide (Taka)	2,856.88	0	65,189	206	1,055.27	0	18,010	262
Fertilizer (Taka)	4,811.25	0	34,930	103	4,487.51	120	27,020	105
Pesticide + fertilizer (Taka)	7,668.13	332	83,949	117	5,542.78	120	40,715	123
Revenue (Taka)	64,369.43	4500	1,372,000	158	49,913.09	5,160	656,000	134
Total costs (Taka)	26,791.03	0	175,448	96	23,039.72	1,692	130,319	97
Profit (Taka)	37,578.40	-37562	1,280,800	239	26,873.37	-85,320	603,235	215
Age (years)	36.36	18	70	32	38.76	17	75	34
Education (categorical: 0-4)	1.25	0	4	94	1.89	0	4	58
Farm size (categorical: 1-7)	3.04	1	7	50	3.54	1	7	41
Ownership (owner=1)	0.83	0	1	46	0.95	0	1	23