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Technical efficiency in crop production and environmental resource management practices in northern Ghana

Abstract

Majority of the people in northern Ghana are peasants who depend almost exclusively on renewable natural resources for their livelihoods and survival, but they are constrained partly by inadequate water availability for their production activities as well as deteriorating soil conditions. As a result, soil management practices are promoted in the area, but the link between the use of the practices and farmer efficiency is yet to be shown empirically. This study, therefore, examines the effect of adoption of the practices on crop production technical efficiency. Data for the study are obtained from a sample of 445 households using a multi-stage sampling approach. The study employs a stochastic frontier framework with an instrumental variables approach. The chosen half-normal model shows adopters are on average 6.0% more technically efficient than non-adopters. This implies that, besides enhancing the environment, adoption of soil management practices also leads to increased productivity.

Keywords: technical efficiency, resource management practice, endogeneity, adoption, Ghana.
JEL Classification: Q12, Q15, Q56.

Introduction

As noted by Barbier (2010), populations in developing countries depend on the natural environment for their subsistence, since most of these countries, like Ghana, are agrarian. But the agricultural sector has long been identified as a cause of environmental degradation and this trend is expected to continue in the next half of the century (Millennium Ecosystem Assessment, 2007). As a result, simultaneously increasing agricultural productivity and maintaining the natural resource base supporting agricultural production remains a difficult goal to be achieved by those countries.

Agriculture is a major contributor to Ghana's Gross Domestic Product (GDP) employing over 56.0 percent of the total labor force (FAO, 2007) with majority of the people in northern Ghana being peasants who depend almost exclusively on renewable natural resources for their livelihoods and survival, but they are constrained partly by inadequate water availability for their production activities as well as deteriorating soil conditions. As a result, environmental/soil management practices such as grass stripping, composting, agroforestry, cover cropping, stone and soil bunding are promoted in the area, but the link between the use of the practices and farmer efficiency is yet to be shown empirically. This study therefore examines the effect of adoption of the practices on crop production technical efficiency.

A number of studies have analyzed smallholder farmers' efficiency in the context of developing countries. Some of these include Rahman and Hasan (2008) in Bangladesh; Ogundele and Okoruwa (2006), and Okike et al. (2004) in Nigeria; Abdulai and Huffman (2000), and Al-Hassan (2008) in Ghana. A study by Solís et al. (2007) examined the connection between adoption of soil conservation practices and the technical efficiency of farmers participating in specific projects in Honduras and El Salvador by comparing high and low adopter farm households. In particular, they address the issue of whether unobserved effects lead farmers to self-select into one of the groups by implementing a switching regression model. Rahman et al. (2009) implemented a frontier sample selectivity model, developed by Greene (2006), to analyze the efficiency of Jasmine rice producers in Thailand. Kumbhakar et al. (2009) proposed a model which allows for technology choice to be dependent on inefficiency and also accounts for endogeneity of the choice. A study by Mayen et al. (2010) also addresses selectivity in stochastic frontier framework using propensity score matching.

Estimates of technical efficiency by these studies vary markedly ranging from 51.0 to 91.0 percent. A number of the studies (for example, Rahman and Hasan, 2008; Solís et al., 2007) come to the conclusion that environmental factors play an important role in determining smallholder farmer efficiency, a position that makes the current study relevant.

The rest of the paper is organized as follows. Section 1 presents a specification of the stochastic frontier model, section 2 discusses the data and variables for the study, empirical results are discussed in section 3, and the final section concludes the study.

1. Stochastic frontier model

The stochastic frontier model is used in this paper to parametrically estimate production frontiers and technical efficiency levels in crop production. The stochastic frontier framework accounts for the stochastic nature of agricultural production and also allows for estimating inefficiency effects in a single approach. Within the stochastic frontier framework, proposed by Aigner et al. (1977), and Meeusen and van den Broeck (1977), the econometric technology of the crop producers can be represented by:

$$y_i = f(x_i;\beta)\cdot \exp\{v_i - u_i\},$$
$$\text{with } \varepsilon_i = v_i - u_i \text{ and } i = 1,2,3,\ldots N, \tag{1}$$

where y_i is the crop output of the ith farm, x_i is a vector of inputs, β denotes a vector of unknown parameters to be estimated, and ε_i is the composed error term with v_i as the symmetric (random) error term accounting for measurement errors and other factors not under the control of operators and u_i is the asymmetric error term denoting technical inefficiency. It is assumed that the two-sided random errors v_i are independently and identically distributed with zero mean and variance σ_v^2 and the v_i and u_i are distributed independently of each other and of the explanatory variables. Further assumptions made regarding the distribution of the u_i, to enable the determination of the density function for ε_i for use in a maximum likelihood estimation procedure, are considered subsequently. Within the framework of equation (1) technical efficiency is given by:

$$TE_i = \frac{f(x_i;\beta)\cdot \exp\{v_i - u_i\}}{f(x_i;\beta)\cdot \exp\{v_i\}} = \exp\{-u_i\},$$
$$\text{with } 0 \le TE_i \le 1. \tag{2}$$

If it is further assumed that u_i are half-normally distributed, then the marginal density function for the composed error term $\varepsilon_i = v_i - u_i$ is given by (see, Greene (2008) and Kumbhakar and Lovell (2000)):

$$f(\varepsilon_i) = \left(2/\sigma\right)\cdot\phi\left(\varepsilon_i/\sigma\right)\cdot\Phi\left(-\varepsilon_i\lambda/\sigma\right), \text{ for } -\infty < \varepsilon_i < \infty, \tag{3}$$

where $\sigma = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u / \sigma_v$ are the parameterized variance parameters, and $\varphi(\bullet)$ and $\varphi(\bullet)$ are the standard normal density and cumulative distribution functions, respectively. The log-likelihood function is then formed from the equation above from which estimates for β, σ and λ are obtained using maximum likelihood estimation procedure. Using the conditional mean function, $E(u_i|\varepsilon_i)$, the inefficiency component, from which individual technical efficiency is predicted, can be separated from the estimate of ε_i as follows (Jondrow et al., 1982):

$$E(u_i \mid \varepsilon_i) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi\left(\varepsilon_i\lambda/\sigma\right)}{1\text{-}\Phi\left(-\varepsilon_i\lambda/\sigma\right)} - \frac{\varepsilon_i\lambda}{\sigma}\right]. \tag{4}$$

Other assumptions regarding the distribution of the u_i include Stevenson's (1980) generalization of the half-normal model which yields the truncated normal distribution; the exponential distribution (proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977)); and the gamma distribution, a generalization of the normal-exponential model (introduced by Greene (1980a, 1980b) and Stevenson (1980), and later extended by Greene (1990)).

Empirically, the stochastic production frontier models estimated in this study, using the stated distributions for the one-sided non-negative error term, assume the translog functional form given by:

$$\ln Y_i = \beta_0 + \sum_{k=1}^{4}\beta_k \ln x_{ik} + \frac{1}{2}\sum_{k=1}^{4}\sum_{j=1}^{4}\beta_{jk} \ln x_{ik} \ln x_{ij} + v_i - u_i, \tag{5}$$

where Y represents value of crop output, x is a set of four input categories (namely, land, purchased input, household labor and capital) used during the 2008/09 agricultural production season, β parameters to be estimated, v is the symmetric disturbance term accounting for random shocks and other statistical noise, and u is the one-sided non-negative random term depicting inefficiency in production. The inefficiency component of the stochastic frontier is further specified as:

$$u_i = \delta_0 + \sum_{l=1}^{4}\delta_l Z_{il} + \in_i, \tag{5a}$$

where δ is a set of parameters to be estimated, Z is a set of variables explaining inefficiency – which are, level of education of operator, proportion of income from off-farm engagement, access to credit, and a variable reflecting adoption of soil management practices – and $\in$ is the error term in the inefficiency component.

A typical statistical issue that remains to be resolved in the model is selectivity and/or endogeneity involving the management practice adoption variable. Technology adoption has been observed in the literature (see, for example, Faltermeier and Abdulai, 2009; Khanna, 2001; Langpap, 2004; Solís et al., 2009) not to be random. As a result, the conservation variable used in the inefficiency component of the frontier is likely to be correlated with the error term. To deal with a potential selectivity issue, the analysis is first pursued within the framework developed by Greene (2006; 2010) for incorporating selectivity into frontier models in a consistent manner. But, there appears not to be evidence of selection bias. A natural second step thus involves a test for endogeneity of the conservation variable, which produced evidence to that effect. On the basis of the evidence and following, for example, Huang et al. (2002) and Solís et al. (2009), the study employs the instrumental variables approach (discussed later) to mitigate the effects of the endogeneity of the conservation variable on the models.

The use of the translog functional form, which belongs to the class of generalized quadratic form, is justified on the basis of its advantages as cited in the literature (see, for example, Chambers, 1988). It is flexible and can thus serve as a second-order differential approximation of an arbitrary function, albeit not globally. However, for the translog functional form to adequately represent a production technology, it must satisfy the regularity conditions of monotonicity, diminishing marginal productivity, concavity or quasi-concavity with respect to inputs (Chambers, 1988; Sauer et al., 2006). The monotonicity and diminishing marginal productivity conditions, respectively, are given by:

$$\frac{\delta y}{\delta x_i} > 0 \text{ and } \frac{\delta^2 y}{\delta x_i^2} < 0. \tag{6}$$

The conditions imply that marginal productivity, and for that matter partial elasticity, of inputs must not only be non-negative, but should also be decreasing in inputs (Sauer et al., 2006). The concavity condition requires that the bordered determinant of the matrix below is negative semi-definite:

$$B = \begin{bmatrix} 0 & f_1 & \cdots & f_4 \\ f_1 & f_{11} & \cdots & f_{14} \\ \vdots & \vdots & \ddots & \vdots \\ f_4 & f_{41} & \cdots & f_{44} \end{bmatrix}, \tag{7}$$

where the matrix is the Hessian bordered by the first derivatives of the production frontier. Negative semi-definiteness of the matrix is depicted by alternating signs of its principal minors beginning with a negative sign (Chiang and Wainwright, 2005; Sauer et al., 2006).

2. Survey data and variables

Data for the study were obtained from a survey of 445 households in the three northern regions (namely Northern, Upper East and Upper West) of Ghana. The survey covered production activities for 2008/2009 agricultural year and was undertaken between November 2009 and March 2010. The households were drawn using a multi-stage sampling procedure which involved identifying a district in each of the regions, randomly selecting 5 communities from each district and finally randomly selecting up to 30 households from each community[1].

The stochastic frontier model is used for this study in which the dependent variable (y) is the total value (in GH¢)[2] of all crops (that is, cereals, legumes, roots and tubers, and vegetables) grown in the 2008/2009 agricultural year. A number of variables have been hypothesized to determine both the production part of the model and the inefficiency part. These variables and their descriptive statistics are presented in Table 1.

The adopter farmers' off-farm income as a proportion of total income is less than that of the non-adopter farmers as shown in the table. This could be explained by the fact that those whose major source of income is from the farm would adopt practices that will enhance their farm production activities. Farmers who use soil management practices allocate, on average, up to 71.0 percent of their total cultivated area to the practices. There is a marginal difference in the level of household labor use on-farm. The combined sample mean is about 333 man-days with the mean for adopters and non-adopters being about 332 and 340 man-days, respectively.

Table 1. Descriptive statistics of variables in the models

Variable	Units	Adopters		Non-adopters		Combined sample	
		Mean	SD	Mean	SD	SD	Mean
Dependent variable							
Crops (y)	GH¢	807.56	619.15	649.44	575.48	788.73	615.63
Explanatory variables (inputs)							
Land (x_1)	Ha	1.99	1.07	1.68	1.13	1.95	1.08
Purchased input (x_2)	GH¢	172.77	196.52	148.65	241.98	169.73	202.31
Household labor (x_3)	Man-day	331.72	300.33	339.64	391.67	332.67	312.10
Capital (x_4)	GH¢	184.45	219.80	184.18	224.64	184.42	220.13
Other explanatory variables (for inefficiency component)							
Education of household head (z_1)	Years	2.11	4.20	3.49	4.91	2.27	4.31
Proportion off-farm income (z_2)	Percent	28.99	28.79	32.81	30.36	29.44	28.98
Credit (z_3)	Dummy	0.13	0.34	0.04	0.19	0.12	0.32
Practice (z_4)	Proportion	0.71	0.32	0.00	0.00	0.62	0.37

[1] Details of the survey are found in Nkegbe (2011).

[2] The average exchange rate for the local currency in 2009 stood at GH¢2.2024 and GH¢1.4132 respectively to GB £1 and US $1 as quoted in the 'Bank of Ghana Annual Report 2009' (BoG, 2010, p. 51) and can be accessed from www.bog.gov.gh.

The explanatory variables for the first part of the frontier model are basically production inputs broadly classified into four groups. *Land* (x_1) is measured as the total area of land under cultivation in hectares. The *Purchased Input* (x_2) variable includes the value of all inputs bought (in GH¢) such as fertilizer, seed, and insecticide, and expenses on implementing soil management practices and labor hired. *Labor* (x_3) is the total man-days spent by household members and reciprocal labor exchange among farmers, also known as *self-help* labor, on-farm during the 2008/2009 agricultural year[1]. The *Capital* (x_4) variable reflects value of services (in GH¢) obtained from capital assets and farm implements. It is the value of costs, such as depreciation and interest, related to the ownership of farm implements like hoe, cutlass, axe and other farm implements used in the 2008/2009 agricultural year. It also includes cost of tractor hire and animal hire services.

Following the literature (for example, Gorton and Davidova, 2004) and also on the strengths of the available data, four variables (z_l) have been incorporated to explain smallholder farm inefficiency/efficiency. The level of education of the farmer in years (*Education* (z_1)) has been added to the inefficiency component to explain the effect of human capital on efficiency. The variable *Proportion Off-farm* (z_2) captures the effects of engagement in off-farm work on farm efficiency. This variable is the percentage of total income generated from activities other than farm work by farmers. The *Credit* (z_4) variable is a dummy which takes a value of 1 if farmer had access to credit and 0 otherwise.

Practice (z_4), as a variable, captures the effect of adoption of soil management practices and it is the proportion of cultivated area under soil management practices such as stone bunding, soil bunding, grass stripping, agro-forestry, cover cropping and composting.

As mentioned earlier, it has been observed that the decision to adopt soil management practices or technologies is a choice variable and so it is likely to be correlated with the error term in the inefficiency equation. Consequently, the management practice adoption variable is considered endogenous; a position justified by the results of both a Durbin-Wu-Hausman and a Wu-Hausman tests. Following the literature (examples are Huang et al., 2002; Rios and Shively, 2005; Solís et al., 2009), this study thus employed the instrumental variables approach to address the endogeneity issue[2]. Length of time (in years) a farmer has been practising soil management practices (*LT_PRAC*), average index for major soil type (*SOILDEX*) on all plots (scored from 1 to 5, with 1 being most fertile and 5 the least fertile/desirable) and *VISDEG*, average index for visible signs of degradation on all plots also ranked from 1 to 5 depending on whether there is no degradation to the existence of deep gullies or even worse, were used to instrument the decision to adopt soil management in the 2008/2009 agricultural year. These were used as a set of explanatory variables to estimate a first step reduced form equation (Adkins and Hill, 2008; Cameron and Trivedi, 2010; Hill et al., 2008). The *Practice* variable used in the inefficiency model is, therefore, the predicted value of the proportion of cultivated land under management practices obtained from the reduced form equation[3]. The chosen instruments meet the requirements for a good instrument (Cameron and Trivedi, 2005) as the tests reveal the instruments are uncorrelated with the error term or valid, and are also not weak (results not shown due to space limitation). Thus the three instruments are relevant (Stock and Yogo, 2005).

3. Empirical results

3.1. Preliminary tests in stochastic frontier. A series of tests were conducted to determine the appropriate functional form to use, to decide on the appropriate modeling platform, i.e. whether a frontier or otherwise, among others (Table 2).

Table 2. Results of hypotheses tests in stochastic frontier model

Type	Null	Test statistic	P-value	Outcome
Panel A				
Functional form test	H_0: all $\beta_{ij} = 0$	LR = 28.02	0.014	Reject H_0: CD is inappropriate
Frontier tests	-	$\Sigma e_i^3 = -0.09$	-	Frontier, not OLS, is appropriate

[1] Labor man-day is the adult equivalent of about 8 hours of work per day.

[2] It is noted that since the sample contained both adopters and non-adopters an interesting modeling framework to deal with a potential selection and/or endogeneity bias would have been the one proposed by Greene (2006), and applied by Rahman et al. (2009) and Greene (2010). However, when this framework was used it did not show selectivity effect and also showed no inefficiency effect probably signalling that the data were not suitable for fitting the model. The Kumbhakar et al. (2009) model was not employed because the assumption of different production technologies (among adopters and non-adopters) underlying the model was rejected for the current sample. These results and those of the endogeneity tests are available on request.

[3] Solís et al. (2009) used a similar approach in studying technical efficiency among farmers participating in three natural resource management programs in Central America.

Table 2 (cont.). Results of hypotheses tests in stochastic frontier model

Type	Null	Test statistic	P-value	Outcome
Panel B				
Distributional assumption test for u_i	$H_0: U \sim N[0, \sigma_u^2]$	LR = 22.22	0.329	Do not reject H_0: Truncated-normal distribution for u_i is inappropriate
Panel C				
Returns to scale	$H_0: \sum_1^4 \beta_i = 1$	Wald(x^2) = 4.50	0.034	Reject H_0: There exists decreasing returns to scale
Panel D				
Regularity conditions check	Monotonicity for inputs $\left(\partial y / \partial x_i > 0\right)$	Diminishing marginal productivity for inputs $\left(\partial^2 y / \partial x_i^2 < 0\right)$	Quasi-concavity of input bundle (negative semi-definiteness)	
Land	154.12	-10.75	$\lvert B_1 \rvert$ = -23752.38 < 0	
Purchased inputs	0.97	-2.80×10^{-3}	$\lvert B_2 \rvert$ = 68.11 > 0	
Household labor	0.56	-4.70×10^{-4}	$\lvert B_3 \rvert$ = -0.05 < 0	
Capital	0.27	-1.80×10^{-3}	$\lvert B_4 \rvert = 9.72 \times 10^{-3} > 0$	
Outcome	Satisfied	Satisfied	Satisfied	

The first test result in Panel A suggests a more flexible functional form, in particular the translog, should be used and not the popular Cobb-Douglas production function. This is because the test rejects the null hypothesis that all interaction terms collectively are not statistically different from zero (i.e. all $\beta_{ij} = 0$). The next set of tests in the panel shows that the appropriate modeling platform is the frontier. Waldman (1982) suggests that in specifying a stochastic frontier model, the first step should involve examining the skewness based on the third moment of the least squares residuals. A negative skew of the third moment is an indication of the existence of inefficiency effects. The other test is the standard normal skewness statistic ($M3T$), proposed by Coelli (1995), also based on the third moment of the least squares residuals. The value of the test statistic is statistically significant at the 0.01 level emphatically justifying the use of the frontier framework. This result is further confirmed by the statistical significance of the reported λ and θ in Table 3.

3.2. Structure of smallholder crop production. Table 3 displays the maximum likelihood results of the estimated stochastic frontier models. Three models were estimated corresponding to the distributional assumptions of half normal, truncated normal and gamma for the one-sided error term u_i[1]. In line with common practice in the literature, the input variables were mean-centred (i.e. each was deflated by its mean) prior to estimation implying the first-order terms' coefficients can be understood to be partial production elasticities.

As a prelude to the discussion of the structure of smallholder crop production in northern Ghana as revealed by the productivity component of the stochastic frontier, a set of tests conducted to aid in the selection of an appropriate functional form for the one-sided error term and also to establish the robustness of the selected model are discussed. The results of these tests are found in Panels B and D of Table 2. The half normal distribution is nested in the truncated normal distribution for the one-sided error term and so a likelihood ratio test (see, Lai and Huang, 2010) was used to choose between these two distributions. The result in Panel B shows that the use of the half normal distribution for u_i could not be rejected. In choosing between half normal and the gamma distributions, the information criteria in Table 3 were used since the two are non-nested. The Akaike and Bayesian information criteria (AIC and BIC) both favor the half normal model since the values for both criteria for the half normal are marginally less than that of the gamma model signifying that the half normal is closer to the data generating process than the gamma.

Following Sauer et al. (2006), the selected model was checked for its theoretical consistency. An estimated flexible functional form should be checked for three basic regularity conditions (as discussed earlier). These include positive marginal products with respect to all inputs, i.e. monotonicity; diminishing marginal products in all inputs reflecting in the negativity of the second derivative of the function with respect to all input variables; and quasi-concavity of the function which shows up in alternating signs of the principal minors of the bordered determinant beginning with a negative sign, referred to as being negative semi-definite (Chiang and Wainwright, 2005; Sauer et al., 2006). All these requirements for the regularity conditions are met, using the mean of the data as the point of approximation (see Panel D of Table 2).

[1] A fourth model estimated with the assumption of exponential distribution for the one-sided error term could not achieve convergence at reasonable convergence criteria; it is, therefore, not reported.

Table 3. Estimates of stochastic frontier models

Variable	Normal-Half Normal		Normal-Truncated		Normal-Gamma	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Constant	7.1514***	0.0617	7.3980***	0.0881	6.9676***	0.1084
ln *Land*	0.3815***	0.0672	0.3505***	0.0641	0.3725***	0.0696
ln *Pinput*	0.2096***	0.0330	0.2254***	0.0350	0.2027***	0.0332
ln *Labor*	0.2350***	0.0392	0.2201***	0.0404	0.2317***	0.0382
ln *Capital*	0.0633**	0.0266	0.0699**	0.0275	0.0648**	0.0281
0.5(ln *Land*)^2	0.1840	0.1659	0.1840	0.1566	0.1705	0.1656
0.5(ln *Pinput*)^2	0.0635***	0.0204	0.0685***	0.0221	0.0624***	0.0206
0.5(ln *Labor*)^2	0.1146***	0.0403	0.1224***	0.0413	0.1058***	0.0395
0.5(ln *Capital*)^2	-0.0183	0.0233	-0.0159	0.0232	-0.0206	0.0242
ln *Land**ln *Pinput*	-0.0919**	0.0385	-0.0914**	0.0416	-0.0842**	0.0407
ln *Land**ln *Labor*	-0.0635	0.0602	-0.0757	0.0576	-0.0396	0.0617
ln *Land**ln *Capital*	0.0114	0.0486	0.0178	0.0490	-0.0040	0.0496
ln *Pinput**ln *Labor*	0.0020	0.0167	-0.0023	0.0161	-0.0048	0.0182
ln *Pinput**ln *Capital*	0.0148	0.0167	0.0166	0.0191	0.0171	0.0170
ln *Labor**ln *Capital*	-0.0190	0.0240	-0.0205	0.0262	-0.0149	0.0245
Inefficiency effects						
Constant	-0.6846*	0.3807	0.6838***	0.2032		
Education	-0.0210	0.0289	-0.0006	0.0101	-0.0148	0.0244
Proportion off-farm	0.0130***	0.0028	0.0077***	0.0028	0.0118***	0.0036
Credit	-0.6573**	0.3270	-0.2888*	0.1677	-0.4815	0.3237
Practice	-0.8855*	0.5132	-0.4143**	0.2007	-0.7955*	0.4736
λ			3.0947***	1.0017		
σ			0.5686***	0.0302		
θ					4.3448***	1.5903
P					1.6706***	0.4830
σ_v					0.4007***	0.0386
Log likelihood	-296.942		-285.911		-297.386	
AIC	1.429		1.384		1.435	
BIC	1.622		1.586		1.638	

Notes: ***, **, *, stand for values statistically significant at 0.01, 0.05, and 0.1 levels, respectively.

The results for the preferred normal-half normal model show that more than half of the coefficients in the productivity part of the model are statistically significant at least at the 0.05 level. All four inputs have positive and significant effect on productivity. The *Land*, *Purchased Input*, *Labor* and *Capital* variables have partial output elasticities of about 0.38, 0.21, 0.24 and 0.06, respectively. This implies that a 1.0 percent increase in each of the *Land*, *Purchased Input*, *Labor* and *Capital* variables will, respectively, lead to productivity increases of 0.38 percent, 0.21 percent, 0.24 percent and 0.06 percent. *Land*, thus, remains the most important input in crop production in the study area since it has the largest elasticity value with *Capital* being the least important input. This observation is easily explained by the relative ease with which land can be accessed in the area than capital. Indeed, the finding highlights the low capital base of smallholders in northern Ghana. The dominant role of land reported here is consistent with that reported by Coelli et al. (2003) and Rahman et al. (2009) for Bangladeshi crop agriculture and Thai jasmine rice production, respectively.

A check for evidence of returns to scale among the sample implemented using a Wald test, rejected constant returns to scale at the 0.05 level (Panel C of Table 3). Since the sum of the elasticities of all the conventional inputs is about 0.89, it implies that there are decreasing returns to scale in crop production among the sample. Decreasing returns to scale suggest that decreasing all inputs by a given proportion leads to a less than proportionate decrease in output, so that productivity could be maintained or even increased by reducing the use of inputs. This result, while consistent with the finding of Wadud and White (2000) in their study of efficiency among farming households in Bangladesh, contradicts the increasing returns to scale reported by Rahman et al. (2009) among their sample of jasmine rice producers in Thailand.

3.3. Technical efficiency and soil management practices. The estimated average technical efficiency in crop production for the sample stands at 63.0 percent from the results of the preferred normal-half normal model (Table 4), implying that the potential exists for crop output to be increased by about 37.0 percent without increasing input use. This compares with other studies in northern Ghana reporting mean efficiency levels of smallholder farmers in the production of various crops to range from 51.2 to 81.0 percent (Abdulai and Huffman, 2000; Al-Hassan, 2008), and very well with the study by Rahman et al. (2009) who reported a mean technical efficiency of 63.0 percent among their sample of Thai rice producers after correcting for selectivity in the use of the jasmine variety. However, the result diverges significantly from that reported by Ogundele and Okoruwa (2006) who found average technical efficiency levels of 90.0 and 91.0 percent respectively for traditional and improved rice varieties growers in Nigeria.

Table 4. Technical efficiency averages and distribution for crop production

	Half normal	Truncated	Gamma
Efficiency levels			
≤ 0.50	26.3	51.9	6.7
0.51-0.60	13.7	15.7	7.7
0.61-0.70	18.0	12.0	18.2
0.71-0.80	24.2	12.3	32.3
0.81-0.90	17.8	7.4	34.0
0.91-1.00	0.0	0.7	1.1
Efficiency scores			
Mean	0.63	0.54	0.73
Standard deviation	0.17	0.16	0.13
Minimum	0.18	0.37	0.05
Maximum	0.90	0.93	0.92

The correlates of technical inefficiency, as shown in Table 3, are proportion of income from off-farm activities, credit and adoption of soil management practices. Except the credit variable which is not significant in the gamma model, the results of the chosen normal-half normal model and the others regarding the determinants of inefficiency are largely consistent. Proportion of income derived from engagement in off-farm economic activities is significant and positive determinant of technical inefficiency, implying that an increase in this variable significantly decreases the level of technical efficiency in crop production. This suggests smallholders earning greater proportion of their income off the farm have the tendency to reallocate labor away from farm production activities, a finding that is in consonance with that of Abdulai and Huffman (2000) in the Northern region of Ghana who found engagement in non-farm employment significantly decreased the profit efficiency of rice producers, and Rahman (2003) who also reported a negative effect of percentage of earnings from off-farm on the profit efficiency among Bangladeshi rice producers. However, Chang and Wen (2011) found differential effects of engagement in off-farm work on different categories of their sample of rice growers from Taiwan.

Higher levels of technical efficiency are associated with access to credit since the variable is both significant and negative determinant of technical inefficiency in the chosen model, a finding that agrees with studies such as Abdulai and Huffman (2000), and Adesina and Djato (1996) in Ghana and Côte d'Ivoire, respectively. This is expected given poverty levels in northern Ghana are very high coupled with the fact just about 12.0 percent of the sample accessed credit in the 2008/09 production year (see Table 1).

Adoption of environmental/soil management practices also exerts negative effect on technical inefficiency. This implies that adoption of soil management practices is associated with higher levels of technical efficiency in crop production in the study area. This finding is further corroborated by the results in Table 5 showing a test of mean differences in the levels of technical efficiency in crop production between adopters and non-adopters is significant at the 0.05 level, with the adopters being about 6.0 percent more technically efficient than non-adopters, from the results of the preferred normal-half normal model. This conforms to the observation by Wadud and White (2000) that soil degradation increased technical inefficiency among their sample, and also the conclusion reached by Rahman and Hasan (2008) that improvement in soil fertility could increase technical efficiency among their sample. Solís et al. (2007) also reported higher levels of technical efficiency among those they classified as high adopters of soil conservation practices in their sample in Honduras and El Salvador than those classified as low adopters.

Table 5. Mean technical efficiency comparison for adopters and non-adopters

	Adopters	Non-adopters	Mean difference [a]	t-statistic
Normal-half normal	0.64	0.58	-0.06**	-2.05
Normal-truncated	0.54	0.51	-0.03	-1.38
Normal-gamma	0.74	0.67	-0.07***	-3.45
F-test statistic	3.78***			
Observations	392	53		

Notes: ***, **, * stand for values statistically significant at 0.01, 0.05, and 0.1 levels, respectively; [a]mean for non-adopters minus mean for adopters.

In line with Abdulai and Huffman (2000) and Al-Hassan (2008) reporting positive effect of operator's level of education on technical efficiency among rice producers in northern Ghana, this study also observed a positive relation between the level of education of the farmer and level of technical efficiency, but unlike the former two studies the current study did not find this to be statistically significant. Other studies (such as, Rahman, 2003; Rahman et al., 2009) in other developing countries also did not find any significant effect of level of education on farmer efficiency.

Conclusion

The study set out to delineate empirically the link between the use of environmental or soil management practices and technical efficiency among smallholder crop producers in northern Ghana. The study employed the parametric stochastic frontier model. The empirical results indicate, given the current technology, there is room for improving productivity through raising technical efficiency. This can be achieved through promoting the adoption of soil or environmental management practices since technical efficiency and adoption of such practices are shown to be positively related, with adopters being on average 6.0 percent more technically efficient.

Further, the proportion of household income derived from engagement in off-farm economic activities is shown to negatively affect technical efficiency. There should be caution in the interpretation of this result. What this result might be suggesting is that off-farm economic activities are more remunerative in the area than farm production activities so that people with off-farm economic opportunities prefer to focus all their attention on that. This thus makes a case for increasing incentives for farm production activities in order to make them competitive. One obvious way of achieving this is through holistic development of rural infrastructure.

The results also reveal *Land* as the most important input in crop production in northern Ghana. Thus, policies that will ensure well defined rights to land and enforcement of those rights will be relevant to the aim of reducing poverty in the area.

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