Soil and water conservation technologies and technical efficiency in banana production in upper Rwizi micro-catchment, Uganda

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Abstract
The determinants of the technical efficiency (TE) of adopters and non-adopters of soil and water conservation (SWC) technologies in the upper Rwizi micro-catchment of south-western Uganda are compared using cross-sectional survey data from 246 smallholder farmers. A Cobb-Douglas stochastic production frontier and a probit selection model fitted to generate inverse Mills ratios for adopters and non-adopters are used in the analysis. On average, the adopters of SWC technologies were found to own more land and livestock and to obtain more output per unit of land than their non-adopter counterparts. In addition, adopters exhibit higher average TE than non-adopters. Banana production technology in the upper Rwizi micro-catchment exhibits decreasing returns to scale, and determinants of TE include education, adoption of SWC and distance to markets. Smallholder farmers in the micro-catchment who adopt SWC technologies attain higher productivity.

Keywords: conservation technologies; technical efficiency; bananas; Uganda

1. Introduction

Stagnant or declining agricultural productivity has been registered in sub-Saharan Africa (SSA). In SSA, both crop output and yield growth lag behind population growth, with declining per-capita crop yields (Cornia 1985; Sanchez & Leakey 1997; Diao *et al.* 2010). The decline in crop yield is attributed to land degradation, which is a result of various factors, among others soil erosion, nutrient mining, and the inability of smallholder farmers to adopt technologies that enhance soil conservation and soil fertility (Bojö 1996; Mbaga-Semgalawe & Folmer 2000).

In Uganda, high rates of land degradation have been reported in areas categorised as land degradation 'hotspots', including the south-western highlands, the eastern highlands, the Lake Victoria crescent and parts of the northeast (Nkonya *et al*. 2005; NEMA 2007, 2009). Limited use of soil fertility-enhancing inputs such as mineral fertilizers by smallholder farmers has also been reported (Pender *et al*. 2001). Soil nutrients are lost as a result of soil erosion, leaching and harvesting practices, especially in the case of root crops (Wortmann & Kaizzi 1998; Isabirye *et al*. 2007). Soil fertility depletion results in a loss of Uganda's natural soil capital, and in reduced agricultural productivity, incomes and food security (Bekunda 1999; Pender *et al*. 1999; Bagamba 2007). Soil fertility mining in Uganda is among the highest in SSA, estimated at 70 kg/ha per year for nitrogen, phosphorus and potassium (Stoorvogel & Smaling 1990; Nkonya *et al*. 2005).

Average crop yields at the farm level are much lower than yields attained at research institutes in Uganda (Nabbumba & Bahiigwa 2003; Pender 2004). This wide discrepancy is attributable to differences in management, limited use of productivity-enhancing technologies and continued soil mining (Bekunda 1999). These low yields imply that returns to factors of production are diminished. The ratio of measured output to the maximum potential output is referred to as technical efficiency (TE) (Aigner *et al*. 1977; Bravo-Ureta & Pinheiro 1993; Quisumbing 1996; Coelli *et al*. 2005; Mayen *et al*. 2010). Similarly, technical inefficiency (TI) is the extent to which observed output deviates from the potential maximum output (Battese & Broca 1997). Knowing the extent and potential sources of TI is an important pre-condition for targeting prescriptions and interventions to address problems (Sherlund *et al*. 2002). TE is estimated using either panel data or cross-sectional data fitted to stochastic production frontier (SPF) functions (parametric methods) or non-parametric approaches through linear programming (data envelopment analysis) (Battese & Coelli 1995; Quisumbing 1996).

In this paper we investigate productivity differentials associated with the adoption of SWC technologies in banana production in the upper Rwizi micro-catchment using a Heckman procedure to correct for self-selection of households into adopters and non-adopters. We use probit models from which inverse Mills ratios (IMR) are generated for adopter and non-adopter groups. The IMRs are used as regressors in a Cobb-Douglas SPF, estimated using maximum likelihood estimation (MLE) techniques. In addition, we account for variation in TE and the returns to scale parameters, and predict TE scores in banana production. The remainder of this paper is organised into four sections. A review of production frontier estimation is contained in section two. Section three outlines the data, section four presents the methods, and the results and discussion are in section five. Finally, section six contains the conclusions and implications of the study.

2. Stochastic Production Frontier

Various methods have been used in the measurement of the TE of farm enterprises. TE can be estimated using either one-step or two-step approaches. In the two-step method, the production frontier is estimated first, and then the TE of each firm is determined. The derived TE variable is then regressed against a set of factors that influence the farm's efficiency (Kalirajan 1981). However, the two-step method has been criticised for lack of consistency in the assumptions about the distribution of the inefficiencies (Battese & Coelli 1992; Kumbhakar & Lovell 2000; Binam *et al*. 2004). Kumbhakar *et al.* (1991) suggested that the inconsistency is fixed by estimating all the parameters using a one-step procedure. The one-step procedure was adopted for this study. TI effects are defined as a function of farm-specific factors and used directly in the MLE, employing the half normal distributional assumption for TI. Output-oriented TE is measured as the ratio of actual output to the maximum possible output (Quisumbing 1996; Mayen *et al*. 2010). Any deviation from the maximal output is considered to be due to the random component reflecting measurement errors, statistical noise and farm-specific TI components (Coelli *et al*. 2005; Ogundele & Okuruwa 2006), and a farm that operates on the production frontier has a TE of 100% (Mayen *et al*. 2010).

The analysis of TE involves two components. The first component considers the estimation of a stochastic production frontierthat serves as a benchmark upon which to estimate the TE of producers (Kumbhakar & Lovell 2000). The objective of the first component is to estimate the efficiency with which producers allocate their inputs in the production process. According to Kumbhakar and Lovell (2000), the second component concerns the incorporation of exogenous variables, which are neither inputs to the production process nor outputs of it, but which nonetheless exert an influence on producer performance. The incorporation of exogenous variables in the second part enables us to explain the observed variation in TE among the producers. These exogenous variables represent the production environment that the producers face and are believed to be beyond the control of the individual farmers. Examples of exogenous variables that explain variation in TE include degree of competitive pressure, network characteristics, form of ownership and various managerial characteristics (Kumbhakar & Lovell 2000). Moreover, these exogenous variables may influence the structure of the technology by which conventional inputs are converted into output(s).

TE is affected by a wide range of factors, ranging from farm-specific to village-specific factors (Bagamba 2007). Other authors have pointed out that farm-level inefficiency is associated with management experience, education, family size and composition, farming experience, proximity to markets and credit (Bravo-Ureta & Pinheiro 1993; Chiang *et al*. 2004; Binam *et al*. 2004; Bäckman *et al*. 2011). Education of the household head has been reported to increase TE, since educated households tend to have more access to information and thus are more able to utilise new technologies to attain higher efficiency levels in production (Battese & Coelli 1995). Access to agricultural extension closes the technology and management gaps of small-scale farmers. Consequently, access to agricultural extension plays an indirect role in contributing to potential output by reducing the TI of farmers through improving managerial ability and efficient utilisation of technologies (Dinar *et al*. 2007).

3. Data

Data for this study were collected in a cross-sectional household survey in the upper Rwizi micro-catchment of south-western Uganda between 2010 and 2011. The survey participants consisted of 246 randomly selected smallholder banana farmers in nine sub-counties in the districts of Mbarara, Bushenyi and Ntungamo (Mugonola *et al*. 2012). This region has high agricultural potential, and with high rainfall it is prone to soil erosion and land degradation (Grisley & Mwesigwa 1994). Variables used in the analysis are defined in Table 1 and in the following discussion.

Table 1: Variables in the SPF, probit and inefficiency effects models

Variable	Model	Definition
SWC	A	Adoption of SWC (1: yes; 0: otherwise)
Log-ban	SPF	Natural log of value of banana output (UGX)
Log-asset	SPF	Natural logo of value of productive assets (UGX)
Log-land	SPF	Natural log of land in banana (ha)
Log-labor	SPF	Natural log of value of labour (UGX)
Manure	SPF	Manure use (1: yes; 0: otherwise)
Total land	A	Total land owned (ha)
Total output	A	Natural log of total output (UGX)
TLU	A	Tropical livestock unit
Famsize	A	Number of people in the household
Age	A/TI	Age of household head (years)
Edu	A/TI	Education level of household head (years)
Farmexp	A	Farming experience (years)
Sex	A/TI	Gender of household head (1: male; 0: female)
Income	A/TI	Main source of income (1: agric; 0: otherwise)
Credit	TI	Access credit (1: yes; 0: otherwise)
Ext	A/TI	Access to extension (1: yes; 0: otherwise)
Travelag	TI	Travel time to agricultural parcel (minutes)
Travelmkts	TI	Travel to time markets (minutes)
TLU	A	Tropical livestock units
Subcounty	SPF/A	Of respondent (where 1 = Bukiro, 2 = Bubaare, 3 = Rwanyamahembe, 4 = Rwengwe, 5 = Bugamba, 6 = Kyangenyi, 7 = Rugando, the omitted or reference variable, 8 = Ndeija, 9 = Itojo)
Dummy-eros	A	Dummy variable for severe erosion (1: yes; 0: otherwise)

Note: A is adoption model, SPF is stochastic production frontier model, and TI is inefficiency effects model.

The value of output Y: Banana (*Musa* spp.) is the major staple food crop for most of Uganda, and the country is the largest producer and consumer of bananas (10.5 million tons per annum) (FAOSTAT 2006). It is mostly in banana production that farmers apply SWC technologies. The gross value of output of each household is derived by multiplying each household's physical production (y_i) by the farm-gate price (p_i) at the time of the study: $Y_i = p_i y_i$.

Value of labour for banana production (L_{ban}): This variable includes all labour supplied for banana production activities during the season. The amount of labour is the sum of labour supplied by the family (l_f) and any hired labour (l_h) measured in man-hours. The average local wage rate (w) is used to determine the value of agricultural labour by multiplying the total number of man-hours[1] by the average local wage rate: $L_{ban} = w\sum (l_f + l_h)$.

Capital: This variable consists of the monetary book value of tools and equipment owned. The tools and equipment are depreciated to determine their book value using the straight-line

[1] A day's work in the study area is five hours and the total man-hours are calculated using the formula: One adult male working for one day equals one man-day; one adult female or one child working for one day equals 0.75 and 0.5 man-days respectively (Battese & Broca 1997).

method of depreciation. These book values are aggregated to arrive at the overall physical asset profiles of the households.

Land: This variable is the total land area (Ha) allocated to banana production. Farmers select land for a particular crop based on its inherent fertility potential, past experience, and local indicators of land suitability to crop-specific production requirements. Farmers rely on soil colour, stoniness, depth and natural vegetation as determinants of underlying fertility potential (Gowing *et al*. 2004).

Soil conservation dummy: A dummy variable is used to capture whether farmers have any of the SWC technologies on any of their parcels of land, such as grass strips, retention ditches, agro-forestry techniques, and so forth.

4. Methods

An SPF was estimated, defining for each farm i the maximum output and a set of inputs as (Kumbhakar & Lovell 2000; Coelli *et al*. 2005; Mayen *et al*. 2010):

$$Y_i^{\bullet} = f(X_i;\beta)\exp(v_i) \tag{1}$$

where $Y_i^{\bullet}$ is the maximum feasible stochastic output obtained from the i^th^ farm that uses a vector of inputs, X_i and v_i are statistical random errors assumed to be independently and identically distributed $N(0,\sigma_v^2)$ (Binam *et al*. 2004; Sipiläinen & Oude-Lansink 2005; Ogundele & Okuruwa 2006; Bäckman *et al*. 2011). The actual production on the i^th^ farm is modelled as follows:

$$Y_i = Y_i^{\bullet}\exp(-u_i) \tag{2}$$

where $\exp(-u_i)$ is the measure of observed output-oriented technical efficiency (TE_i) of the i^{th} farm, where $TE_i \leq 1$ implies that $u_i \geq 0$. When u_i equals zero, the i^{th} farm is technically efficient and realises its maximum possible output. Therefore TE_i in the SPF framework can be defined (Battese & Coelli 1992; Coelli *et al.* 2005) as the ratio of the observed output to the corresponding frontier output, conditional on the levels of inputs used by the i^{th} farm:

$$TE_i = \exp(-u_i) = \frac{Y_i}{Y_i^{\bullet}} = \frac{\exp(X_i\beta + v_i - u_i)}{\exp(X_i\beta + v_i)} \tag{3}$$

By substituting equation (1) into equation (2) and taking the log of both sides, we get:

$$\ln Y_i = \ln f(X_i;\beta) + v_i - u_i \tag{4}$$

where u_i is a one-sided non-negative random variable representing the TI on the i^{th} farm (Binam *et al*. 2004; Ogundele & Okuruwa 2006; Bäckman *et al*. 2011). $TE_i = e^{-u}$ and TE is bounded by [0, 1]; when $u_i = 0$, then TE = 1 and production is said to be technically efficient. Otherwise production is inefficient. The term u_i can take on various distributional forms, ranging from the half normal distribution with zero mean and the truncated normal distribution, to truncated (at mean, μ), or be based on a conditional expectation of the exponential ($-u_i$), or have gamma distribution (Bravo-Ureta & Pinheiro 1993; Kumbhakar & Lovell 2000). The model for TI effects by Battese and Coelli (1995) is used to estimate and define TI as:

$$u_i = z_i\delta + \eta_i \tag{5}$$

where z_i is vector of the explanatory variables of TI effects; δ is a vector of unknown parameters to be estimated; η_i are unobservable random variables; and u_i is defined by the half normal distribution with zero mean and variance, σ_u^2 (Kumbhakar & Lovell 2000; Chiang *et al*. 2004). The parameters, δ, indicate the impacts of the variables in **z** on TE. A negative value for any δ means that an increase in the variable improves TE and vice versa. The null hypothesis that the TI effects are not random is expressed by H_0: $\sigma_u = 0$. Accepting the null hypothesis that $\sigma_u = 0$ indicates that σ_u^2 is zero, and thus the term u_i should be removed from the model, leaving the specification that can be consistently estimated by ordinary least squares (OLS) (Coelli, 1994). In addition, the null hypothesis that the impact of the variables in vector **z** in equation (5) on the TI effects is zero is given by H_0: $\delta` = 0$, where $\delta`$ denotes the vector δ, with the constant term δ_0 omitted (Battese & Broca 1997). The MLE of the parameters of the model is parameterized as $\sigma_v^2 + \sigma_u^2 \equiv \sigma_s^2 \; and \; \lambda \equiv \sigma_u^2 / \sigma_v^2$ (Aigner *et al*. 1977).

4.1 Model specification

In this paper we adopt an approach used by Savadogo *et al*. (1994) but, instead of fitting a production function, we estimate the Cobb-Douglas[2] (C-D) SPF, to determine productivity differentials in terms of average TE and factors that explain variation in TE of adopters and non-adopters of SWC technologies. We estimate and compare the results of the C-D SPF using the specification:

$$\ln \mathrm{Y}_i = \beta_0 + \sum_{k=1}^{4} \beta_k \ln X_{ik} + \gamma_i \Gamma_i + v_i - (\mathrm{z}_i \delta + \eta_i) \tag{6}$$

where Y_i is the value of banana output; X_{i1} is land under banana production; X_{i2} is the value of labour for banana production; X_{i3} is the book value of the productive assets; X_{i4} is manure use (1: yes; 0: otherwise); Γ_i = IMR for adopters and non-adopters; β_0, β_i, δ and γ_i are parameters to be estimated; and v_i is the idiosyncratic random error.

The model for the TI effects from equation (5) is:

$$u_i = \delta_0 + \delta_1 \mathrm{Farmexp} + \delta_2 \mathrm{Edu} + \delta_3 \mathrm{Ext} + \delta_4 \mathrm{Travelmkt} + \delta_5 \mathrm{Travelag} + \delta_6 \mathrm{Famsize} + \eta_i \tag{7}$$

where the variables are as defined in Table 1.

The individual household's decision on whether or not to adopt a technology is dependent on the expected benefits from their actions. The decision to adopt SWC technologies can be calculated as follows:

$$SWC_i^* = W_i \theta + D_i \gamma + \varepsilon_i, \; i = (1,2,......,N) \tag{8}$$

where SWC^* is an unobserved latent variable underlying the household's decision to adopt SWC. The observed dichotomous variable SWC has the value 0 for $SWC^* \leq 0$ (non-adoption), or 1 for $SWC^* > 0$ (adoption of SWC). W_i refers to household socio-economic characteristics and institutional services (Table 1), D_i is a dummy for the presence of severe soil erosion on the farm, and θ and γ are parameters to be estimated. The probability that an individual household adopts SWC technology is:

[2] Our choice of the Cobb-Douglas production frontier is motivated by the fact that it is simple to estimate and fulfils the strong monotonicity condition desirable for the output-oriented measure of TE (Kumbhakar & Lovell 2000).

$$\Pr(SWC_i = 1) = \Pr[W_i\theta + D_i\gamma + \varepsilon_i > 0] = \Phi[W_i\theta + D_i\gamma] \quad (9)$$

where $\Phi[W_i\theta + D_i\gamma]$ is the standard normal cumulative distribution function (Evans & Schwab 1995).

Using equation (9) and the estimated parameters (θ and γ), the IMR corresponding to self-selection of the households into adopters or non-adopters is generated (Savadogo *et al*. 1994). Self-selection arises because individuals self-select into certain behaviours or programmes, thus participation is not determined randomly (Wooldridge 2009). Initially, equation (9) is estimated and the resulting values of the vector θ are used to compute the vectors of the IMRs, Γ_1 and Γ_0 for adopters and non-adopters. The second step is to estimate the SPF by including the IMRs (Γ_1 & Γ_0) as regressors. A test of significance of Γ_1 & Γ_0 determines the relevance of the selectivity model (Sipiläinen & Oude-Lansink 2005).

4.2 Endogeneity

While we use a discrete probit model to correct for the self-selection of smallholder farmers into adopters and non-adopters of SWC technologies, some of the regressors are potentially endogenous. Endogeneity arises if the decision to use observed inputs is conditioned on the unobserved attributes (Jacoby 1992; Evans & Schwab 1995). For instance, land size may be correlated with land quality characteristics and hence may not be exogenous (Quisumbing 1996). Therefore, any estimation techniques that do not adequately correct for these unobservable variables may result in biased estimates (Sherlund *et al*. 2002). Due to a lack of suitable instruments, we are unable to correct for endogeneity in some of the regressors. We estimate five C-D SPF models. Model I presents results of the SPF and TI effects for the pooled sample, model II presents results of the SPF, TI effects, SWC adoption dummy and instrumental probit residuals, while model III presents results of the SPF and TI effects and the SWC adoption dummy. In the last two models, IV and V, the SPF, IMR and TI effects are estimated for the adopters and non-adopters.

5. Results and Discussion

The results for the adopters and non-adopters of SWC and the pooled sample in the upper Rwizi micro-catchment are presented in Table 2. The sample has 246 observations, consisting of 116 adopters and 130 non-adopters. The book value of tools and equipment, the value of banana output, the TLU and land allocated to banana cultivation were significantly higher for the adopters than their non-adopter counterparts. The average time of travel to markets was significantly higher for the non-adopters than the adopters.

The mean differences of the remaining characteristics are not significantly different across the two groups (Table 2). For instance, Famsize does not differ across adopters and non-adopters. This implies that the adopters and non-adopters roughly had the same amount of family labour available.

Table 2: Description and summary statistics of variables

Variable	Adopters N = 116	Non-adopters N = 130	Mean diff	Pooled N = 246
Age	46.4 (1.3)	45.4 (1.3)	1.0 (1.8)	45.9 (0.9)
Edu	5.9 (0.4)	5.6 (0.3)	0.3 (0.5)	5.8 (0.2)
Famsize	7.0 (0.3)	6.9 (0.2)	0.1 (0.4)	6.9 (0.7)
Farmexp	24.3 (1.3)	22.6 (1.2)	1.7 (1.8)	23.4 (0.9)
Log-land	0.5 (0.1)	0.4 (0.1)	0.1 (0.1)*	0.4 (0.05)
Log-asset	10.3 (0.1)	10.1 (0.1)	0.2 (0.1)**	10.2 (0.04)
Log-labor	10.5 (0.1)	10.6 (0.1)	-0.02 (0.1)	10.6 (0.03)
Log-ban	12.8 (0.1)	12.4 (0.1)	0.4 (0.1)***	12.6 (0.1)
TLU	2.8 (0.7)	1.3 (0.3)	1.6 (0.7)**	2.0 (0.4)
Travelag	30.8 (3.2)	31.1 (2.8)	-0.3 (4.2)	31.0 (2.1)
Travelmkt	76.6 (4.7)	94.0 (7.0)	-17.4 (8.7)**	85.8 (4.3)

Note: Numbers in parentheses are standard errors; ***, ** and * imply significance at 1%, 5% and 10% respectively; variables are defined in Table 1.

5.1 Results of the C-D SPF

The results of the different C-D production frontiers, I to V, are presented in Table 3. These models are all estimated using MLE techniques, assuming the half normal distribution for the TI effects. Moreover, a likelihood ratio test confirms the presence of stochastic TI and warrants SPF estimation techniques.

The probit selection models used to generate IMR fit the data well. Predicted residuals from the probit modelling were used as regressors in frontier model II (Table 3). The probit models adequately fit the data, with a 70% correct prediction of adopters and non-adopters. The results of the probit models are not presented, but are available upon request.

Table 3: Results of Cobb-Douglas SPF function estimation for the pooled sample, adopters and non-adopters in the upper Rwizi micro-catchment

Variable	Model I N = 246	Model II N = 246	Model III N = 246	Model IV N = 116 Adopters	Model V N = 130 Non-adopters
Constant	7.97 (1.250)***	7.53 (1.09)***	7.82 (1.23)***	11.25 (1.11)***	8.74 (1.05)***
Log-land	0.33 (0.078)***	0.32 (0.070)***	0.32 (0.080)***	0.35 (0.070)***	0.33 (0.070)***
Log-labor	0.26 (0.102)*	0.24 (0.088)***	0.27 (0.100)***	0.16 (0.090)*	0.16 (0.090)*
Log-asset	0.23 (0.085)***	0.23 (0.072)***	0.23 (0.083)***	0.10 (0.08)	0.10 (0.073)
Manure	0.15 (0.103)	0.06 (0.092)	0.15 (0.100)	0.02 (0.10)	0.04 (0.09)
Sub county1	0.20 (0.210)	0.45 (0.189)**	0.070 (0.210)	0.61 (0.18)***	0.63 (0.19)***
Sub county2	0.37 (0.210)*	0.71 (0.177)***	0.44 (0.202)**	0.71 (0.18)***	0.75 (0.19)***
Sub county3	-0.10 (0.220)	-0.17 (0.173)	-0.11 (0.211)	-0.28 (0.18)	-0.31 (0.19)
Sub county4	-0.22 (0.212)	0.04 (0.181)	-0.18 (0.210)	0.18 (0.19)	0.19 (0.19)
Sub county5	0.32 (0.207)	0.41 (0.171)**	0.34 (0.200)*	0.40 (0.18)**	0.31 (0.18)*
Sub county6	0.11 (0.205)	0.40 (0.177)**	0.15 (0.200)	0.48 (0.18)***	0.50 (0.19)***
Sub county8	0.67 (0.22)***	1.10 (0.220)***	0.72 (0.220)***	1.33 (0.19)***	1.35 (0.20)***
Sub county9	0.17 (0.198)	0.56 (0.175)***	0.22 (0.194)	0.83 (0.18)***	0.81 (0.19)***
IMR	Na	Na	Na	-1.37 (0.14)***	1.41 (0.16)***
Log likelihood	-286	-247	-282	-244	-247
Wald chi-square	125***	172***	133***	290***	267***

Note: Numbers in parentheses are standard errors; ***, **, * imply significance at 1%, 5% and 10% respectively;
Na = not applicable; variables are as defined in Table 1.

In models I, II and III land, labour and productive assets all significantly (1%) and positively influence banana output among smallholder farmers, except for labour in model I, at 10%. Based on these results, a 1% increase in land allocated to banana production is likely to increase the value of banana output by 0.32%, a 1% increase in the value of labour is likely to increase the value of banana output by 0.27%, while a 1% increase in productive assets is likely to result in a 0.23% increase in the value of banana output *ceteris paribus*. The results of models I, IV and V are different in terms of significant variables. The partial elasticity of banana output with respect to land is significant (1%) and positive in these three models, but the partial elasticity with respect to assets is not significant in models IV and V (Table 3). For adopters and non-adopters, the partial elasticities of banana output with respect to labour and assets are equal at 0.16 and 0.10; with labour significant at 10%, but insignificant for assets (Table 3, models IV &V). The partial elasticity of manure is not significant, although positive, in all models. This finding suggests that the manure quantities being used are insufficient to have any meaningful impact on banana output.

In addition, banana output varies from one sub-county to another, relative to the base case (sub-county 7). Banana output is significantly higher in sub-county 2 and 8 in model I, and in sub-counties 1, 2, 5, 6, 8 and 9 in model II. However, banana output declines in sub-county 3 (although not significant) relative to the base case sub-county 7. This result is not surprising, because livestock keeping predominates in sub-county 3, with limited banana production. Similarly, sub-county 4 is relatively dry and hilly, with limited banana production except in the valley bottoms.

The results of model IV and V further indicate that the self-selection of smallholder farmers into adopters and non-adopters is an issue (Table 3). The coefficient on the IMR is significant (1%) and negative for the adopter sub-sample, but positive and significant (1%) for the non-adopters, thus estimating the SPF without accounting for self-selection leads to selectivity bias.

5.2 Determinants of technical efficiency

The TE of the various models is presented in Table 4. Factors that influence the TI/TE include adoption of SWC technologies, age, level of education, sex of the household head, agricultural extension, income source, credit access, distance to agricultural parcels and distance to markets. The factors that consistently show negative signs include education, access to agricultural credit, distance to agricultural parcels and adoption of SWC technologies in models II and III. Increasing these factors with the negative signs increases technical efficiency (decreases technical inefficiency) with varying levels of significance. Education level is particularly significant, given that more educated farmers have higher TE. However, the negative sign of travel time to agricultural parcels is counterintuitive, as TE is expected to decrease with increasing travel time to land parcels from the homestead. As the travel time increases it becomes cumbersome to transport bulky inputs like manure and mulching materials. On the other hand, travel time to markets is consistently positive and significant across all the models (Table 4), indicating that TE decreases as it becomes more time consuming for the household to reach markets.

Using the pooled sample in model I, average TE is calculated to be 51%, which implies that, with no distinction between adopters and non-adopters, the farmers produce 51% of the maximum attainable output on average. With 49% of output lost due to inefficiency, there is great potential for improvement, provided the farmers allocate their production inputs efficiently. Comparison of average TE between adopters and non-adopters of SWC technologies also reveals that the mean difference in TE is about 7%, at a significance level of 1% (using a two sample t-test), with the adopters being more efficient than the non-adopters.

5.3 Returns to scale and elasticity of production

The elasticity of production with respect to land, labour and productive assets, and the returns to scale in banana production for the adopters and non-adopters of SWC and the overall sample for banana production in the upper Rwizi micro-catchment are given (in Table 5), based on the coefficients in Table 3. The partial output elasticities are in the same range for both adopters and non-adopters. However, the partial elasticity for labour and productive assets in the overall sample models is bigger than the corresponding values for the adopters and non-adopter models (Table 5).

The sum of the elasticities of production of land, labour and productive assets is less than one for the adopters, non-adopters and overall sample, indicating the existence of decreasing returns to scale (DRS) in banana production in the upper Rwizi micro-catchment (Table 5). DRS arise where proportional changes in all inputs in production result in less than the proportional change in output.

Table 5: Returns to scale and elasticity of production for banana in the upper Rwizi micro-catchment

	Elasticity of production			Returns to scale
Model	**Log-land**	**Log-labour**	**Log-assets**	
Model I	0.33	0.26	0.23	0.82
Model II	0.32	0.24	0.23	0.79
Model III	0.32	0.27	0.23	0.82
Model IV	0.35	0.16	0.10	0.61
Model V	0.33	0.16	0.10	0.59

Note: Variables are as defined in Table 1.

5.4 Robustness tests

Various tests were used to test the robustness of the SPF models. These tests include likelihood ratio tests, the lincom test and linktest, and t-tests for individual coefficients and average TE of adopters and non-adopters of SWC technologies. The chi-square tests confirm the presence of TI in the production structure, and therefore fitting an SPF with TI effects is appropriate. This implies that the use of OLS techniques is insufficient to account for the variation in output, because some of the variation is due to TI and statistical noise in the data. Moreover, the results suggest that the variation attributable to TI is larger than that from random statistical noise. Further, with a chi-square of 5.98 ($p = 0.0144$) we reject the null hypothesis of constant returns to Scale (CRS). Indeed, in all five models the null hypothesis of CRS is rejected at the 10% significance level.

Table 4: Results of TI effects model estimation and determinants of TE in the upper Rwizi micro-catchment

Variable	**Model I N = 246**	**Model II N = 246**	**Model III N = 246**	**Model IV N = 116 Adopters**	**Model V N = 130 Non-adopters**
Probit residuals	Na	-12.2 (2.34)***	Na	Na	Na
SWC	Na	-0.07 (0.43)	-0.65 (0.240)***	Na	Na
Age	0.001 (0.009)	-0.002 (0.015)	0.003 (0.0088)	0.0002 (0.01)	0.001 (0.01)
Edu	-0.037 (0.034)	-0.12 (0.065)*	-0.0357 (0.036)	-0.10 (0.04)**	-0.08 (0.04)**
Ext	-0.004 (0.271)	1.78 (0.555)***	-0.021 (0.276)	0.92 (0.33)***	0.92 (0.32)***
Sex	0.344 (0.301)	1.80 (0.580)***	0.48 (0.309)	1.55 (0.56)***	1.20 (0.43)***
Income	-0.830 (0.313)***	1.27 (0.585)**	-0.67 (0.318)**	-0.21 (0.37)	-0.57 (0.34)*
Credit	-0.249 (0.266)	-0.04 (0.455)	-0.19 (0.271)	-0.29 (0.31)	-0.45 (0.28)
Travelag	-0.005 (0.004)	-0.013 (0.006)*	-0.004 (0.004)	-0.005 (0.004)	-0.001 (0.004)
Travelmkt	0.006 (0.002)***	0.005 (0.002)*	0.006 (0.002)***	0.01 (0.002)***	0.006 (0.002)***
σ_v	0.46 (0.06)	0.46 (0.060)	0.460 (0.06)	0.449 (0.06)	0.412 (0.06)
Mean TE	0.511	0.706	0.518	0.584	0.556

Note: Numbers in parentheses are standard errors; ***, **, * imply significance at 1%, 5% and 10% respectively; Na = not applicable; variables are as defined in Table 1.

6. Conclusions

In this paper we determined the productivity differential between the adopters and non-adopters of SWC technologies in banana production in the upper Rwizi micro-catchment of south-western Uganda. Since adoption decisions are dependent on the farmers and may not be entirely random, a Heckman procedure for correcting self-selection bias was used. After generating the inverse Mills ratios for the adopter and non-adopter groups, SPF functions were fitted to determine the factors affecting TE.

The results of the C-D SPF show that TE gains of 49% are possible in smallholder banana production. The smallholder farmers exhibit high levels of inefficiency in banana production, obtaining on average 51% of the maximum potential output. Further, the land area has the highest production elasticity among adopters and non-adopters. The production elasticities are in order of decreasing magnitude from land to labour and, finally, productive assets.

That the banana production technology in the upper Rwizi micro-catchment exhibits DRS implies, *ceteris paribus*, that the smallholder farmers in the upper Rwizi micro-catchment are in a production stage at which they should not just be adding more traditional inputs to banana production. That is, other land quality-enhancing inputs are needed to further improve the productivity of the existing traditional inputs. For example, the adoption of SWC technologies enhances the productivity of smallholder farmers in the upper Rwizi micro-catchment. That is, adopters of SWC are significantly more efficient than their non-adopting counterparts.

In analysing the sources of TI, two factors have consistently shown the same signs across the different models. These are education level and distance to markets. Education level positively impacts on TE, presumably because farmers who are more educated more easily learn about and adopt new technologies and efficiently allocate production inputs. Thus, in the longer term, increasing the education level of the banana producers could increase their TE.

Our results further reveal that TI is also positively correlated with increasing travel time to markets. This indicates that the farther away smallholder farmers are from markets, the lower their TE in banana production. Improved market access enables smallholder farmers to acquire the production inputs and improved farm-gate prices that could act to incentivise them to embrace land improvement technologies. Therefore, a shorter term programme for improving TE could be to improve infrastructure to reduce travel time to markets.

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