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Impact of soil and water conservation technology adoption on smallholder farms in South-Western Uganda

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For countries where the agricultural sector supports a majority of the population as in Uganda, the link between poverty and land degradation is of great significance. Soil and water conservation technologies are a recommended means of reducing degradation rates. However, *ex-ante* and *ex-post* analyses of the impact of these technologies remain few. Using survey data collected from 338 randomly selected households in the Kabale district of South-Western Uganda, this study used a Tradeoff Analysis for Multi-Dimensional Impact Assessment (TOA-MD) model to analyze the impact of adoption on household agricultural income and poverty levels. In the survey, households in the district either had or had not adopted the soil and water conservation technologies that had been disseminated. Results indicate that the simulated range of adoption rates is between 55 and 85%, with a potential to increase to about 90% amongst households with higher non-farm income. Households are also anticipated to benefit from adoption of soil and water conservation technologies through higher income from farming and poverty reduction; adoption is positively correlated with household non-farm income. Increased access to inputs, credit and improvement in infrastructure are recommended, especially for low income households. Dissemination of soil and water conservation technologies needs to be combined with other income generating measures in order to have a bigger impact on household welfare.

Key words: Trade-off analysis, tradeoff analysis for multi-dimensional impact assessment (TOA-MD), soil and water conservation, Uganda, adoption impact, household welfare, smallholder farms.

INTRODUCTION

The link between poverty and land degradation is of great significance, especially in developing countries where the agricultural sector supports a majority of the population, and is the main focus for future growth and development (Shiferaw and Holden, 1998; Dey et al., 2010). Agriculture in sub-Saharan Africa is mainly subsistence, relying on little or no external inputs or land conservation measures. More intensive use of the land to meet increasing demand

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Table 1. Common soil and water conservation technologies in Uganda.

Soil and water conservation technologies		
Terracing	Grass strips	Agro-forestry
Mulching	Bench terraces	Minimum tillage
Trash lines	Trenches	Irrigation
Contour cultivation	Live fences	Infiltration ditches
Woodlots	Stone walls	Soil/Stone bunds
Live fence	Infiltration/Retention ditches	Irrigation

Source: Abesiga and Musali (2002), Nkonya (2002), Buyinza and Naagula (2009).

for food is now associated with a deterioration in its productivity (Barbier and Bishop, 1995; Dey et al., 2010), in part because conventional agricultural practices lead to soil erosion, as well as nutrient depletion (Umar et al., 2011). This has led to more efforts to promote soil and water conservation practices (Adgo et al., 2013).

Uganda heavily relies on agriculture; 73% of the total population are employed by the sector, 85% of the rural population derive their livelihood from it (MAAIF, 2010a), and it accounts for about 25% of exports (MFPED, 2014). Low production and productivity are major challenges facing the sector because of high levels of land degradation, low levels of adoption and delivery of agricultural technologies, and pests and diseases (MAAIF, 2010a). As a result, food production has not met consumption needs for a population that between 1970 and 1997 grew by 109%; total food production grew by only 17% (Bahiigwa, 1999). The number of people affected by food insecurity increased from 12 million in 1992 to 17.7 million in 2007 (MAAIF, 2010b).

Many solutions have been suggested as means to address this decline in productivity (DFID, 2004). Most have centered on sustainable use of the resources, especially conservation of soil and water through the use of low cost inputs. Besides the low cost, the argument for use of soil and water conservation technologies is that they mostly utilize inputs available to rural farming communities, rather than high cost inputs like inorganic fertilizers and pesticides (Pender, 2009).

In Uganda since 2010, 45 to 80% of the country's annual sustainable land management budget has been allocated to the promotion and dissemination of soil and water conservation technologies (MAAIF, 2010a). These technologies are the most widely used in Uganda as opposed to other technologies geared towards sustainable land management. These are largely a combination of traditional knowledge, individual innovation shaped by response to local conditions and knowledge introduced from external sources. Farmers utilize different soil and water conservation practices on their land depending on the terrain, perception of effectiveness, costs involved, and access to information about the conservation technologies, among other factors (Table 1).

Studies that assess the impact of soil and water conservation technologies on household poverty and agricultural income among smallholder rural farmers remain limited, with most of the extant literature focused on factors that influence the decision to adopt soil and water conservation technologies of different types (Miiro, 2001; Pender et al., 2001; Nkonya, 2002; Buyinza and Naagula, 2009; Barungi et al., 2013). Yet one of the conditions for sustainable adoption of agricultural technologies and successful adjustment in farmers' behavior towards application of new production systems is that additional income derived from those new activities favorably compares to the opportunity cost of labor and overall profitability is higher (Teshome et al., 2013; OECD, 2001). This study estimates adoption rates of soil and water conservation technologies and their impact on one of the key performance indicators of rural welfare, crop income and poverty rates. To do this, a Trade-off Analysis for Multi-Dimensional Impact Assessment (TOA-MD) model is applied to a sample of smallholder farmers from Kabale district in the South-Western Highlands of Uganda.

METHODOLOGY

The study area

This study was done in Kabale district, in the South-Western Highlands of Uganda. This district was chosen because it represents the social, economic and environmental characteristics of highland areas but also because it has one of the highest population densities in the country, at 314 persons km^{-2} *vs*. an average of 173 persons km^{-2} for the rest of the country (UBOS, 2014, 2016). To meet the food demand, the farming system in this district is characterized by highly fragmented agricultural land that is intensely and continuously cultivated (Were, 1997). This has contributed to degradation levels of up to 90% of cultivated land in some areas (NEMA, 2001). The source of livelihood for the population is mainly farming, with off-farm income contributing about 30% of annual household incomes (Bagamba et al., 2009; Bagamba et al., 2012). In 2005, 35% of the households in the district were listed as below the poverty line *vs*. 31% at country level (UBOS, 2011). Up to 70% of swamps and other areas highly susceptible to soil degradation have been reclaimed and brought under cultivation in Kabale district (Were, 1997). The resulting negative effects have led to a conscious effort on the part of farmers working with development partners to devise means of

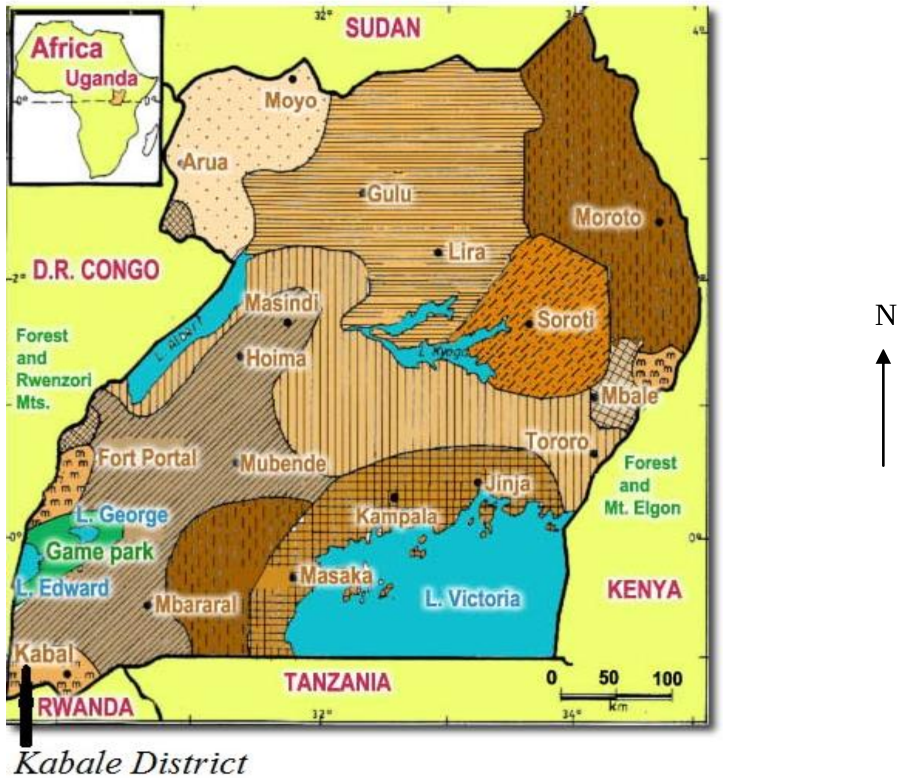

Figure 1. A map of Uganda showing location of the study area (Kabale district).
Source: Mwebaze (1999).

lowering the degradation rates using soil and water conservation technologies (Figure 1).

Sampling and survey data collection

The sampling of respondents followed three stages. First, a list of government programs and NGOs disseminating soil and water conservation technologies was obtained. A visit was then made to each of these organizations to obtain information on disseminated technologies, target areas and villages, and the names of farmers receiving training or extension services. From this information, a list of 1,350 households that received training and extension services and were using soil and water conservation technologies was compiled and used as the primary sampling frame for what are referred to as the 'treated farms[1] in this paper. From this list, 273 farm households were selected using random numbers.

To be able to estimate the impact of the soil and water conservation technologies, households that were not trained in their use and were not using these technologies were sampled to provide a control group. For their selection from each of the communities at local council-one (LC1)[2] level where the treated farms were selected, a list all households was obtained from LC1 offices. From each of the LC1 lists, for every 10 sampled treated farms, 2 to 3 control farms were randomly chosen. The decision to choose about 25% of the respondents as controls was based on personal communication with the technology disseminating organization leaders, who estimated that > 70% of farmers in the district were practicing at least one of the soil and water conservation technologies[3]. A total of 65 control households were sampled, making a total sample of 338 respondents. The respondents were from all the three counties of Kabale, viz. Rubanda, Ndorwa, and Rukiga. Survey data were collected between June and August, 2012 using questionnaires, and was based on information related to both household and parcel levels for the 2011 cropping seasons.

Soil and water conservation technologies

The soil and water conservation technologies used in the study area were trenches/diversion channels, trash lines, grass strips, *fanya chini* and *fanya juu* terraces, manure/compost, intercropping, crop rotation, cover crops, agro-forestry, fallowing, contour ploughing, minimum tillage, alley cropping and bench terraces (Miiro, 2001; Abesiga and Musali, 2002; Nkonya, 2002; Buyinza and Naagula, 2009). For this study, six of these 15 technologies were selected (Table 2) and their impact evaluated. Their selection was based on being the recommended technologies for the study area.

TOA-MD model and the challenge of sample selection

The TOA-MD method is normally used for *ex-ante* impact assessment, that is, for a situation where a technology has not

[1]In this paper, a "farm" is the "household". All the agricultural resources (land labour etc.) and characteristics of a household comprise a farm.
[2]LC1 is the lowest administrative unit in Uganda

[3]70 percent does not necessarily mean trained farmers, it is an estimation made based on what the leaders observe, including those farmers that have not been trained under them.

Table 2. Soil and water conservation technologies considered in the study.

Technology	Percent of households using (n=338*)
Trenches/diversion channels	26.63
Grass strips	24.56
Fanya chini terraces	55.92
Agro-forestry	11.24
Fanya juu terraces	0.3
Bench terraces	2.37

*Some households utilize more than one technology.
Source: Survey Data (2012).

been disseminated, or at least not widely, and data are available that can be interpreted as representing "control" and "treatment" groups of farm households. The two groups should not have self-selected themselves for the results to be free from bias. For this study, this means that the sample of non-adopters, the controls, should be random and representative of what would have been observed before any soil and water conservation practices were in use. Ideally, these farm households would be located in areas where such technology dissemination programs had not been carried out and there was no access to information about these practices. For the adopters, the sample should also be randomly selected. Thus for this study, the farm households now using soil and water conservation practices should have been selected randomly by the various organizations that disseminated these technologies. Because of these conditions, using the TOA-MD model introduces potential bias. For example, the adopters were not necessarily randomly selected; adopters may have chosen to "dis-adopt"; non-adopters may have observed or talked to adopters.

However, this model was still considered suitable for use by this study, in the first instance because the selection of participating households through disseminating organizations (DOs) would be considered acceptable under TOA assumptions. This is because the DOs purposely selected communities prone to or faced with serious soil erosion, announced the delivery of training, and created the awareness so that all community dwellers could either choose to participate or not. All those who chose to participate were enrolled in the programs and trained. Because of the way farm households were selected for this study, and since the call for training was announced publically, the randomly selected "treated" farm households represent the adopters and those who received the announcement from the DOs but chose to ignore it are the non-adopters, who are in broad terms representative of practices used prior to the introduction of soil and water conservation technologies. If dis-adoption occurred, this was likely at negligible levels only. It should be noted that the 1,350 farm households that received training represent about 1.3% of the total rural households in Kabale district[4]. This means that provision of opportunities for adopting soil and water conservation technologies by DOs is still low, which is a requirement for TOA-MD model use. Therefore, the potential adoption rates and their impacts on poverty and crop income which are simulated in this paper should be representative of what should happen if all farm households had the opportunity to be adopters.

TOA-MD

Use of the TOA-MD model (Antle and Valdivia, 2006, 2011; Antle, 2011) in this study was motivated by the need to estimate adoption rates of soil and water conservation technologies, as an important step towards estimation of returns to adoption (Walker and Crissman, 1996). Adoption rates are often difficult to predict with other models, mostly due to unavailability of data (Dey et al., 2006; Antle, 2011; Jahan et al., 2013). The TOA-MD is less demanding in terms of data needs and can be used with less complex data from surveys, experiments and institutional data bases, and is amenable to expert judgment (Antle and Valdivia, 2011). For this study, the TOA-MD model was found suited to the sources and nature of the data being used: for example, the subsistence farm settings where technologies get disseminated and the level and extent of adoption varying greatly among farms due to factors that determine adoption and intensity of adoption. The TOA-MD model also "allows a technology to be represented as a set of management practices, but all farms need not to use the technology in precisely the same manner. Thus, in this model, the only distinguishing feature of each farming system is that it gives rise to different expected returns for producers" (Antle, 2011). In this study area, the components of the technologies, the number of technologies and the extent to which they are applied vary, a scenario that is probably common to most farming systems in developing countries.

Systems in the TOA-MD model

This model offers a choice between two alternative farming systems: System 1 and System 2. System 1 is the baseline case, or "control" in which conventional methods are used, is the study households that have not adopted any soil and water conservation technologies. System 2 comprised households that use soil and water conservation technologies, the "treatment" group in this study; all households that have taken up any number or combination of soil and water conservation technologies are in System 2.

Sub-systems and activities

In each system are two sub-systems: crop and livestock. Both adopter and non-adopter farmers can have similar crop and livestock enterprises. Because livestock farming was not a major agricultural activity in the study area, it was not included in the analysis. The crop sub-system can comprised different crop activities. A baseline study indicated a high crop diversity in the study area but very small scales of production. Consequently, crop activities were grouped into "main crops" and the "minor crops" based on the number of households that appeared to grow them in the two cropping seasons of 2011. Returns for each of the respective activities were then aggregated in the analysis. The main crops were beans, maize and potatoes; the minor crop were

[4]Estimate based on a total of 252,750 rural households (UBOS, 2017).

tobacco, coffee, artemisia, millet, bananas, cassava, yams, wheat, soybeans, pumpkins, fruits and vegetables, peas and sorghum.

Strata and scenarios

Farms were stratified according to their level of annual non-farm income. Two strata were formed, those households with annual non-farm income ≤US$100, and those with >US$100[5], hereafter referred to as the low and high income groups, respectively. The strata were based on the observation that >50% of the households had an annual non-farm income of <US$100.

The adoption process is gradual and adoption is often incomplete (Jahan et al., 2013). In this study, some of the initial adopters may continue to use soil and water conservation technologies and due to other factors such as the farmers' characteristics and other external factors, other farmers are expected to take up the technologies later. Also, during the adoption process, some of the previous adopters may dis-adopt. For this study, an attempt was made to see how the adoption rate can change with time. This was done by creating two different scenarios under the aforementioned two strata (low and high non-farm income) during the analysis, with the aim of determining how adoption rate varies with farm income and poverty rates over time. These were created based on the number of years a household had spent with a technology. For the first scenario, stratification was based on non-farm income as stated, but considered only the sub-sample of household that had used soil and water conservation technologies for only up to three years (hereafter referred to as recent adopters). The second scenario follows the same procedure as the first scenario, but considered only the sub-sample of households that had used soil and water conservation technologies for more than three years (hereafter referred to as early adopters). The use of three years as the cutoff point was based on the assumption that by the end of that period after adoption, the benefits of conservation on the farm would be visible especially in terms of better yields.

The TOA-MD model is based on the economic feasibility of the alternative practices, in other words the difference in returns between Systems 1 and 2. Households are assumed to maximize returns, such that beyond a certain threshold a (which can represent expected returns from switching to system 2), they switch from System 1 to System 2 because adoption of soil and water conservation is assumed to result into an improvement in yields and returns. Following Antle (2011), let v_h be the expected returns to system h, where $h=1,2$. The difference $v_1 - v_2 = \omega$ represents the opportunity cost of changing from System 1 to System 2. Based on ω, the model simulates the proportions of households that would adopt System 2 and that would continue to use System 1. When $v_1 > v_2$, $\omega > 0$, and households use System 1; when $v_1 < v_2$, $\omega < 0$, and households use System 2.

Farms are heterogeneous, such that the difference in expected returns, $\omega = v_1 - v_2$ varies across households. The mean of ω,

$$E(\omega) = \mathrm{E}(\mathrm{v}_1) - \mathrm{E}(\mathrm{v}_2) = \mathrm{NR}_1 - \mathrm{NR}_2 \quad (\$/ha) \tag{1}$$

where NR_1 is net returns to system 1 and NR_2 is net returns to system 2. The variance of ω is:

$$\sigma_w{}^2 = \sigma_1{}^2 + \sigma_2{}^2 - 2\sigma_{12}\,. \tag{2}$$

[5]In the subsequent sections these two strata (annual non-farm income less or equal to US$100 and those above US$100) will be referred to as low income and high income sub-populations, respectively.

where σ_1^2 and σ_2^2 are the variance of returns to Systems 1 and 2, respectively, and σ_{12} is the covariance between the Systems. It may be difficult to obtain data to estimate the covariance σ_{12}. In many cases (such as this study), the covariance σ_{12} is likely to be large relative to the variances, e.g., the returns to a crop grown with improved soil fertility management practices should have a relatively high and positive, but not perfect correlation with the returns to the same crop grown with conventional practices (Antle et al., 2010). If $\sigma_1^2 \approx \sigma_2^2 = \sigma^2$, then by substituting σ^2 into the expression for σ_ω^2 (Equation 2) it follows that $\sigma_\omega^2 = 2\sigma^2(1-\rho_{12})$, where ρ_{12} is the correlation between returns for Systems 1 and 2 (between-system correlation).

Land management decisions are determined by the spatial distribution of opportunity cost $\varphi(\omega)$ (Antle et al., 2010; Antle and Valdivia, 2011). As demonstrated by Antle (2011), farms will select themselves into adopter and non-adopter groups, and the rate of farms switching to System 2 (the adoption rate) is defined by the cumulative distribution function:

$$r(2,\mathrm{a})\int_{\infty}^{a}\phi(\omega)\,\mathrm{d}\,\omega,\ \ 0 \le r(2,a) \le 1, \tag{3}$$

where $\phi(\omega)$ is the density function, which is a function of prices and other exogenous variables. The proportion of farms that stay in system 1 is $1-r(2,a)$.

Generalizing to a case in which there are multiple activities in each system requires determining how the complete system is composed of the individual activities and then deriving the means and variances of each system (Antle et al., 2010). Each crop activity k uses a share W_{1k} of farm land in a stratum. For example, in the case of two crop activities, such that activity 1="major crop" and activity 2="minor crop",

$$\left.\begin{aligned} \mathrm{E}(\mathrm{v}_1) &= NR_1 = W_{11}\,\mathrm{NR}_{11} + W_{12}NR_{12} \\ \mathrm{E}(\mathrm{v}_2) &= NR_2 = W_{21}\,\mathrm{NR}_{21} + W_{22}NR_{22} \end{aligned}\right\} \tag{4}$$

where there are two subscripts, the first subscript represents the system and second an activity. For example, W_{11} represents the share of farm land occupied by system 1 major crop and NR_{22} represents the net returns from System 2 minor crop. The rest are as defined earlier. Mean net returns for sub-systems and systems are computed in the model, and so is opportunity cost. The standard deviation of returns for sub-systems, variance of returns for systems and variance of opportunity cost are also computed in the model. Let the variance of returns to activity k in system h be $\phi^2{}_{hk}$ and the covariance between activities 1 and 2 be $\phi^2{}_{12}$. Then the variance in returns for system h=1, 2 is:

$$\phi_h^2 = \sum\nolimits_{k=1}^{g} W_{hk}^2\phi_{hk}^2 + 2\sum\sum\nolimits_{1\neq 2}^{g} W_{h1}W_{h2}\phi_{h12} \tag{5}$$

In the assessment of impact, economic, environmental and social outcomes are associated with each system. Outcomes are jointly distributed with opportunity cost ω in the population. Farms self-select into non-adopter (System 1) and adopter (System 2) groups. Each of these groups has a distinct distribution for each outcome. The relationship between adoption, outcomes and impacts depends on the correlations between opportunity cost and outcomes (Antle, 2011). Based on the adoption rate of System 2, the model simulates these associated economic, environmental and social impact indicators for adopters, non-adopters and the entire population (Claessens et al., 2009; Bagamba et al., 2012). The selection effects of adoption depend on the correlations between variables determining adoption such as expected returns, and outcome variables used to measure impact such as household income and soil erosion (Jahan et al., 2013).

The TOA-MD model utilizes means, variances and correlations of outcome variables from the available data. Specifically, the main variables utilized by the TOA-MD model include: (1) Population means and variances of production; (2) Output prices; (3) Cost of production of the activities in the different systems (the activities may be a combination of crop, livestock, and aquaculture or one or two of the three); (4) Population means and variances of (environmental, social and economic) outcomes associated with each system; (5) Correlations between system returns and outcomes; (6) Population means and variances of farm household characteristics (farm size, pond size, household size, off-farm income, etc.) (Antle and Valdivia, 2011). For this paper, the economic outcomes, namely household income and poverty level were used in the analysis. The indicators in the model were defined as mean agricultural income (US$/farm/year) and poverty rate in terms of percentage of farms below the poverty line. Suppose outcomes are defined as k , systems are defined as $h = 1, 2$, and $k(h)$ refers to outcome k for system h , the following parameters of the joint and marginal distributions for all farms are used in the model:

$$\mu_k(h) \equiv \text{ mean of } k(h)$$
$$\sigma_k^2(h) \equiv \text{variance of } k(h)$$
$$\sigma_\omega^2(h) \equiv \text{variance of } \omega$$
$$\rho_k(h) \equiv \text{correlation between outcomes } k(1) \text{ and } k(2)$$
$$\kappa_k(h) \equiv \text{correlation between outcomes } v(h) \text{ and } k(h)$$
$$\theta_k(h) \equiv \text{correlation between outcomes } k(h) \text{ and } \omega$$

Three correlations play a role in the model (Antle, 2011): ρ_k which represents between system correlations of a given outcome k ; $\kappa_k(h)$ represents within system correlations between economic returns v and outcome k ; and $\theta_k(h)$ is the correlation between outcome $k(h)$ and opportunity cost ω. Because of insufficient data, the analysis did not include the time dimension of the adoption process.

The poverty line used in the TOA-MD model

The poverty line in the TOA-MD model was used to determine poverty rates and the cut-off point below which households were considered poor (Appleton, 1999). It was adjusted for inflation using the consumer price indices for the base year, 1993 (P_b) and the year of data collection 2012 (P_s). Following World Bank (2015a), the poverty line was computed as:

$$P_s \equiv P_b * (\frac{CPI_s}{CPI_b}) \tag{6}$$

where CPI_s and CPI_b are the consumer price indices of the years of data collection and the base year, respectively. Based on 1993 prices (Appleton, 1999), the nominal rural poverty line for rural Western Uganda was 10,877, Uganda shillings per adult equivalent per month, which was equivalent to 0.30US$ per adult equivalent per day. From Equation 6, the poverty line used for this study was 0.82 US$ per adult equivalent per day using CPIs for 1993 and 2012 of 72.4 and 196.43, respectively (BOU, 2004/5; UBOS, 2014).

The poverty line was also used to estimate the poverty gap (*PG*) and the squared poverty gap. The poverty gap is the sum over all households, of the shortfall of their real private consumption per adult equivalent from the poverty line (counting the non-poor as having zero shortfall) divided by the poverty line (Ssewanyana and Kasirye, 2014; World Bank, 2015b). It is the 'distance' poor people have to go to reach the poverty line, measured as a percent of the poverty line (Emwanu et al., 2004). It was computed as:

$$PG = \frac{1}{N}\sum_{i=1}^{N}(1-\frac{x_i}{z})\, I(x \le z) = \frac{1}{N}\sum_{i=1}^{q}(1-\frac{x_i}{z}) \tag{7}$$

where *q* is the number of poor households and *N* is the sample size.

$I(.)$ is an indicator function, such that if income (X_h) is less than the poverty line (z), then I (.) equals to 1 and the household would be counted as poor. It accounts for the intensity (or depth) of poverty (Giovanni, 2007). The squared poverty gap (*SPG*) was calculated as:

$$SPG = \frac{1}{N}\sum_{i=1}^{N}(1-\frac{x_i}{z})^2\, I(x \le z) = \frac{1}{N}\sum_{i=1}^{q}(1-\frac{x_i}{z})^2 \tag{8}$$

The squared poverty gap is the "sum over all individuals of the square of the shortfall of their real private consumption per adult equivalent and the poverty line divided by the poverty line" (Ssewanyana and Kasirye, 2014). The squared poverty gap measured the severity of poverty, that is, the degree of inequality amongst the poor themselves (World Bank, 2005; Giovanni, 2007).

The analysis for this study utilized the Tradeoff Analysis Model for Multi-Dimensional Impact Assessment (TOA-MD) version 5.0 (http://tradeoffs.oregonstate.edu). The data were entered into EXCEL. The resulting two dimensional simulated "Tradeoff curves" generally representing economic outcomes on one axis and adoption rates on the other axis are presented in appendices section.

RESULTS AND DISCUSSION

Farm characteristics

For System 1 households, those with low non-farm income had higher average returns from individual crops than those with high non-farm income (Table 3). As the low income sub-group mostly derive their livelihood from

Table 3. Socio-economic characteristics of the sample sub-groups used in this study.

System 1 (Non adoption)	Low income group (n=40)		High income group (n=39)		t test#
	Mean	**St. Dev.**	**Mean**	**St. Dev.**	
Household size	6.70	3.29	5.13	2.48	t(72)= 2.28*
Education of the farmer	6.48	3.59	6.67	2.94	t(73.62)= -1.71*
Farm size (ha)	0.75	0.48	0.72	0.63	t(70.98)= 0.22)
Non-farm income (US$/year)	49.22	5.08	332.41	434.67	t(38.43)=-4.44***
Total mean agricultural returns (US$/farm/year)	553.13	725.68	260.79	351.41	t(55.78)= 2.26*
Returns from crops (US$/farm/year)					
Beans	86.66	108.21	66.99	105.60	-
Maize	20.26	31.11	16.64	40.79	-
Irish potatoes	403.81	741.99	335.74	825.91	-
Sweet potatoes	32.06	60.19	51.91	104.96	-
Peas	14.33	36.64	8.66	18.11	-
Millet	0.42	2.39	0.00	0.00	-
Sorghum	84.02	162.74	36.49	50.25	-
Cabbage	0.22	1.38	12.09	46.27	-
Bananas	0.00	0.00	0.00	0.00	-
System 2 (Adoption)	**Low income group (n=113)**		**High income group (n=128)**		
Household size	6.73	2.99	6.66	2.55	t(208.30)= 0.21
Education of the farmer	6.20	2.72	6.93	3.26	t(235.78)= -2.20*
Years spent using SWC practices	5.595	6.880	4.638	5.827	t(212.47)= 1.14
Farm size (ha)	0.99	0.70	1.26	0.82	t(234.0)= -2.61**
Non-farm income (US$/year)	51.94	28.91	393.17	364.38	t(129.45)=-11.39***
Total mean agricultural returns (US$/farm/year)	617.73	719.67	812.02	748.20	t(233.53)=-2.03*
Returns from crops (US$/farm/year)					
Beans	96.26	125.99	110.75	151.40	-
Maize	18.83	36.14	27.10	57.93	-
Irish potatoes	427.78	677.00	536.09	799.18	-
Sweet potatoes	85.03	312.33	99.53	142.19	-
Peas	19.17	40.80	22.10	43.25	-
Millet	5.26	16.75	15.18	63.83	-
Sorghum	59.49	99.28	81.83	99.24	-
Cabbage	40.70	216.25	52.06	211.79	-
Bananas	16.50	106.37	27.50	161.23	-

#t test: Figures in parentheses are degrees of freedom. Figures not in parentheses are t values. ***, **, * denote estimated parameter difference is significantly different from zero at the 1, 5 and 10% test levels, respectively.

farming, they are likely to put more effort into growing their crops. Farm sizes were greater for System 2 than System 1 households, and in System 2, greater for the high than the low non-farm income sub-group. In contrast to System 1 households, the high non-farm income group in System 2 had higher returns from crops. As the demands for investment in land increase, the higher non-farm income group is more likely to have the resources for greater investment of inputs necessary for adoption.

When recent adopters are compared with early adopters, the latter group has higher values on all parameters focused on (Table 4). Early adoption is a function of technology characteristics as well as other socio economic characteristics including expected returns, amount of investment required, farmer endowments (education, capital), information and credit access, uncertainty associated with the technology and risk behavior of potential adopters (Mansfield, 1961; Rogers, 1983; Simtowe et al., 2012). Separating early and recent adopters implies that the two groups are likely to have different socio-economic characteristics, with early adopters in the favorable position, especially in terms of resource availability. Ability of households to afford the necessary ingredients of adoption makes them more efficient, and they are able to reap higher returns on investment (Karanja, 2012).

Adoption rates of soil and water conservation technologies among the farm categories

Figure 2a shows the adoption curves for the low and high non-farm income categories and also the adoption curve representing the entire population. Figure 2b shows the adoption rates when the population is sub-divided according to years of adoption. The x-axes represent the adoption rate, while the y-axes show the opportunity cost of changing from System 1 to System 2. The adoption rate is the point at which the adoption curve crosses the x-axis. A main assumption of the TOA-MD model is that farms can only adopt if the returns from adoption are higher than returns from non-adoption. At the adoption rate, the opportunity cost is zero. Given that opportunity cost is the difference between returns to system 1 and returns to system 2, a negative cost would mean that farmers will switch to system 2, while a positive cost would indicate the opposite. The points on the curve to the left of where it crosses the x-axis show the percentage of farms that would adopt soil and water conservation technologies, and for which adoption is economically feasible. The points on the right show those that would not adopt. The predicted adoption rate is the one that gives the highest average returns in the population.

Predicted adoption rates of soil and water conservation technologies as a function of the opportunity cost of changing from System 1 to system 2 (the point where the curve crosses the horizontal axis) are 55.029 and 84.745% for low and high income farms, respectively, while for the entire population, the adoption rate is 70.538 (Figure 2a and Table 4).

Results in Figures 2a and b and Table 4 point to the fact that non-farm income plays a key role in increasing adoption rates. In Figure 2a, the adoption rates among the high non-farm income group are estimated to be about 30% higher than for the low income group (84.7% compared to 55% for the low income group). Similar results are seen when the sample is divided into recent and early adopters; within a sub-population considered as recent adopters, when exposed to soil and water conservation technologies, the adoption rate among farmers with high off-farm income would be considerably high, at least twice as much as that of farmers with low off-farm income in the same category (79% compared to 33%, respectively). More interestingly, however, the adoption rate between the would-be early and recent adopter sub-populations would be almost the same if the two sub-populations had same off-farm income levels; the adoption rate in the recent adopter sub-population is 79%, while it is 75% in the early adopter sub-population. This suggests that late adoption of SWC in the study area is partly driven by lack of off-farm income to finance initial investment, not necessarily risk aversion which is often attributed to late adoption. Adoption rates and intensity are positively correlated with household endowment, such as non-farm income, which is an indicator of their ability to afford necessary inputs for adoption (Diiro, 2013).

The simulated adoption rate for the population is contrary to that reported by Nkonya (2002), who estimated 46 and 56 as the percentage of respondents in the South-Western Highland region of Uganda and the rest of Uganda, respectively, who use soil conservation technologies. These figures are lower than the 70.5% (Table 5) reported in this study as an estimate for the adoption rate of the entire population. This disparity in estimated adoption rates is also a possible reflection of the dynamics that have occurred since the study by Nkonya (2002). In addition, the adoption rates generated by the TOA-MD model and reported in this study are those that would occur if farmers are behaving economically rational, maximizing expected returns to their farms. This is not always the case since maximization of returns requires that other factors that influence adoption such as proper institutional arrangements and infrastructure are in place and functioning well (Stroud and Khandelwal, 2006; Mazvimavi and Twomlow, 2009). Farm technologies and production decisions may be inhibited by limited access to input and output markets, lack of sufficient credit to acquire inputs and make necessary investments, inadequate information about, and unfamiliarity with technologies (Kassie et al., 2010). Constraints on adoption are not captured by the TOA-MD model, which

Table 4. Socio-economic characteristics of the recent and early adopters.

System 2 with recent adopters only (Scenario 1)	Low income group (n=59)		High income group (n=69)		t test[#]
	Mean	St. Dev.	Mean	St. Dev.	
Household size	6.08	2.93	6.04	2.23	t(101.19)=-0.09
Education of the farmer	5.98	2.36	6.80	2.84	t(124.56)=-1.30)
Years spent using SWC practices	1.660	0.964	1.553	0.910	t(116.71)=0.6319
Farm size (ha)	0.81	0.66	1.05	0.82	t(122.95)=-1.81*
Non-farm income (US$/year)	42.06	29.13	319.09	253.04	t(70.24)=-9.78***
Total mean agricultural returns (US$/farm/year)	346.57	545.74	613.83	649.25	t(124.86)=-2.50*
Returns from crops (US$/farm/year)					
Beans	48.64	98.53	85.52	108.50	-
Maize	7.56	20.06	14.18	34.83	-
Irish potatoes	241.86	559.45	319.20	480.58	-
Sweet potatoes	45.08	98.59	78.13	113.83	-
Peas	17.51	43.38	14.32	36.42	-
Millet	4.41	15.36	19.93	82.64	-
Sorghum	34.24	41.64	62.31	78.14	-
Cabbage	4.51	25.44	17.94	64.93	-
Bananas	1.38	7.51	2.32	19.26	-
System 2 with early adopters only (Scenario 2)	**Low income group (n=54)**		**High income group (n=59)**		
Household size	7.46	2.91	7.37	2.72	t(104.15)=0.16
Education of the farmer	6.47	3.11	7.07	3.69	t(111.63)=-1.80*
Years spent using SWC practices	9.834	7.937	8.245	6.986	t(104.31)=1.11
Farm size (ha)	1.20	0.69	1.50	0.77	t(110.96)=-2.12*
Non-farm income (US$/year)	61.82	25.57	479.80	448.89	t(58.85)=-7.65***
Total mean agricultural returns (US$/farm/year)	904.23	773.20	1043.80	793.85	t(111.28)=-0.94
Returns from crops (US$/farm/year)					
Beans	146.56	13.30	140.26	186.41	-
Maize	30.73	44.79	42.22	74.12	-
Irish potatoes	624.24	737.77	789.74	1003.15	-
Sweet potatoes	127.25	434.49	124.56	167.02	-
Peas	20.92	38.23	31.21	48.83	-
Millet	6.16	18.21	9.62	29.27	-
Sorghum	86.18	131.25	104.66	115.86	-
Cabbage	78.94	305.84	91.97	300.44	-
Bananas	32.47	151.44	56.95	234.20	-

[#]t test: Figures in parentheses are degrees of freedom. Figures not in parentheses are t values. ***, **, * denote estimated parameter difference is significantly different from zero at the 1, 5 and 10% test levels, respectively.

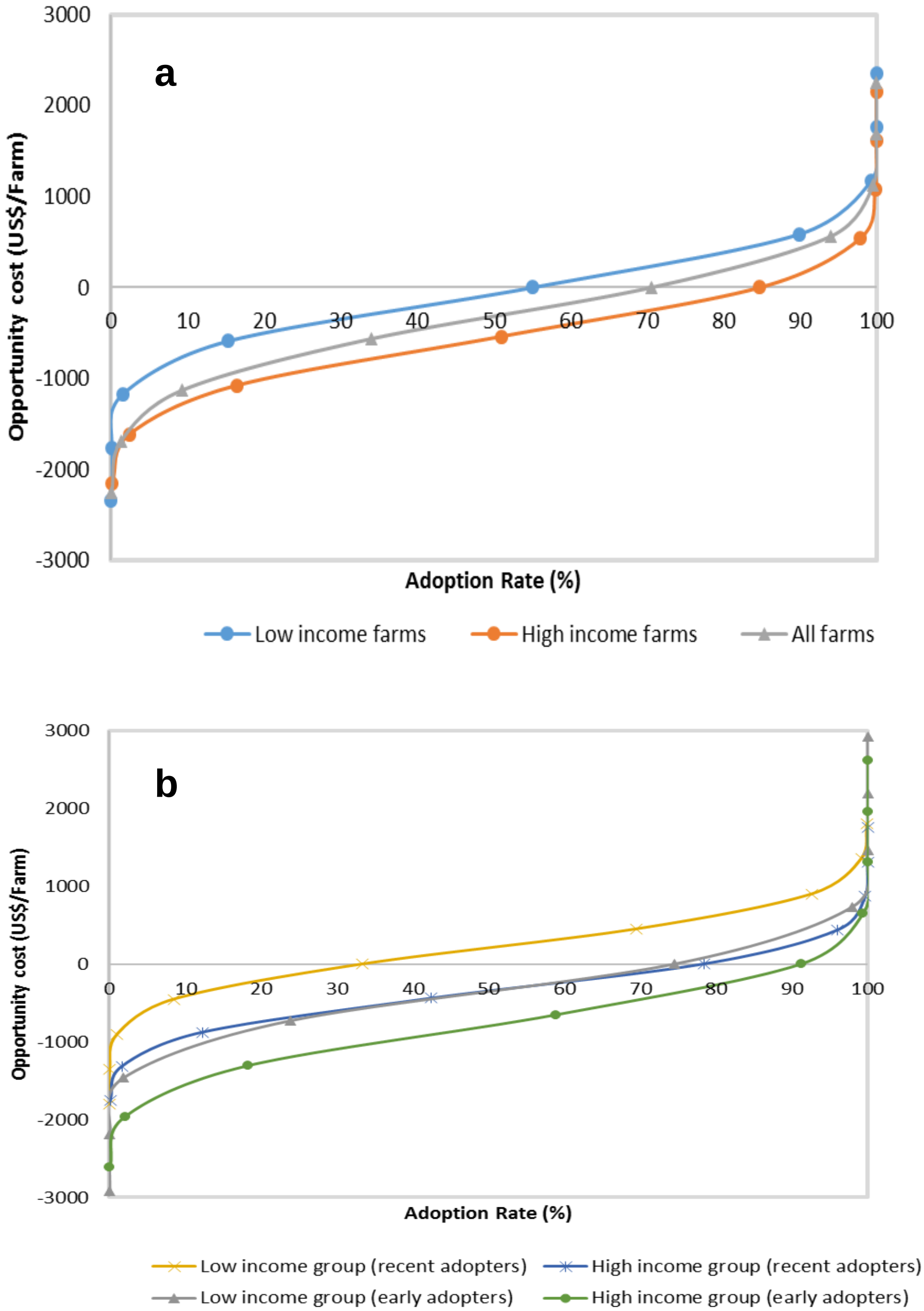

Figure 2. Adoption curves for soil and water conservation technologies, Kabale district. (a) Adoption curves for soil and water conservation technologies (entire sample farms/households). (b) Adoption curves for soil and water conservation technologies (scenarios 1 and 2 households simulated separately).

implies that in their presence, the simulated adoption rate may be lower than actual adoption rate. For example, the adoption rate of stratum 1 (low non-farm income), which most likely has less resources than stratum 2 (high non-farm income) is lower than the adoption rate for the population in all simulated scenarios.

The impact of adoption of soil and water conservation technologies on annual returns from agriculture

Figure 3a to c shows the results of a simulation of the relationship between the adoption rate and mean farm

Table 5. Summary of impacts of adoption of SWC technology on farms and the population.

Strata	Adoption rate	Mean crop income per farm ($/year)			Mean per capita income ($/year)			Poverty rate (% below poverty line)		
		Base (Non-adopters)	% Change		Base (Non-adopters)	% Change		Base (Non-adopters)	% Change	
			Population	Adopters		Population	Adopters		Population	Adopters
All sample										
1. Non-farm income ≤$100/year	55.03	785.49	1.26	0.69	154.75	-2.57	-1.41	88.53	0.74	1.35
2. Non-farm income>$100/year	84.75	48.85	1946.5	1649.6	96.77	161.17	136.59	96.77	-26.05	-30.74
Study population average	70.54	424.21	111.12	93.82	123.26	58.39	49.96	92.65	-13.25	-15.41
Scenario 1 (Adoption time ≤3 years)										
1. Non-farm income ≤$100/year	33.35	814.11	-57.21	-19.08	160.05	-50.60	-16.87	88.86	3.80	11.39
2. Non-farm income>$100/year	78.35	117.49	599.68	469.84	108.31	98.03	76.81	95.08	-15.75	-20.10
Study population average	56.83	472.43	22.92	40.56	134.18	9.39	20.94	91.97	-6.31	-4.89
Scenario 2 (Adoption time >3 years)										
1. Non-farm income ≤$100/year	74.54	804.52	30.18	22.49	158.27	8.24	6.14	87.51	-0.65	-0.87
2. Non-farm income>$100/year	91.18	-7.83	15052.3	13724.5	78.14	225.70	205.79	97.78	-32.83	-36.00
Study population average	83.22	406.57	172.55	152.26	118.21	80.11	72.13	92.65	-17.63	-19.41

returns. Figure 3a shows the relationship for non-adopter and adopter groups, while Figure 3b and c shows the same relationships when the adopters have been categorized into recent and early adopters. The figures show what happens to the mean agricultural income of the groups as the adoption rate is varied by changing the adoption threshold. With a zero adoption threshold such as in the case of this study, results indicate the mean agricultural income that would be realized at different adoption rates, if all farms chose the system that gives them the highest returns. The predicted rate is the optimal adoption rate, and when the model is forced away from it as is the case when adoption rates are below or above this point, the aggregate (or average) returns in the population must be lower than at the "economically optimal" adoption rate, and farms are "forced" to adopt or not adopt, reducing the returns (Tran et al., 2013). Thus, maximum returns for a given population are attained at the predicted adoption rate.

The impact of adoption of soil and water conservation technologies on annual income from agriculture per farm is shown by the change in mean annual agricultural income at the simulated adoption rate (Table 5). The base line for comparison is the mean income at zero adoption (non-adopter figures). Results generally indicate that adoption of soil and water conservation technology leads to an increase in agricultural income, with possibility of over 1000% increase for the adopter sub-population and about 94% when simulated for the entire population, using all sample farms.

Results in Figure 3b indicate that the change in mean agricultural income as a result of adoption of soil and water conservation technologies varies between the different strata. At the economically rational adoption rate (zero opportunity cost), the lower income stratum is seen to attain an increase in agricultural income of 1.3% as compared to 1946.541% for the higher income stratum, when simulated at population level (all sample). When analysis is done after categorizing adopters into recent and early adopters, the trend of the results stays similar as earlier stated, with the lower income group having comparatively less positive change in annual agricultural income as a result of adoption in all cases (Figure 3b and c, and Table 5).

At zero adoption, the group with low non-farm income farms has higher average agricultural returns, as can also be seen in Table 2, where among non-adopters, the low income group has mean agricultural income as 553US$ per farm per year, compared to about 50% less (261US$ per

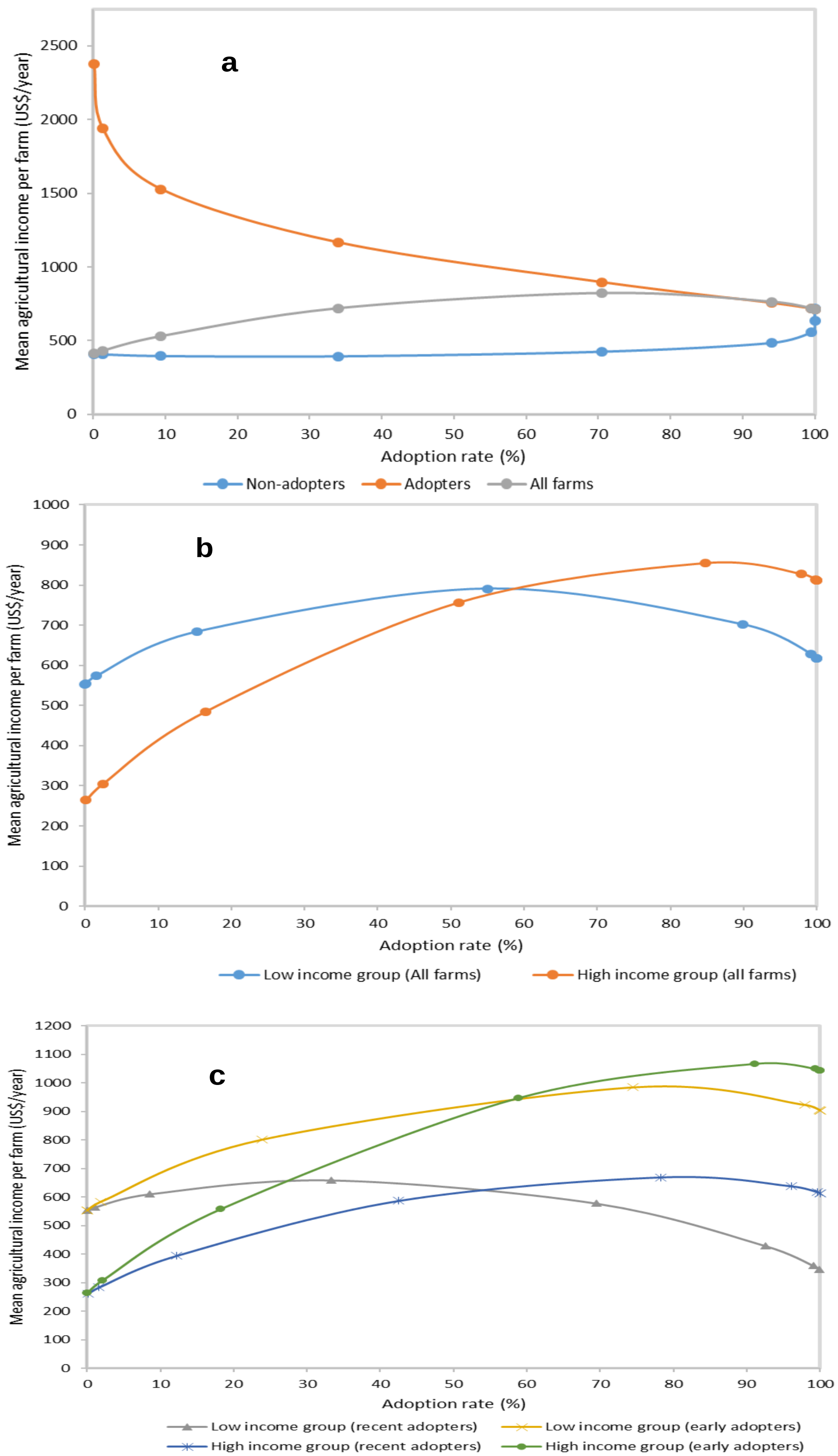

Figure 3. Mean agricultural income for Kabale district, with adoption of soil and water conservation technologies. (a) Mean agricultural income for Kabale district, with adoption (all farms). (b) Mean agricultural income for Kabale district, with adoption (all farms, by strata). (c) Mean agricultural income for Kabale district, with adoption (by strata and scenarios).

farm per year) for the high income group. As the adoption process takes place as shown by the simulation in Figure 3c, the agricultural income of the high income group becomes comparatively higher.

The general gain in agricultural income does not seem true for the low income group in the recent adopter sub-population (Table 5 and Figure 3c). Results indicate that for this group, mean agricultural income of the adopters and the sub-population seems to be less than that of non-adopters in the same group, by 57 and 19%, respectively, and it would appear as though it is not profitable to adopt soil and water conservation technologies. This ‘apparent’ loss from adoption implies that in the short run during and after adoption (less than three years in the case of this study), soil and water conservation technologies are likely to involve more costs than returns. Like for many agricultural land management technologies, the benefits of adoption of soil and water conservation are long term in nature (Tenge et al., 2004; Mitiku et al., 2006), and it is possible for an otherwise profitable technology to look less viable in the short run when initial costs of investing in adoption have not yet been recovered in terms of returns from the invested-in land. In the short run, costs have already been incurred, yet returns to investment in adoption are not yet realized. But at the same time, the temporary “loss” is more visible with low income sub-populations. The adoption process in terms of adoption intensity and rate, of resource constrained households is likely to be slower than that of resource rich counterparts, which means that the expected benefits are also slow to be realized. Also, when limited resources are allocated between non-farm activities, direct/traditional farm inputs (labor, seed, etc.), and soil and water conservation, the crop output is also compromised, due to sub-optimal levels of investment. If returns are to be realized from investment in soil and water conservation technologies, investment levels must be above break-even.

The impact of adoption of soil and water conservation technologies on poverty rates

Figure 4a to c shows the predicted poverty rates as related to the adoption rate of soil and water conservation technologies. The curves indicate how poverty rates would vary with adoption rates if farmers are behaving economically rational. The poverty rate for this study is defined as the percentage of the farm population (total households) living on less than US$0.82 per adult equivalent per day. The y-axis indicates the poverty rate, while the x-axis shows the corresponding adoption rate of soil and water conservation technologies. Different adoption rates of soil and water conservation technologies are shown to be associated with different poverty rates, depending on the groups considered, and generally shows a positive relationship with poverty reduction, with most of the groups’ poverty levels decreasing with the adoption rate.

Figure 4a shows that at zero adoption rate, the poverty rate for the adopters is comparatively lower, but as more farms adopt, the average poverty rate for the adopter sub-population tends towards the population average. At zero adoption, the poverty rate for the adopters is about 26%, while it is about 92% for the non-adopter sub-population. Increase in adoption rate means that some more “poor” farms are joining the adopters group, changing the average poverty rate for the adopter group.

Poverty rates for the high non-farm income group are lower than those of low non-farm income group under all scenarios and for all ranges of the adoption rate. The low income sub-population, in addition to having the lowest adoption rates, shows a comparatively lower increase in returns from agriculture as well as the least benefit in terms of reducing the poverty rates on adoption of soil and water conservation. Comparatively, lower decrease in poverty rate can be attributed to less than optimal investment levels for the low non-farm income households.

The general picture from Figure 4c shows that poverty rates would tend to decrease with increase in adoption rates. However, the magnitude of change realized as the adoption rate increases varies with the different categories of adopters, and follows the same trend as the agricultural income and mean per capita income. The high income group has the highest positive change in poverty reduction as the adoption rate increases.

Results in Table 6 show the poverty gap and the square of the poverty gap for the different sub-groups under analysis, evaluated at US$0.82 as the poverty line. Paired t-test results indicate significant differences between the poverty values of the low and high non-farm income groups for all the systems and scenarios at 5% significant level. In addition, there is a significant difference between the poverty gap and squared poverty gap values of the low income group in System 1 (non-adopters) and the low income groups of the recent adopters and early adopters (5%), respectively.

Results in Table 6 indicate that the highest poverty gap is for the low non-farm income, recent adopter sub-group; on average, the poor in this category have an income shortfall of 47% of the poverty line (also 47% higher than the non-adopters), compared to 15% (53% lower than the non-adopters) for the low income early adopter group. The result conforms to the earlier findings that in the short run when returns from investment in agricultural technologies are not yet realized, it may seem as though it is better not to adopt. From Table 6, recent adopters seem worse off in terms of poverty, than their non-adopter counterparts. Where meagre resources have to be spread too thin in order for adoption to take place, short run benefits are likely to appear way below expectation. The role of non-farm income in facilitating adoption and thus reducing poverty can also be seen from Table 6. For example, among recent adopters, the

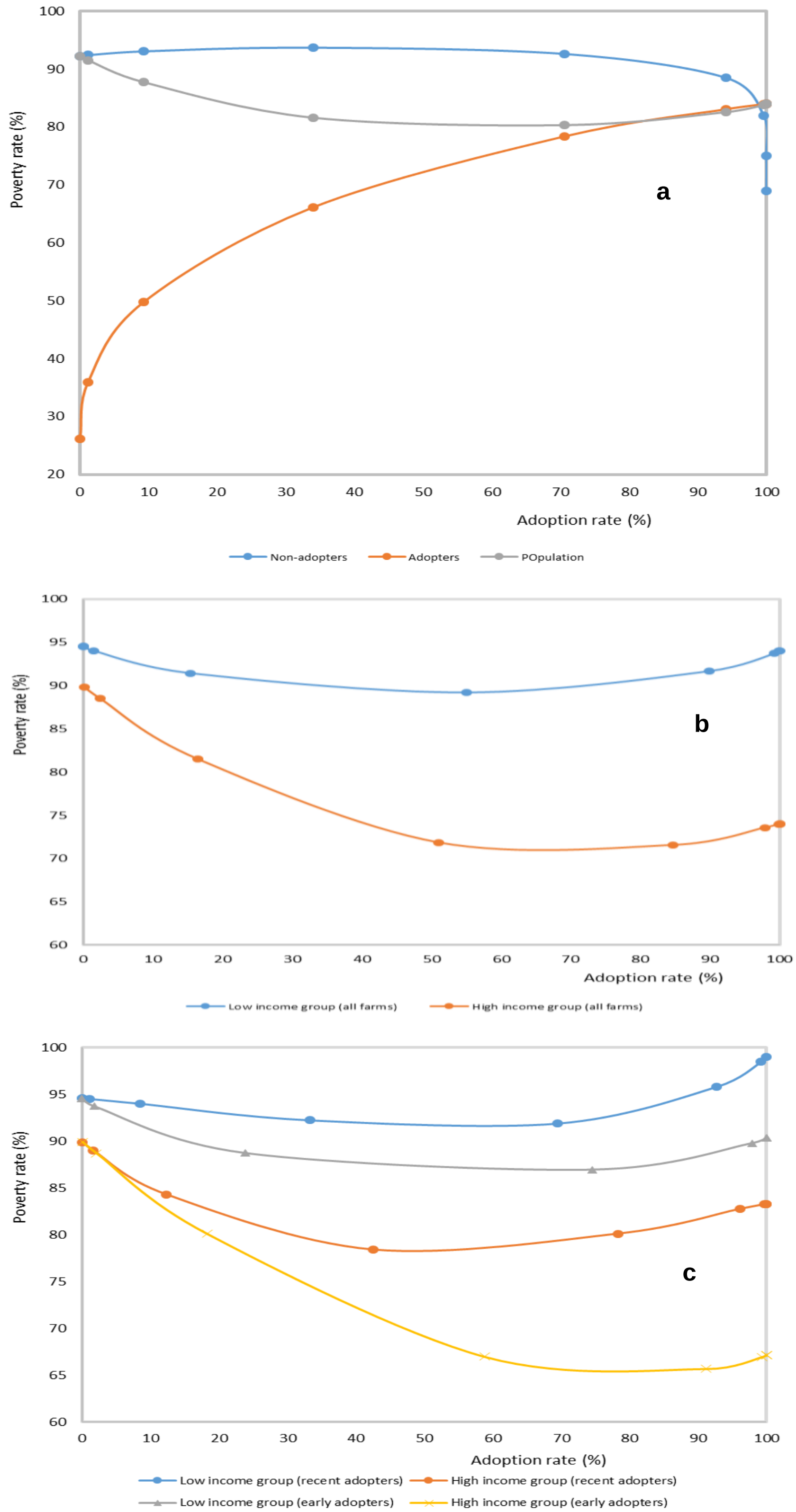

Figure 4. Poverty rate and adoption rate of soil and water conservation technologies. (a) Poverty rate and adoption rate (All farms)**. (b) Poverty rate and adoption rate (by strata). (c) Poverty rate and adoption rate (by strata and scenario). **The y-axes of Figure 3a, b and c have been truncated for a closer view of the curves.

Table 6. The poverty gap and squared poverty gap of the study population.

Strata	Poverty gap				Squared poverty gap			
	Base (Non adopters	Adopters (all sample)	Recent adopters	Early adopters	Base (Non adopters)	Adopters (all sample)	Recent adopters	Early adopters
Low income	0.32	0.31 (-0.03)*	0.47 (0.47)	0.15 (-0.53)	0.22	0.22 (-0.00)*	0.34 (0.55)	0.08 (-0.64)
High income	0.15	0.04 (-0.73)	0.07 (-0.53)	0.01 (-0.93)	0.06	0.02 (-0.67)	0.03 (-0.50)	0.01 (-0.83)
Sub-population	0.23	0.17 (-0.26)	0.25 (-0.09)	0.07 (-0.70)	0.14	0.11 (-0.21)	0.17 0.21)	0.04 (-0.71)
All sampled population	0.18				0.12			

Numbers in parentheses are the gaps below or above the non-adopters (base for comparison) poverty gap and squared poverty gap.

poverty gap for the low non-farm income group is 15% (53% below that of non-adopters in the same category), while for the high non-farm income group, it is 1% (93% below that of non-adopters in the same category).

Studies that have attempted to estimate the effect of adoption of agricultural technologies have attained mixed results. Mendola (2007) found that while modern seed technology adoption increased the income of poor household, it did not help them in getting above the poverty line. Simtowe et al. (2012) found that less capital-intensive legume crops are important for reducing poverty among the land poor. In Uganda, Nkonya et al. (2002) and Jagger and Pender (2003) note that many land management technologies are not profitable, especially in the short run.

CONCLUSIONS AND RECOMMENDATIONS

The difference in adoption rates between low and high non-farm income farms is an indicator that there is still potential for adoption among both sub-populations. With time, adoption rates and adoption related benefits are likely to be higher. Higher positive returns and more significant contribution to poverty reduction can only be achieved when the technologies are adopted and retained long enough. However, the sustainability of this depends on whether the number of new adopters is higher than the number of dis-adopters, which stresses the need for farmers to see “tangible” results out of adoption of soil and water conservation technologies if they are to keep these structures on their farms. This requires that soil and water conservation technologies are combined with other short term productivity enhancing technologies such as fertilizer use, to sustain adoption. This can be also boosted by follow-ups by the implementing and disseminating organizations in form of trainings and inputs where necessary.

There are three possible reasons for limited profitability of agricultural technologies; one is that land management technologies have not been evaluated for profitability ex-ante, such that they may not have been suitable for the targeted areas in the first place, while the other is that potentially profitable technologies are being applied to less potentially profitable agricultural enterprises. This calls for local research and feasibility surveys before technologies are disseminated to areas. In addition, the timing of impact evaluations and profitability analyses is crucial, and should be tailored to specific technologies and their gestation periods. Evaluations of the impacts of the technologies that take place earlier (or much later) than the optimal evaluation time, are not likely to capture the full impact of those technologies, making them seem a lot less attractive to adopt.

Adoption rates are relatively lower for farm households with comparatively lower non-farm income, and so are the returns from crops in all cases. One can generally conclude that poorer farm households benefit the least from recommended and disseminated soil and water conservation technologies. One of the possible explanations can be attributed to spreading resources too thin, and adopting at less than optimal levels on all operated parcels. One way to rectify this would be through advising the resource constrained households, not to adopt on too many parcels at the same time, but to adopt progressively, step by step, until all the targeted land is covered. In this case, adequate adoption is done on the manageable sizes of land at a particular time. Once that has been achieved, the technologies are gradually spread out to the rest of the land as resources would allow. Institutional related factors such as access to inputs, credit, and other markets can also create differences. Adoption related incentives such as inputs and credit that target lower income household may help in reducing the impact gap.

The comparatively less benefits of the low income group from adoption could be an indicator that other income sources are necessary to boost adoption. These incomes are a source of inputs into adoption. For projects aimed at poverty reduction, emphasizing soil and water conservation technology adoption itself may not be enough and other means to improve household incomes need to be combined with it.

This being an ex-post assessment, we observe farms who adopted soil and water conservation technologies, but we are not able to observe the same farms before they took up those technologies. This means that although the System 1 (non-adopter) sample chosen is comparably similar to System 2 (adopters), it is not totally a representative of what would have been observed if farms in System 2 had not adopted soil and water conservation technologies. This means the impacts of adoption of soil and water conservation technologies are likely to be slightly under- or over-estimated and need to be interpreted with caution.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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