Assessing the Potential of a Locally Adapted Conservation Agriculture Production System to Reduce Rural Poverty in Uganda's Tororo District

Jarrad Godwin Farris

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George W. Norton, Chair

Jeffrey R. Alwang, Co-Chair

Catherine Larochelle

Bradford F. Mills

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ABSTRACT

This paper demonstrates the utility of small area estimation (SAE) of poverty methods for researchers that wish to conduct a detailed welfare analysis as part of a larger survey of a small geographic area of interest. Researchers studying context-specific technologies or interventions can incorporate the survey-based SAE of poverty approach to conduct detailed poverty analyzes of their specific area of interest without the expense of collecting household consumption data. This study applies SAE methods as part of an impact assessment of a locally adapted conservation agriculture production system in Uganda's Tororo District. Using SAE, I assess the Tororo District's Foster-Greer-Thorbecke (FGT) rural poverty indices, estimate the effects of per acre farm profit increases to poor households on the district's rural poverty indices, and compare the findings to current estimates of the net returns from conservation agriculture in the Tororo District. The SAE results suggest that increasing the farm profits of the bottom 30% of households by two U.S. dollars per acre per season could reduce the district's rural poverty incidence by one percentage point. The available data on the net returns to conservation agriculture in the Tororo District, however, indicate that these modest increases may only be achievable for adopting households that face high land preparation costs.

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Chapter 1: Introduction

1.1. Preface and Problem Statement

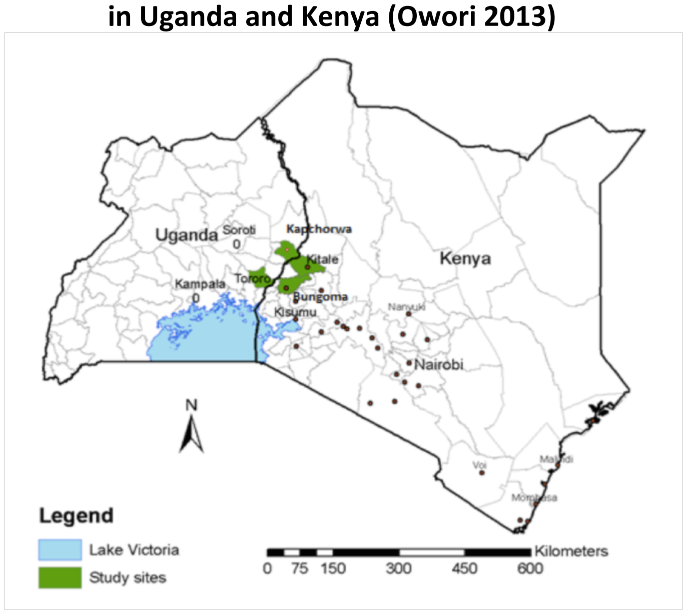
Elbers, Lanjouw, and Lanjouw (2002; 2003) developed small area estimation (SAE) of poverty methods that combine the detail of consumption survey data with the scope of census data to estimate poverty for small geographic areas. Since this seminal work, an expanding literature of in-depth poverty analyzes for small geographic areas has immerged that uses the ELL methods to extend the reach of available consumption surveys and save resources on welfare measurement (e.g. Cuong 2011; Kijima & Lanjouw 2003; Okwi et al. 2003; Tarozzi & Deaton 2009; World Bank 2013). The relevancy of the techniques in ELL (2002, 2003) for the general researcher, however, has been masked by their focus on census micro-data, which are generally only accessible to select organizations. Similarly, past studies that have applied the ELL methods without census data have typically done so using surveys that are representative at the same level of aggregation as the original consumption survey (e.g. Christianson et al. 2011; Dang et al. 2014; Daniels 2011; Stifel & Christiaensen 2007). Researchers interested in studying the localized poverty impacts of a context-specific intervention or technology can also benefit from incorporating SAE methods. This study makes a contribution towards broadening the appeal of ELL (2002; 2003) by illustrating how researchers could use these methods to conduct detailed welfare analyzes of small geographic areas using a representative survey in place of a census. Researchers studying context-specific technologies or interventions can incorporate the survey-based SAE of poverty approach to conduct detailed poverty analyzes of their specific area of interest without the expense of collecting household consumption data. This allows researchers to assess poverty impacts while focusing their resources and efforts on the specifics of other research questions of interest.

This paper applies the ELL methods as part of an impact assessment of a locally adapted conservation agriculture production system in Uganda's Tororo District. Conservation agriculture (CA) is a package of techniques which aims to generate sustained improvements to food security and farm profits by reducing soil erosion, increasing soil organic matter, and restoring soil fertility. The technology is based on three core principles: minimum tillage, a permanent vegetative cover, and diversified crop rotations. When these CA principles are practiced together, the agricultural systems that result are called conservation agriculture production systems (CAPS) (SANREM CRSP 2013). CAPS concentrate on addressing the link between soil fertility, farm profits, and rural poverty. In Uganda, where the average annual rate of nutrient depletion is more than 60 kilograms of NPK per hectare, an estimated 85% of the population earns more than half of its income from agriculture (FAO 2001; IFPRI 2011). If the decline in soil fertility and the general degradation of the natural resource base is contributing to increased poverty, then the expectation is that CAPS that reverse the trend could play a role in reducing poverty. By concentrating on improvements to farmer livelihoods that protect the natural resource base, CAPS are marketed as win-win solutions that harmonize environmental and economic concerns (SANREM CRSP 2013). Such a promise has led CA to become an increasing area of focus among international agricultural research organizations, including the U.S. Agency for International Development (USAID), the Food and Agriculture Organization of the United Nations

(FAO), and the International Maize and Wheat Improvement Center (CIMMYT) (USAID 2012; FAO 2014; CIMMYT 2014).

Unlike chemical fertilizers and other more easily transferable technologies, CAPS cannot be developed offsite and shipped to where they are needed; while the core principles of CA can be shared, the specifics of the CAPS must be developed locally to fit the agroclimactic and cultural conditions of potentially adopting farmers. The context-specific nature of the technology has led international agricultural research organizations to co-develop and co-test CA practices with local partners. USAID, for example, is currently undergoing such a process in 14 different countries through its Sustainable Agriculture and Natural Resource Management (SANREM) Project. In Uganda, US-based SANREM researchers are working with Appropriate Technology (AT) Uganda, a local NGO, to develop CAPS in the Tororo and Kapchorwa Districts of the country's Eastern Region (SANREM CRSP 2013). Figure 1.1. shows the location of these sites as well as the sister sites in Kenya; their geographic proximity emphasizes the context-specific nature of CA. In each of these areas, the realized CAPS will look slightly different in response to local characteristics (Owori 2013).

Figure 1.1. SANREM Project Sites in Uganda and Kenya (Owori 2013)



Wherever they are developed, the profitability of CAPS relative to current farmer practices will be a critical factor in their ability to reduce poverty. A recent multidisciplinary consortium of 44 scientists conducting CA research highlighted this point when they reached a consensus that improving rural households' farm profits is both a major goal of CA and a main driver of its adoption (Stevenson et al. 2014). This study builds on this understanding by estimating the necessary increase in poor Tororo District households' farm profits per acre from CAPS adoption if the technology is to measurably reduce rural poverty rates in the district. These estimates are then compared with SANREM field data from the Tororo District on the net returns from CAPS adoption. The initial poverty estimates and estimated poverty reductions are generated by utilizing the SAE methods in ELL (2002; 2003) to combine the detailed consumption data from a World Bank Living Standards of Measurement Study (LSMS) survey of Uganda with data on variables correlated with household consumption from a representative survey of the rural Tororo District.

1.2. Objectives

The general objective of this research is to assess the potential of a locally adapted CA production system to alleviate rural poverty in Uganda's Tororo district. This study achieves this by the following specific objectives:

- Applying SAE to assess the Tororo District's current level of rural poverty;
- Estimating how large the per acre increase in farm profits to poor households would need to be in order to measurably impact the district's rural poverty;

- Comparing the targeted incremental profit per acre to current estimates of the net returns from CA in the Tororo District—how much farther does CA development have to go if it is to achieve its poverty reduction goals?

1.3. Chapter References

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Chapter 2: Methods and Conceptual Framework

2.1. General Conceptual Framework

The first objective of the analysis is to estimate rural poverty in the Tororo District. This study estimates poverty using the Foster-Greer-Thorbecke (FGT) series of additively decomposable poverty indices. These indices are commonly used to measure poverty within a subset of the overall population (e.g. rural households) and allow for analysis of the various dimensions of poverty (FGT 1984; Moyo et al. 2007). The FGT indices can be expressed as follows:

$$P_\delta = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{z - y_i}{z}\right]^\delta * 1[y_i < z] \tag{2.1}$$

where n is the number households in the population of interest, z is the poverty line, y_i is the consumption or income per capita of the *ith* household, and δ is a measure of inequality aversion. The final term is an indicator which is one if y_i is less than z and zero otherwise. When δ equals zero, one, or two, P_δ becomes a measure of poverty headcount, depth, or severity respectively (FGT 1984). Thus, the FGT indices allow estimation of the proportion of people living in the rural segment of Tororo who are below the poverty line (poverty headcount) as well as how far below the population is from the poverty line on average (poverty depth). Furthermore, the severity index gives an indication of rural poverty in Tororo which is more sensitive to the well-being of the poorest of the poor. By enabling an analysis of poverty from different angles, the FGT indices facilitate a more nuanced understanding of rural poverty in the Tororo District. These three measures of poverty are assessed by estimating household consumption per capita for a representative sample of rural households in the district and comparing the estimates to the poverty line.

After assessing the current rural poverty levels, this study estimates how changes in the consumption of poor households would impact each poverty measure. These estimates give an indication of the necessary increase in poor households' farm profits from conservation agriculture adoption if the technology is to measurably reduce rural poverty in Tororo. Adapted from Moyo et al. (2007), farm profits for a given household can be expressed as:

$$\pi_i(\tau) = pq_i - \int_0^{q_i} c_i'(q_i, \tau)dq_i \qquad 2.2$$

where τ is a technology shifter representing the use of conservation agriculture, pq_i are the household's farm revenues, $c_i'(q, \tau)$ is the marginal cost function, and $\int_0^{q_i} c_i'(q_i, \tau)dq_i$ represent variable costs of production. Taking the derivative of (2.2) with respect to τ yields the change in farm profits from conservation agriculture adoption:

$$\frac{\partial \pi_i}{\partial \tau} = q_i \frac{\partial p(\tau)}{\partial \tau} + p\frac{\partial q_i(\tau)}{\partial \tau} - \int_0^{q_i} \frac{c_i'(q, \tau)}{\partial \tau} dq_i - c_i'(q_i)\frac{\partial q_i(\tau)}{\partial \tau} \qquad 2.3$$

This derivation shows how profit increases from conservation agriculture result from changes in the net value of production, not just from increases in sales. The change in farm profits is dependent on the effect of adoption on output price, quantity, and the variable costs of production. Since conservation agriculture adoption in Tororo is not expected to generate large yield increases, this study assumes the open economy case where farmers are price takers. Therefore, the change in output price due to adoption is zero and (2.3) simplifies to:

$$\frac{\partial \pi_i}{\partial \tau} = p\frac{\partial q_i(\tau)}{\partial \tau} - \int_0^{q_i} \frac{c_i'(q,\tau)}{\partial \tau} dq_i \; - \; c_i'(q_i)\frac{\partial q_i(\tau)}{\partial \tau} \qquad 2.4$$

If the open economy assumption holds, the change in farm profits from adoption is composed of the value of the change in output (yield) minus the total change the variable costs of production (Moyo et al. 2007). The poverty analysis estimates how large this increase in farm profits would need to be in order to observe a measurable impact on rural poverty in the Tororo District. The required increase is then compared with field data on the net returns from conservation agriculture adoption.

2.2. Measuring Welfare: Theory and Data

Although the two main measures of well-being for poverty analysis, income and consumption, are theoretically equivalent in the long-run, the latter is generally preferred for measuring the welfare of rural households in developing countries. The income of such households measured at any point in time is likely to be quite variable, in many cases increasing substantially after harvests and dropping off otherwise; such fluctuations can make the welfare ranking of rural households based on an income snapshot at a given point in time relatively unstable. In contrast, consumption has been shown to be less susceptible to seasonal fluctuations as households have more flexibility in smoothing consumption over time. Additionally, self-reported consumption tends to be more reliable than self-reported income when a significant portion of the population relies on self-run agricultural or small business enterprises (Deaton & Zaidi 2002). These concerns are particularly applicable to the Tororo District where over three quarters of households rely on farming as their main source of livelihood (UBOS 2006). Thus, this study bases welfare comparisons on household consumption.

At the start of this research, the best available household consumption data were from the 2011/2012 Uganda National Panel Survey (UNPS) conducted by the World Bank in conjunction with the Uganda Bureau of Statistics (UBOS). This multi-topic survey is part of the World Bank's Living Standards of Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) project of which a major objective is to produce reliable estimates of consumption expenditures for use in poverty analysis. The survey, which is broken out into a household, agriculture, and community questionnaire, collected data from a sample of 2,716 Ugandan households on an extensive range of topics including household demographics, education, health, food and non-food consumption, asset ownership, agricultural landholding, input use, crop production, and livestock ownership. The micro-level data from the survey are publicly available from the World Bank (World Bank LSMS-ISA 2014).

The lowest level of disaggregation at which the 2011/2012 UNPS survey is representative is the urban or rural portions of Uganda's four regions. The rural portion of the Tororo District is a subset of Uganda's Eastern Region. Thus, despite the exhaustive detail of the survey data, due to the relatively small sample size this dataset alone cannot provide a reliable estimate of rural poverty levels in the Tororo District. A common means of overcoming such a problem is the small area estimation (SAE) technique for welfare analysis developed by Elbers, Lanjouw, and Lanjouw (ELL 2002, 2003). SAE links the detailed consumption data from surveys like the 2011/2012 UNPS with census data from the small geographic area of interest to generate welfare estimates that are representative at the desired level of disaggregation. The next section gives a non-technical overview of this technique.

2.3. Non-Technical Overview of Small Area Estimation of Poverty

This section introduces the concept of small area estimation (SAE) of poverty; subsequent sections describe the technical details as applied in this study. A non-technical explanation adapted to the Ugandan context is as follows: First, data from the regionally representative household consumption survey are used to estimate annual consumption per capita for each surveyed household in the region of interest. Second, the household consumption per capita estimates are regressed on a set of observable household characteristics that are common to the survey and the latest Ugandan census (e.g. household size, the education levels of household members, household ownership of various assets, etc.). This regression is not intended to imply a causal relationship between the observed variables and household consumption, but rather, accurately predict household consumption based on the estimated correlations. Lastly, the regression is combined with census observations on those same variables to predict household consumption per capita for the smaller geographic area of interest (ELL 2002, 2003). Okwi et al. (2003) applied this technique using Uganda's 1991 Population Census and compared the regional SAE poverty estimates to those from Uganda's 1992/93 National Household Survey; the pairs of regional estimates of Uganda's poverty measures were "…statistically indistinguishable at better than 95 percent significance level and almost coinciding in several instances" (Okwi et al. 2003).

There are, however, two basic problems with applying the conventional SAE technique in this study. First, it requires classified census micro-data only released to select organizations. Second, at the start of this research it had been nearly 12 years since the last Ugandan population census was conducted.[1] It is reasonable to assume that the observable characteristics of Tororo households which may be correlated with household consumption have changed significantly over the past decade. As a result, the 2002 Census micro-data are not likely to be useful for an analysis of present poverty levels. For these reasons, a representative survey of households in the Tororo District was conducted in the summer of 2014. This survey collected data on household characteristics which are available in the 2011/2012 UNPS survey and correlated with household consumption. The survey data are substituted for the census data when applying the SAE technique.

As the collection of detailed consumption data is an expensive and arduous process, conducting the 2014 Tororo Household Survey (THS) in this way and linking it to the 2011/2012 UNPS allows for a detailed poverty analysis while keeping the study's agricultural focus. The 2014 THS surveyed 480 households and conducted focus group discussions in 24 villages. The time and resources required to collect comprehensive consumption data for Tororo households would have restricted the survey's sample size and limited its ability examine the district's agriculture. Effective conservation agriculture practices are context-specific and must be well adapted to the agroclimactic and cultural practices of a given area (Owori 2013). The main advantage of employing the SAE technique developed in ELL (2002, 2003) on survey data is to save resources on welfare measurement and focus instead on the characteristics of specific farm operations.

The following sections of this chapter describe the development of the key components of the SAE poverty analysis: Section 2.4. details the aggregation of

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[1] This research began in late 2013 when the 2002 Population Census was Uganda's latest census. Originally scheduled for 2012, the new census had been delayed several times and it was unclear when it would be completed. The new census was completed in late 2014 and preliminary results were released in November 2014.

household consumption per capita using the 2011/2012 UNPS survey data, Section 2.5. explains the questionnaire development and sampling design of the 2014 THS, and Section 2.6. details the choice of the poverty line. After developing these components, Section 2.7. gives a detailed, technical explanation of the SAE technique used to estimate rural poverty in the Tororo District.

2.4. LSMS Household Consumption Measure

The measures of household consumption per capita, which form the basis of the subsequent SAE poverty analysis, are estimated using micro-data from the Living Standards of Measurement Study's (LSMS) 2011/2012 Uganda National Panel Survey (UNPS). A major objective of the survey was to collect high quality consumption data for use in poverty analysis. The 2011/2012 UNPS collected consumption expenditure data for three general categories: (i) food, beverages, and tobacco; (ii) non-durable goods and frequently purchased services; and (iii) semi-durable and durable goods and services. Within each section, sampled households reported their consumption of specific items based on a recall period of seven days, 30 days, and 365 days for section one, two, and three respectively (World Bank LSMS-ISA 2014). The following subsections detail how household consumption per capita estimates are generated using the 2011/2012 UNPS micro-data.

Aggregating Food Consumption

Each survey respondent reported on his or her household's consumption of more than 50 food items, including beverages and tobacco, over the prior seven days. For each item, the respondent estimated the quantity, unit price, and value of consumption from home production, purchases, and in-kind over the recall period.[2] The value of reported consumption of each food item from all sources is summed to generate an aggregated estimate of the household's total value of food consumption in the last week. These aggregate consumption values are then multiplied by the approximate number of weeks in a year (52) to generate estimates of the value of each household's yearly food consumption including beverages and tobacco.

Aggregating Non-Durable and Semi-Durable Goods Consumption

Each respondent also reported on his or her household's consumption of more than 40 non-durable goods and services, including items related to rent, fuel use, personal care, transportation and medical care over the last 30 days. As before, the value reported consumption of each item is summed. The consumption of items related to medical care, however, is purposefully excluded from the summation. The potential welfare improvement from these items does not account for the welfare loss from being sick. Including such expenditures may register a net welfare improvement to a household with ill members even if a net welfare loss has occurred. Similarly, some households may have subsidized medical care while others may not, biasing potential comparisons (Deaton & Zaidi 2002). After summing the value of the non-medical items, the resulting aggregated monthly values of non-durable consumption for each household are converted to annual values by multiplying by the approximate number of 30-day periods in a year (12).

Along with non-durable goods, the respondents also reported on consumption of more than 20 semi-durable goods and services related to clothing, tableware, and

[2] In relatively few cases, the respondent reported that his or her household consumed some quantity of a food item, but the value of consumption was missing. For these observations, the reported quantity consumed is multiplied by the reported unit price to approximate a consumption value. Reported values that appear to be data entry errors are also cleaned.

education. Expenditures for items in these subcategories were collected based on a one-year reference period and are already expressed in the desired time frame. Summing the value of each item from all sources generates an estimate of each household's annual value of semi-durable consumption. Adding in the converted non-durable consumption values results in an estimate of the annual value of each household's consumption of non-durable and semi-durable goods.

Aggregating Durable Goods Consumption

The LSMS survey respondents also reported the quantity and current estimated value of their household's durable goods. Since durable goods last over many periods, the appropriate measure of welfare enhancement in a given period is not the full value of new or previous durable goods purchases. Instead, the appropriate measure of welfare enhancement is an estimate of the user cost of consuming the flow of services from these goods in the given reference period. This user cost can be defined formally as:

$$v_t(r_t - \kappa_t + \theta) \tag{2.5}$$

where v_t is the value of the good at time *t*, r_t is the nominal rate of interest at time *t*, κ_t is the rate of inflation for the given good at time *t*, and θ is the rate of depreciation for the given good (Deaton & Zaidi 2002). Deaton and Zaidi emphasize that the appropriate method of estimating user cost depends on the specifics of the survey data from which the consumption aggregate is being calculated. In the case of the 2011/2012 UNPS survey, no data were collected on the age of the durable goods owned by the household. Furthermore, the broad characterization of asset categories complicates the estimation of new values. This analysis utilizes the method employed by Deaton and Zaidi (2002) when detailed data were scarce; that is, this analysis uses nationally available data on nominal interest and inflation rates and assumes a reasonable average annual depreciation rate.

For the nominal interest rate, this study uses the July 2011 to July 2013 period average of the Bank of Uganda's official nominal interest rate, which was approximately 16% (Trading Economics 2014). As a measure of the inflation rate, this study uses the average annual percent change in Uganda's household and personal goods price index over the 2011 to 2013 period, which was approximately 12% (Bank of Uganda 2014). The household and personal goods price index is the most relevant available index for household assets. The 2011 to 2013 period is used because it follows the basic timeframe of the survey data. Using these two measures, the average annual real interest rate $(r_t - \kappa_t)$ is estimated at 4%.

Using straight-line depreciation and the conservative assumption that the useful life of durable goods in Uganda is 20 years, the average annual depreciation rate (θ) is estimated at 5%. In aggregate then, $(r_t - \kappa_t + \theta)$ is estimated at 9%. In accordance with the method outlined in Deaton and Zaidi (2002), this percentage is applied to the sum of the total value of household assets for a given household for all categories except buildings and land.

Nominal Household Consumption Aggregate

Nominal household consumption is aggregated by summing of the value of food consumption, non-durable and semi-durable goods, and the user cost of durable goods for each household. Standard practice dictates that nominal consumption should be divided by a food price index which adjusts for spatial variation in prices. Respondents' reported prices in the 2011/2012 UNPS survey, however, are given in non-standard units. For example, prices for sweet potatoes, a major food item in the Eastern Region, are reported in 14 different unit types including heap (size unspecified), 20 liter tin, and medium-sized piece. Given this incongruence in reported unit prices and the focus of this analysis on one relatively small district, spatial variation in prices is assumed to not significantly affect the district's welfare measures.

Using the nominal household consumption aggregate, an estimate of household consumption per capita is generated by dividing the aggregate consumption measure by the number of persons present for at least half of the household's meals during the seven day food recall period.[3] This method of measuring per capita consumption accounts for the possibility that all household members may not have been present during the seven day food recall period. Since food makes up the majority of household consumption, including members not present for the food recall period in the division of aggregate consumption would likely underestimate the per capita welfare estimate.

2.5. Tororo Household Survey Development

Survey Development

In order to analyze the welfare and agricultural practices of rural households in the Tororo District, a representative survey of the district was conducted in July and August of 2014. There were three major objectives of the survey: (i) to collect updated data from the Tororo District on household characteristics present in the 2011/2012 UNPS which are correlated with household consumption; (ii) to characterize the diffusion of conservation agriculture practices throughout the district; and (iii) to obtain an updated

[3] Four of the sampled rural households in the Eastern Region had positive food consumption values but no person listed as present for at least half of the last week's meals. To prevent the exclusion of these observations, the aggregate consumption value for each of these households is divided by the current number of household members listed on its household roster.

understanding of current agricultural practices in the district. To accomplish these objectives, the survey requested information on the education levels of household members, housing conditions, major assets, households' use of agricultural loans, input use, conservation agriculture adoption, etc. The complete household survey is reproduced in Appendix A. Since this survey was to be linked with the 2011/2012 UNPS, the questionnaire design mimics the national survey as closely as possible. For instance, a household and its members were defined using an equivalent set of criteria to those listed in the interviewer manual of the UNPS. Questions were also phrased in the same manner as the UNPS survey wherever possible (UBOS 2011a; UBOS 2011b; World Bank LSMS-ISA 2014). Similarly, questions were adapted from previous surveys on conservation agriculture practices in the district (Gunter et al. 2015; Vaiknoras 2014). To improve consistency, the survey team agreed on the correct oral translation of the questionnaire into Japadhola and Ateso, the two most commonly spoken languages in the Tororo District.

The survey team also conducted focus group discussions in each of the sampled villages. The purpose of these focus groups was to collect additional information about agriculture in the district. While the household survey allows for a formal analysis of household characteristics and agricultural practices, the focus groups provide the opportunity for a more informal discussion of each village's agriculture. The information collected included changes in the average landholding size, yields and seasonal prices of major crops, the average wage rate of agricultural workers, costs of growing crops on one acre, etc. The focus group discussion questions are reported in Appendix B. For each focus group, the participation of the locally elected village chairperson was requested, along with three other farmers whom he or she identified as being widely knowledgeable about the village's agriculture. Requesting the chairperson's participation was important for two reasons. First, it signaled respect for the village's choice of their local leader. Second, it provided the opportunity to learn from the chairperson's insights about the village. Of the three other farmers identified by the chairperson for the discussion group, the survey team requested that at least one be a woman. This helped facilitate a more well-rounded group discussion about the village's agriculture.

Sampling Strategy

As a balance between survey representativeness and cost, the 2014 Tororo Household Survey (THS) used a stratified, multistage cluster sampling design. Sub-counties were the stage one primary sampling units (PSUs), villages were the stage two secondary sampling units (SSUs), and households were the stage three ultimate sampling units (USUs). The survey used the sub-county boundaries for the Tororo District before the Sop-Sop Parish of Paya Sub-County and the Magola Parish of Iyolwa Sub-County split off to form their own sub-counties. Due to the focus on rural poverty and agriculture, the district's three urban municipalities were excluded from the sampling frame. The excluded urban municipalities were Malaba Town Council on the border of Kenya and the Eastern and Western Divisions of Tororo Town. The rural municipality of Nagongera Town Council was purposefully included in the sampling frame as part of Nagongera Sub-County.

With assistance from the Appropriate Technology (AT) Uganda development team working in the Tororo District, the 15 rural PSUs were grouped into strata defined by geography and similarity. This resulted in the 5 strata shown in Figure 2.1. The objective of this stratification was to ensure that the drawn sample of PSUs would be

Figure 2.1. Tororo District Strata

representative of the district as a whole. Based on Uganda's 2002 population census, the strata population shares as a proportion of the total population in the sampling frame were 0.165, 0.261, 0.175, 0.188, and 0.211 for Stratum 1, 2, 3, 4, and 5 respectively (UBOS-ILRI 2007). Stratum 2 is composed of the PSUs bordering the excluded urban municipalities and had the largest of the 2002 population shares. Apart from Stratum 2, the other four strata had relatively similar 2002 population shares. Due to uncertainty over how the population shares of these strata changed over the last decade, the same number of sampling units were drawn from Stratum 2, 3, 4, and 5.

Stratum 1 is a special case. Along with population representativeness for welfare analysis, another objective of the 2014 THS sampling design was to characterize the diffusion of conservation agriculture practices. One of the PSUs in Stratum 1, Molo, has been a site for extensive conservation agriculture research. Due to this research, conservation agriculture adoption may be more widespread in this PSU. To account for the unique case of Molo, the survey team modified the sampling design by splitting

Stratum 1 into two separate strata: Stratum 1A containing only Molo and Stratum 1B containing Mukuju and Kwapa.

In stage one of the multistage cluster sampling, Molo was selected from Stratum 1A with certainty and Mukuju was randomly selected from Stratum 1B with probability one half. From each of the other four strata, one PSU was randomly selected with probability one third. The randomly selected PSUs were Rubongi, Merikit, Nagongera, and Iyolwa from Stratum 2, 3, 4, and 5 respectively. In order to stay within the budget constraints of the survey, only one PSU was drawn per stratum. Surveying within a sub-county lowered transportation and enumeration costs. As the strata were defined based on similarity, each of the six drawn PSUs is taken to be representative of its stratum.

In stage two, the survey team used an administrative list of the villages (SSUs) in each PSU to randomly select four SSUs from each of the six PSUs. Lastly, in stage three, the survey team traveled to the 24 randomly selected SSUs and requested the current public record of households (USUs) directly from each village's locally elected chairperson. Twenty USUs were then randomly selected from each list. This resulted in a sample of 80 households each from Stratum 2, 3, 4, and 5 and 160 households from the overrepresented Stratum 1. The total sample size of the 2014 THS is 480 households (USUs) from 24 villages (SSUs) and 6 sub-counties (PSUs).

The only up-to-date population information in this sampling design came from the household lists collected in each randomly selected village. This population-uncertainty was the motivation for not sampling the PSUs and SSUs with probability proportional to size. Households are weighted in the analysis by the inverse probability of their selection.[4] The sample's calculated population size for the rural Tororo District is 88,993 households, the sum of the household weights. This calculated population size is very close to the preliminary 2014 Population Census estimate for the rural Tororo District of 89,930 households which was released by the UBOS in November 2014 (UBOS 2014b).

Since the strata were not sampled in proportion to their size, each stratum's weighted sampling fraction differs from its actual population fraction in the preliminary 2014 Census results. This is particularly evident for the purposefully oversampled Stratum 1. Table 2.1. shows each stratum's population estimate and fraction from the preliminary 2014 Census results beside its uncorrected weighted population and fraction from the survey. Post-stratification adjustment factors (PSAFs) are calculated by dividing the 2014 Census strata population fractions by their 2014 THS sampling fractions. The strata sampling fractions are adjusted to match their 2014 Census strata population fractions by multiplying each household weight by its stratum's PSAF. The PSAFs and corrected sampling populations and fractions are also listed in Table 2.1. The purpose of this census-based adjustment is to improve the representativeness of the 2014 THS in light of the updated stratum population estimates.

[4] The probability of selection is:
$$\frac{1}{No.\ PSUs\ in\ the\ Stratum} * \frac{4}{No.\ SSUs\ in\ the\ PSU} * \frac{20}{No.\ USUs\ in\ the\ SSU}$$

Table 2.1. Census-Survey Population Comparison and Weight Adjustment							
Stratum	Prelim. 2014 Census Results		2014 Tororo Household Survey				
	Population Estimate (Households)	Population Fraction	Uncorrected Sampling Population[2]	Uncorrected Sampling Fraction	PSAF	Corrected Sampling Population[3]	Corrected Sampling Fraction
1A	3,670	0.0408	2,988	0.0336	1.22	3,632	0.0408
1B	11,370	0.1264	18,124	0.2037	0.62	11,252	0.1264
1[1]	15,040	0.1672	21,111	0.2372		14,883	0.1672
2	19,838	0.2206	18,330	0.2060	1.07	19,631	0.2206
3	17,281	0.1922	14,344	0.1612	1.19	17,101	0.1922
4	16,784	0.1866	16,052	0.1804	1.03	16,609	0.1866
5	20,987	0.2334	19,157	0.2153	1.08	20,768	0.2334
Total	89,930	1.00	88,993	1.00		88,993	1.00

[1]Stratum 1 is the sum of 1A and 1B.
[2]The uncorrected sampling population is the sum of the household weights.
[3]The corrected sampling population is the sum of the household weights scaled by their stratum's PSAF.

2.6. Choice of Poverty Line

It has been well documented that poverty estimates are sensitive to the choice of poverty line (World Bank 2015). An individual might be considered impoverished under one poverty line yet "not poor" under another. The choice of a poverty line can influence which segment of the population benefits from development initiatives and policies targeted towards improving the wellbeing of the poor. Therefore, care should be taken to select a poverty line that adequately reflects the cost of meeting basic needs in the area under consideration (World Bank 2015). Global assessments of international poverty typically use $1.25 per capita per day at 2005 Purchasing Power Parity (PPP). This international poverty line is the result of averaging the poverty lines in the 15 poorest countries and is considered to be a minimum threshold for meeting basic needs (Chen & Ravallion 2010; World Bank 2015). The United Nation's Millennium Development Goals initiative used this line as a benchmark for its target of halving the proportion of the world population living in extreme poverty from 1990 to 2015 (UN 2014).

While this international poverty line allows for a comparison across countries, it has the disadvantage of not being locally adapted to fit a specific country's standards for wellbeing. In some contexts, such as Latin America where the median poverty line among countries in the region is around $4 at 2005 PPP, it may not be appropriate to apply the international poverty line of $1.25 at 2005 PPP. In Sub-Saharan Africa, however, the median national poverty line among countries in the region is approximately equal to the international line. In Uganda, for example, the national poverty line is $1.27 at 2005 PPP, just $0.02 higher than the international line (Ravallion, Chen, and Sangrula 2008). Given that $1.25 at 2005 PPP is very close to Uganda's national poverty line, this study uses the international poverty line. This extends the reach of the research by facilitating the possibility of cross-country comparisons without loss of applicability for policy makers and researchers in Uganda.

Following standard practice, $1.25 per capita per day at 2005 PPP is converted to the Ugandan context by multiplying it by the country's 2005 PPP conversion factor for private consumption. The conversion factor of 612.70 Ugandan shillings per international dollar is based on estimates from the 2011 round of the International Comparison Program (ICP) (World Bank 2014). The converted 2005 poverty line is then deflated to 2012 using the International Monetary Fund's (IMF) official consumer price index for Uganda (IMF 2014). The poverty line is expressed on an annual basis by multiplying by 365. The resulting 2012 international poverty line is 567,475 Ugandan shillings (UGX) per person per year.

2.7. Technical Overview of Small Area Estimation of Poverty

As outlined briefly in Section 2.3., this study's first SAE objective is to use the 2011/12 UNPS data to create a model that relates household consumption per capita in the rural portion of the Eastern Region with variables common to the 2011/12 UNPS and 2014 THS. Adapted from ELL (2002, 2003), a linear mixed effects model is specified as follows:

$$\ln(y_{ch}) = x_{ch}\beta + \eta_c + \varepsilon_{ch} \qquad 2.6$$

where the subscript ch represents a given rural household h in a cluster c in the Eastern Region. For this analysis, a cluster describes a group of households located in the same enumeration area or village. In (2.6), $\ln(y_{ch})$ is the natural log of the per capita consumption aggregate estimated from the 2011/12 UNPS using the methods outlined in Section 2.4. [5] The fixed portion of the right-hand side (RHS) of (2.6) consists of two parts: x_{ch} and β where the former is a household's vector of *k* observable characteristics correlated with $\ln(y_{ch})$ and the latter is a vector of *k* parameters describing the correlation between log-consumption and the observable characteristics. The β vector of parameters also includes an overall intercept. The remaining two terms of the RHS of (2.6), η_c and ε_{ch}, are the cluster-specific and household-specific random effects respectively. These decomposed error components are assumed to be independent.

[5] For the analysis of household-level data, each household is weighted by the inverse probability of its selection; for this SAE analysis of household consumption *per capita*, however, observations are weighted by *individual* weights. These individual weights are calculated by multiplying a given households inverse probability of selection by its household size (World Bank 2009, Appendix 3). Stata's *svy* estimation commands for survey data are also used; *svy* uses Taylor-linearized variance estimation to take into account the multistage sampling design of the 2011/2012 UNPS when calculating the standard errors of the estimated coefficients (StataCorp 2013).

It is important to emphasize that the role of the model in (2.6) is not to interpret the parameter estimates, but rather, to predict consumption for households in the Tororo District as accurately as possible. The model does not incorporate all of the explanatory variables correlated with consumption and is likely characterized by endogeneity due to reverse causality and omitted variables (ELL 2002, 2003). The potential for reverse causality is illustrated in the relationship between the number of household members and consumption per capita. Although the two are typically negatively correlated, Lanjouw and Ravallion (1995) debate which of the two should be considered the "cause" and which the "effect." The potential for omitted variables is illustrated in the variables describing the square footage and floor type of each respondent's house. Although square footage is likely positively correlated with consumption, since the 2011/2012 UNPS and the 2014 THS did not ask respondents to report square footage it must be omitted from x_{ch} in (2.6). Floor type, however, was reported in both surveys. A non-mud floor type is positively correlated with consumption and also likely positively correlated with square footage. As a result, the coefficient estimate for non-mud floor type may "pick up" some of the effect of the omitted square footage. These two examples illustrate that the β vector in (2.6) captures indirect effects and the model does not imply a causal relationship between the observable household characteristics and household consumption. For the purposes of SAE, however, it is actually *preferred* that the included explanatory variables pick up correlations between unobserved variables and household consumption if it helps to reduce prediction error (ELL 2002, 2003).

The consistency of the subsequent analysis rests on several key assumptions. First, it is assumed that the Measurement of Predictors (MP) and the Area Homogeneity

(AH) assumptions typical of SAE hold (Tarozzi & Deaton 2009). The MP assumption requires that the household characteristics from the 2011/2012 UNPS be measured in the same way as those in the 2014 THS. As described in Section 2.5., the 2014 THS questionnaire and household definition were developed specifically to mimic the 2011/2012 UNPS. It is possible, however, for measurement differences to have surfaced; for instance, the 2011/2012 UNPS survey has more sections and is significantly longer than 2014 THS (Rao 2003; Tarozzi & Deaton 2009). In a typical SAE analysis, the equivalence of the explanatory variable candidates would be assessed by comparing survey and census means at the regional level. Since this study uses a representative survey of the Tororo District in place of the census data, it is impossible to make regional mean comparisons and the analysis rests on the assumption that MP holds. The 2014 THS has the advantage, however, of having been developed with the specific purpose of linking to the 2011/12 UNPS.

Along with the MP assumption, the AH assumption requires that the conditional distribution of household consumption per capita given the values of the explanatory variables be the same for rural households in the Tororo District as it is for rural households in the Eastern Region as a whole. Similarly, this conditional distribution must be stable over the two time periods. That is, the β vector of parameters in (2.6) must be the same in the rural portion of the Eastern Region in 2011/2012 as it is in the rural portion of the Tororo District in 2014 (Cuong 2011; Daniels 2011; Tarozzi & Deaton 2009). While AH is a standard assumption of SAE, the findings from Tarozzi and Deaton (2009) suggest that if it does *not* hold in practice then the precision of SAE estimates will be overstated. They conclude that the necessity of both MP and AH should be emphasized when conducting SAE. This study's estimation of the vector of parameters in (2.6) specifically for rural households in the Eastern Region rather than some larger, more heterogeneous group increases the likelihood that AH holds. Furthermore, the relatively short time gap between the two surveys of approximately two years increases the likelihood that the conditional distribution is stable.

Along with MP and AH, the estimates rely on the assumption that the 2011/2012 UNPS survey and the 2014 THS are representative of rural households in the Eastern Region and rural households in the Tororo District respectively (Cuong 2011; Daniels 2011). The 2011/2012 UNPS was designed specifically to allow for representative estimates of the rural and urban portions of each of Uganda's four regions (World Bank LSMS-ISA 2014). Similarly, as described in Section 2.5., the 2014 THS was designed specifically to be representative of rural households in the Tororo District. Thus, it is likely that the representativeness assumption holds in practice.

Returning to the linear mixed effect model specification in (2.6), η_c and ε_{ch}, the cluster-specific and household-specific random effects respectively, pose special challenges for predicting household consumption. The 2011/2012 UNPS randomly sampled 58 clusters in the rural portion of the Eastern Region. Since there are many more than 58 clusters ("villages") in the rural portion of the Eastern Region, the sampled clusters represent a random draw from the larger population. Within each cluster, an average of ~10 randomly sampled households were selected for a total of 565 household observations (UBOS 2014a). The challenge, then, is that it may be the case that households within a given cluster are related in some unmeasured way. If present, such intraclass correlation reduces the amount of unique information present in each household observation and the total error can no longer be thought of as independent (Steele 2008). Furthermore, because SAE makes out-of-sample predictions for households in non-sampled clusters, each cluster cannot simply be modeled as a fixed effect.

The model in (2.6) accounts for intraclass correlation by decomposing the total model error into two independent, nested random effects. The cluster-specific random effect, η_c, allows for a portion of the model error to be correlated for households within the same cluster. By AH, the values of the β vector are assumed to be homogenous throughout all clusters in the Eastern Region; the incorporation of η_c, however, allows for cluster-specific heterogeneity in the realized intercept (Tarozzi & Deaton 2009). The nested household-specific random effect then allows each household to further deviate from its cluster in a unique way. Greene (2012, Section 11.5.1) notes that the "parameters of the random effects model can be estimated consistently, though not efficiently by ordinary least squares (OLS)." Therefore, working towards the derivation of the random effects, the following simpler model is estimated using OLS:

$$\ln(y_{ch}) = x_{ch}\beta + u_{ch} \qquad 2.7$$

where u_{ch} is the combined model error. The estimated residuals from (2.7) are then decomposed into the cluster-specific and household specific components:

$$\hat{u}_{ch} = \hat{\eta}_c + \hat{\varepsilon}_{ch} \qquad 2.8$$

where the estimate of the cluster-specific random effect, $\hat{\eta}_c$, is the average total residual of the sampled households in a particular cluster. Specifically:

$$\hat{\eta}_c = \frac{1}{M_c}\sum_{h=1}^{M_c}(\ln(y_{ch}) - \ln(\widehat{y_{ch}})) \qquad 2.9$$

where M_c is the number of sampled households in a given cluster c and $\ln(\widehat{y_{ch}})$ is the fitted value from (2.7). The estimate of the household-specific random effect, $\hat{\varepsilon}_{ch}$, then becomes:

$$\hat{\varepsilon}_{ch} = \hat{u}_{ch} - \hat{\eta}_c \qquad 2.10$$

$\hat{\varepsilon}_{ch}$ is therefore a measure of how far away a particular household is from the average residuals in its cluster.

Having decomposed the estimated total residuals into the two component parts, the next challenge is to generate estimates of σ_η^2 and σ_ε^2, the variances of η and ε respectively. It is plausible that these variances could be heteroskedastic. Greene (2012, Section 11.6.2) references the possibility of heteroskedasticity in the cluster-specific random effect before describing the "insurmountable problem" with empirically estimating it. In essence, the problem is that since every household in a given cluster shares the same cluster-specific effect, there are only 58 unique observations on η. Therefore, just as in ELL (2002, 2003), this study must assume that the cluster-specific random effect is homoskedastic.

As η and ε are independent, the variance of the total estimated residual from (2.7) is simply the sum of σ_η^2 and σ_ε^2. Therefore, the general approach to estimating σ_η^2 is summarized as follows:

$$\begin{aligned} \sigma_\mu^2 &= \sigma_\eta^2 + \sigma_\varepsilon^2 \\ \Rightarrow \sigma_\eta^2 &= \sigma_\mu^2 - \sigma_\varepsilon^2 \end{aligned} \qquad 2.11$$

where σ_μ^2 is the variance of the total estimated residual from (2.7). A complicating factor in the estimation of (2.11) is that the sums of the weighted observations in each cluster are not equal. That is, the observations in one cluster may have larger sample weights than the observations in another cluster. This study applies the method derived by ELL (2002, 2003) to account for unequal cluster weights in the estimation of σ_η^2. Adapted from Appendix I of ELL (2002), σ_η^2 is estimated as follows:

$$\hat{\sigma}_\eta^2 = max\left\{\frac{\left(\sum_{c=1}^{C} w_c\left(\hat{\eta}_c - \bar{\hat{\mu}}\right)^2\right) - \left(\sum_{c=1}^{C} w_c(1-w_c)\frac{\sum_{h=1}^{M_c}\left(\hat{\varepsilon}_{ch} - \bar{\hat{\varepsilon}}_c\right)^2}{M_c(M_c-1)}\right)}{\sum_{c=1}^{C} w_c(1-w_c)}; 0\right\} \quad 2.12$$

where C is the number of clusters, w_c is the weight of cluster *c*, $\hat{\eta}_c$ is the cluster-specific random effect for cluster *c* from (2.9), $\bar{\hat{\mu}}$ is the overall average of the total residuals from (2.8), M_c is the number of sampled households in cluster *c*, $\hat{\varepsilon}_{ch}$ is the household-specific random effect for household *h* from (2.10), and $\bar{\hat{\varepsilon}}_c$ is the average of the household-specific random effects for cluster *c* from (2.10). The weight of cluster *c* is given by:

$$w_c = \frac{\sum_{h=1}^{M_c} \lambda_h}{\sum_{h=1}^{N} \lambda_h} \quad 2.13$$

where λ_h is the sample weight of household *h* multiplied by its household size and N is the number of sampled households.

Unlike the limited observations on η, the more than 500 unique observations on ε permit the modeling of heteroskedasticity in this component. As described in Greene (2012, Section 11.6.2), in order to consistently estimate the heteroskedastic variance of ε_{ch}, any residual cluster effects are first purged from $\hat{\varepsilon}_{ch}$ by regressing $\hat{\varepsilon}_{ch}$ on a series of dummy variables corresponding to all but one of the 58 clusters. The residuals from this regression become the purged $\hat{\varepsilon}_{ch}$ used throughout the estimation of $\sigma_{\varepsilon_{ch}}^2$. The household-specific variance is then modeled using the modified logistic form proposed by ELL (2002, 2003):

$$\sigma_{\varepsilon_{ch}}^2 = Ap_{ch} + B(1-p_{ch}) \quad 2.14$$

where *A* and *B* are the upper and lower variance bounds respectively and p_{ch} is:

$$p_{ch} = \left[\frac{e^{z_{ch}\alpha}}{1 + e^{z_{ch}\alpha}}\right] \qquad 2.15$$

where z_{ch} is a vector of *k* observable characteristics for a given household h and α is a vector of *k* parameters. As noted by ELL (2003), this logistic functional form "…avoids both negative and extremely high predicted variances." Where a given household's predicted variance falls on the interval between *A* and *B* depends on the household's z_{ch} vector of characteristics and the estimate of α. To simplify the estimation of (2.14), ${\hat{\varepsilon}_{ch}}^2$ is taken as an unbiased estimate of the household-specific variance and the upper bound, *A*, is set as 1.05 times the max ${\hat{\varepsilon}_{ch}}^2$. Similarly, the lower bound, *B*, is set at 0. This allows, through the rearrangement of terms, an estimation of the α vector in (2.14) via OLS:

$$ln\left(\frac{{\hat{\varepsilon}_{ch}}^2}{A - {\hat{\varepsilon}_{ch}}^2}\right) = z_{ch}\alpha + \upsilon_{ch} \qquad 2.16$$

where υ_{ch} is a disturbance term such that $\mathrm{E}(\upsilon_{ch}|z_{ch}) = 0$. For the initial estimation of (2.16), z_{ch} is identical to x_{ch} from (2.6). Any characteristics with coefficient estimates not significant at the 10% level are then dropped from z_{ch} and equation (2.16) is re-estimated using the paired-down z_{ch}. ELL (2002, 2003) note that estimates of the α vector using (2.16) tend to be similar to those derived directly from (2.14). Using the estimated $\hat{\alpha}$ vector from (2.16) and the assumed *A* and *B*, the variance of each household's $\hat{\varepsilon}_{ch}$ is predicted using (2.14).

Having estimated $\hat{\sigma}_{\eta}^2$ and $\hat{\sigma}_{\varepsilon_{ch}}^2$, the estimated variance-covariance matrix in (2.7) for the households in a given cluster *c* is given by:

$$\Sigma = \begin{bmatrix} \hat{\sigma}^2_{\varepsilon_{ch}} + \hat{\sigma}^2_{\eta} & \hat{\sigma}^2_{\eta} & \dots & \hat{\sigma}^2_{\eta} \\ \hat{\sigma}^2_{\eta} & \hat{\sigma}^2_{\varepsilon_{ch}} + \hat{\sigma}^2_{\eta} & \dots & \hat{\sigma}^2_{\eta} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\sigma}^2_{\eta} & \hat{\sigma}^2_{\eta} & \dots & \hat{\sigma}^2_{\varepsilon_{ch}} + \hat{\sigma}^2_{\eta} \end{bmatrix} \qquad 2.17$$

Since all the error components are assumed to be independent, the covariance between households in different clusters is zero. Therefore, the full estimated variance-covariance matrix for all *N* observations is given by:

$$\Omega = \begin{bmatrix} \Sigma & 0 & \dots & 0 \\ 0 & \Sigma & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \Sigma \end{bmatrix} \qquad 2.18$$

where the Σ matrices for each cluster are as defined in (2.17) (Greene 2012, Section 11.5). In the presence of non-spherical errors, Feasible Generalized Least Squares (FGLS) can provide more efficient estimates of the β vector in (2.7) than OLS (Green 2012, Section 9.3.2). As this would allow for tighter predictions of household consumption per capita, the β vector from (2.7) is re-estimated using the estimated variance-covariance matrix and FGLS. To guard against potential violations of the error component assumptions used to derive the estimated Ω, village-level cluster robust standard errors are reported along with the estimated FGLS coefficients.

Consistent and efficient estimation of the β vector and the associated fitted values, $x_{ch}\hat{\beta}$, is not sufficient for estimating poverty, however, since the Foster-Greer-Thorbecke series of poverty indices are functions of the distribution of y_{ch} and not its conditional expectation (Tarozzi & Deaton 2009). Therefore, in order to estimate the Tororo District's rural poverty indices, the distribution of y_{ch} is recreated via simulation. These simulations are conducted using a modified version of residual bootstrapping which takes into account the uncertainty in estimating the parameters, the within-cluster correlation of the error terms, and the heteroskedasticity in the household-specific error component (ELL 2002, 2003; Kennedy 2003, Section 4.6; Tarozzi & Deaton 2009).

Before beginning these simulations, new sets of the cluster-specific and household-specific random effects are prepared by decomposing the residuals from the FGLS estimation into $\hat{\eta}_c$ and $\hat{\varepsilon}_{ch}$ as in (2.8). The estimated $\hat{\alpha}$ vector from (2.16) and the set of $\hat{\sigma}^2_{\varepsilon_{ch}}$ from (2.14) are then re-estimated using this new set of decomposed residuals and the previously described methods. The $\hat{\varepsilon}_{ch}$ are then standardized based on the new predictions of $\sigma^2_{\varepsilon_{ch}}$ as follows:

$$\hat{\varepsilon}^*_{ch} = \frac{\hat{\varepsilon}_{ch}}{\sigma_{\hat{\varepsilon}_{ch}}} \qquad 2.19$$

where $\sigma_{\hat{\varepsilon}_{ch}}$ is the square root of the predicted household-specific variance for a given household h. The purpose of this transformation is to make each $\hat{\varepsilon}_{ch}$ comparable by rescaling them based on their estimated variances. These newly prepared sets of $\hat{\varepsilon}^*_{ch}$ and $\hat{\eta}_c$ are drawn from throughout the simulation procedure (ELL 2002, 2003). After these preparations, the steps for each r^{th} simulation are as follows:

a) To account for the uncertainty in estimating β and α, new parameter vectors $\hat{\beta}^r$ and $\hat{\alpha}^r$ are drawn from their asymptotic, normal distributions using the point estimates and variance-covariance matrices from the FGLS estimation of (2.7) and the accompanying estimation of (2.16).

b) For each of the 24 sampled clusters in the 2014 THS, a random cluster-specific effect, $\hat{\eta}^r_c$, is drawn with replacement from the prepared set of all $\hat{\eta}_c$ with the probability of selection proportional to its cluster weight from (2.13).

c) For each of the 480 sampled households in the 2014 THS, a random standardized household-specific effect, $\hat{\varepsilon}^{*r}_{ch}$, is drawn with replacement from the set of all $\hat{\varepsilon}^{*}_{ch}$.

d) The heteroskedastic variances of the household-specific effects, $\hat{\sigma}^2_{\varepsilon_{ch}}$, are predicted based on the model of heteroskedasticity in (2.14), each household's z_{ch} vector of characteristics, the drawn $\hat{\alpha}^r$, and the assumed *A* and *B* bounds.

e) Estimates of the *non*-standardized household-specific effects, $\hat{\varepsilon}^{r}_{ch}$, are generated by multiplying each household's drawn $\hat{\varepsilon}^{*r}_{ch}$ by the square root of its associated result from step (d).

f) Simulated values of household consumption per capita, y^r_{ch}, are generated as:

$$y^r_{ch} = exp\left(x_{ch}\hat{\beta}^r + \hat{\eta}^r_c + \hat{\varepsilon}^r_{ch}\right) \qquad 2.20$$

g) The results from step (f) are then used to estimate the headcount poverty rate as:

$$\hat{P}^r_0 = \frac{1}{480}\sum_{i=1}^{480}\left[\frac{z - y^r_{ch}}{z}\right]^{\delta=0} * 1[y^r_{ch} < z] \qquad 2.21$$

where $\hat{P}^r_0$ is the r^{th} simulated headcount poverty rate conditional on the 2014 THS, 480 is the number of sampled households, z is the poverty line specified in Section 2.6., and y^r_{ch} is the simulated result from (2.20) for the *ith* household weighted by its individual sampling weight. The final term is an indicator which is one if y^r_{ch} is less than z and zero otherwise.

h) Step (g) is then repeated with $\delta = 1$ to generate $\hat{P}^r_1$, the r^{th} simulated poverty depth rate conditional on the 2014 THS.

i) Step (g) is then repeated with $\delta = 2$ to generate $\hat{P}^r_2$, the r^{th} simulated poverty severity rate conditional on the 2014 THS.

(Cuong 2011; ELL 2002, 2003; Tarozzi & Deaton 2009)

These simulation steps are repeated 10,000 times to generate 10,000 estimates of each of the three poverty indices based on the simulated household consumption per capita values. The expected values of the poverty indices conditional on the 2014 THS are then calculated as:

$$\bar{P}_\delta = \frac{1}{R}\sum_{r=1}^{R} \hat{P}_\delta^r \qquad 2.22$$

where R is the total number of replications, $\hat{P}_\delta^r$ is the r^{th} simulated poverty estimate conditional on the 2014 THS, and δ is 0, 1, or 2 for poverty headcount, depth, or severity respectively. The estimated variance of each $\bar{P}_\delta$ is then given by:

$$Var(\bar{P}_\delta) = \frac{1}{R}\sum_{r=1}^{R} \left(\hat{P}_\delta^r - \bar{P}_\delta\right)^2 \qquad 2.23$$

Due to the form of residual bootstrapping described above, this estimated variance takes into account the uncertainty in estimating the parameters along with the realization of the unobserved components of household consumption (ELL 2002, 2003). The 95% confidence intervals for each poverty measure are estimated directly from their empirical distributions by calculating the 2.5^{th} and 97.5^{th} percentiles of the 10,000 estimates.

2.8. Estimating the Poverty Reductions from Consumption Changes

After applying SAE to estimate the Tororo District's rural poverty rates, this study analyzes how changes in the consumption of poor households would impact the poverty measures. The objective is to assess a "best case" scenario for the poverty impacts of conservation agriculture adoption in the rural Tororo District; that is, this study evaluates how large the per acre increase in farm profits to poor households would need to be in order to measurably impact rural poverty in the district.

Due to the stochastic component of the household consumption predictions, the consumption of a given household in relation to the poverty line cannot be known with certainty. In order to target those households most likely to be poor, this study defines poor households as those whose predicted consumption falls below the poverty line in more than 70% of the initial 10,000 simulations described in Section 2.7. This group encompasses 151 of the 480 sampled households and corresponds to approximately 30% of the rural Tororo District's households and about 38% of the people in the District. Therefore, this group aligns well with the World Bank's recent shared prosperity goal which focuses efforts on increasing the well-being of the bottom 40 percent of every country's population (World Bank 2015). Targeting this poorest segment of the population is a useful starting point for development efforts that aim to improve livelihoods.

Having identified the poor households, the next step is to apply simulated consumption changes. A change in annual consumption is simulated for each poor household as follows:

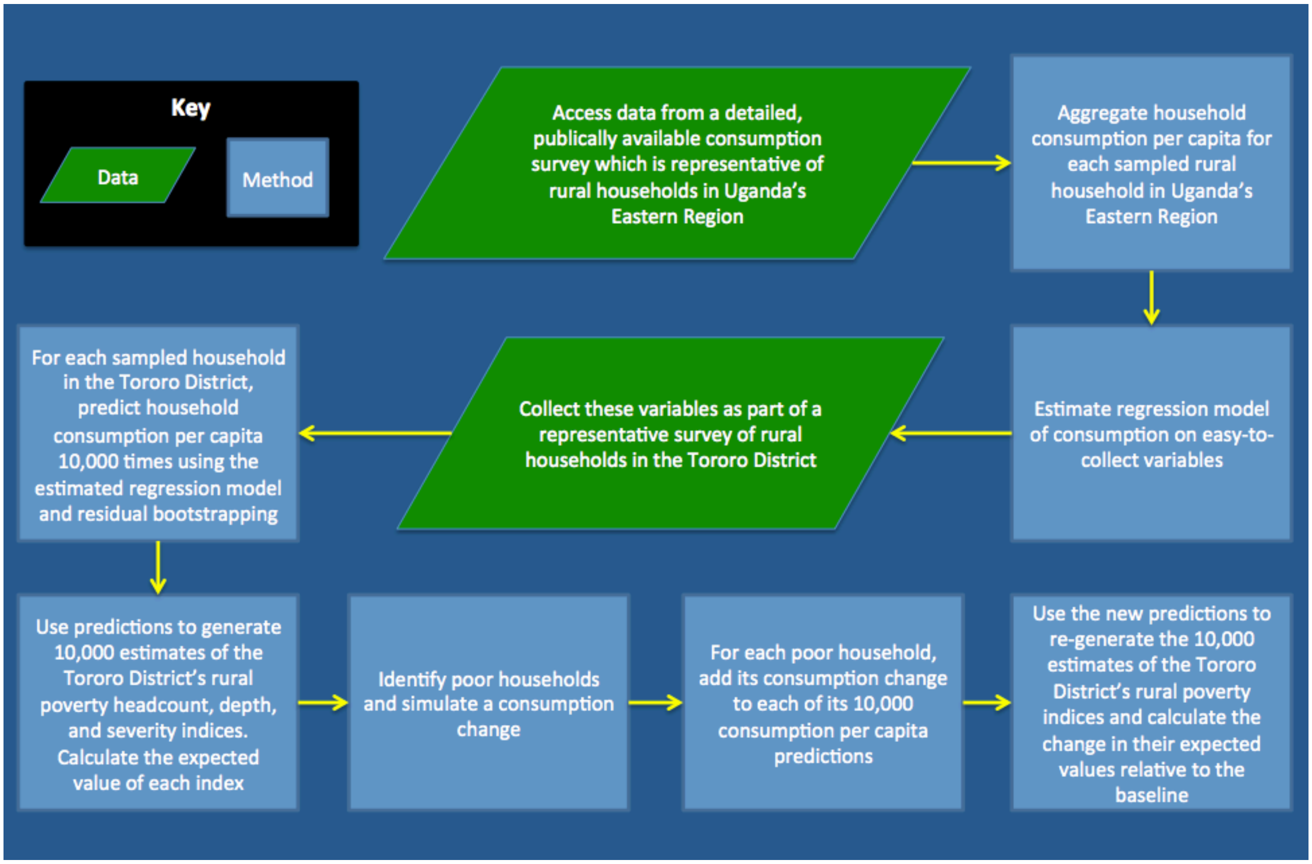
$$\Delta y_{ch} = 2(\gamma l_{ch}) \qquad 2.24$$

where Δy_{ch} is the annual change in consumption for a given household h, γ is the per acre change in farm profits, and l_{ch} is the number of acres affected by the per acre profit change for the given household. As rainfall in the Tororo District is bimodal, γl_{ch} is multiplied by two to reflect the semi-annual cropping seasons. This specification assumes that the per acre change in farm profits translates directly to a change in household consumption and that CAPS adoption has the same effect in both seasons.

This study assesses two possibilities for l_{ch}. In the first case, the per acre change in farm profits, γ, is applied to the number of acres that the household cultivated in the first season of 2014, regardless of ownership status. In the second case, γ is only applied to the number of acres that the household owns. The first case reflects the possibility that immediate cost savings or subsidies could incentivize a household to adopt soil-improving CAPS on any available plot, even if the household only has temporary rights to it. In the second, less optimistic case, a household only invests the time and resources to adopt CAPS on plots where it has secure property rights, thus ensuring that any long-term benefits from adoption will be captured.

In order to assess the effect of the consumption changes to poor households on the estimated poverty rates, Δy_{ch} is added to the corresponding predicted household consumption estimate in (2.20) of simulation step (f). For those households whose predicted consumption did not fall below the poverty line in more than 70% of the initial 10,000 simulations, y_{ch}^{r} remains unchanged. The rest of the simulation procedure is repeated as described in Section 2.7. Using the same sets of draws of $\hat{\beta}^{r}$, $\hat{\alpha}^{r}$, $\hat{\eta}_{c}^{r}$, and $\hat{\varepsilon}_{ch}^{*r}$ as the initial 10,000 simulations, the impact of the consumption changes on the estimated rural poverty indices is assessed. A simplified schematic of these small area estimation of poverty methods is shown in Figure 2.2. This process is repeated at varying levels of γ in order to estimate how different per-acre changes to the farm profits of poor households would impact the estimated poverty indices. These values of γ and their associated changes in the estimated poverty indices are then compared with field data on the net returns from conservation agriculture adoption.

Figure 2.2. Overview of Small Area Estimation of Poverty Methods



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Chapter 3: Results

3.1. Major Findings from the Tororo Household Survey

General Agricultural Practices

Section C.1. of Appendix C provides a detailed list of descriptive statistics pertaining to the general agricultural practices of households in the rural portion of the Tororo District during the first season of 2014. The tables in the appendix list the point estimates, village-level cluster robust standard errors, and 95% confidence intervals. The major findings are summarized here.

On average, rural households in the Tororo District owned about the same amount of agricultural land as they cultivated during the first season of 2014; households owned an average of 3.08 acres and cultivated an average of 3.07 acres. Additional land access came in the form of land rented in for money and land borrowed for free, which averaged 0.66 acres and 0.35 acres respectively. Among the estimated 42% of households that rented in positive amounts of land, the average amount rented in was 1.56 acres. On average, households rented out their land to others for money and lent it out for free in approximately equal amounts; the estimated average for each category was 0.31 and 0.28 acres respectively. The estimated average amount of land left fallow was 0.42 acres. A formal land title for land owned is extremely rare; the point estimate of the percent of households with a formal land title for any of their land is 0.84% with a 95% confidence interval of 0.23% to 1.46%.

Estimates of farm implement and livestock ownership follow expected trends. Ownership of basic tools and “lower rung” livestock is relatively high. For instance, over 99% of households own at least one hoe and about half own at least one goat. Pig and cow ownership is also somewhat common with approximately 38% of households owning at least one pig and 33% owning at least one cow. Ownership of more expensive farm implements and livestock used for ploughing, however, is relatively rare; only 11% report owning a working ox plough and only 9% own an ox. The estimated proportion of households that own a working ox plough and at least *two* oxen and are therefore "fully equipped" for ploughing is rarer still; only about 5% of households fall into this category. Not surprisingly then, approximately 51% of households reported having hired labor for more than half of their land preparation for the first season of 2014. Hiring labor for weeding was also relatively common, with an estimated 42% of households having hired labor for more than half of their weeding in the first season of 2014.

Cassava and maize were by far the crops most commonly ranked first or second in terms of a given household's land area planted. Other common "major" crops include groundnuts, rice, millet, beans, and sweet potatoes. Apart from hiring labor for land preparation and weeding, other input use on these major crops is not common. About 12% of households applied manure, compost, or mulch on any of their top three major crops. Similarly, less than 2% applied chemical fertilizer on their top three major crops. The use of pesticides and herbicides was somewhat higher, however, with an estimated 29% having applied them in some form on at least one of their top three major crops. Groundnuts is the most common major crop that households reported to have sprayed with pesticides and/or herbicides followed by beans and rice.

The survey data indicate that approximately 75% of households grew maize as one of their top three major crops during the first season of 2014. Focusing specifically on this subpopulation of maize-producing households, nearly three quarters reported growing maize mainly for home consumption. Their top two main sources for maize seed were local markets and saved seed from the previous season. Only an estimated 11% of households acquired most of their maize seed from an agro-input shop. Organic and chemical fertilizer use on maize followed the same general trend as on other crops. Pesticide and/or herbicide use, however, was considerably lower; only an estimated 3% of these maize producing households used either of them on maize.

Conservation Agriculture Adoption

Section C.2. of Appendix C provides a detailed list of descriptive statistics pertaining to households' awareness and adoption of conservation agriculture practices including point estimates, village-level cluster robust standard errors, and 95% confidence intervals. The major findings are summarized here.

Over half of households in the rural portion of the Tororo District have heard of the practice of spraying herbicides and planting directly without ploughing or only slightly disturbing the soil.[6] Only an estimated 0.54% of households, however, are currently practicing this form of Minimum Tillage (MT). Another estimated 0.81% of households have practiced MT in the past, but did *not* practice it during the first season of 2014. Among the households that had heard of MT, but never tried it, approximately half gave a lack of information about MT as a reason for not having used the practice. This

[6] Minimum tillage (MT) was defined within the context of the 2014 THS as using herbicides to prepare the land so that crops can be planted directly without ploughing or by only slightly disturbing the soil. Herbicides were specifically mentioned as they are an integral part of the minimum and reduced tillage practices developed on the SANREM experimental plots. Enumerators prompted each survey respondent with this MT definition before asking if he or she had heard of this practice before. If the respondent replied yes, the enumerators asked follow-up questions about whether the respondent's household had practiced MT on any of their fields during the first season of 2014 or had ever practiced it in the past. Qualitative information about why the given household had or had not practiced MT was also collected.

suggests that the SANREM focus on the research and development of a locally adapted CAPS rather than the active dissemination of an already developed technology may have contributed to the limited adoption of MT. Many of the households likely only heard of this form of MT from neighbors and secondary sources. More than one third of these households also cited a lack of enough money to buy herbicides as a reason for not practicing MT. An inability to *access* an herbicide supplier and an expressed concern that using herbicides could spoil the soil were also each given as reasons by about 11% and 9% of the households in this group respectively. The qualitative responses by households that are currently practicing MT suggest that reduced land preparation and weeding costs are their main incentive for adopting the practice. Among the households that had practiced MT in the past, but were not practicing it in the current season, the qualitative responses were more mixed. A lack of money to buy the herbicide, worry that herbicide use could damage soil fertility, and weeds overtaking the field were all given as reasons for stopping the practice.

The 2014 THS survey data indicate that approximately 61% of rural households in the Tororo District have heard of the general practice of cover cropping, that about 49% of households currently practice it in some form, and that about 10% of households have practiced cover cropping in the past, but not in the second season of 2013.[7] Among adopting households, the estimated average acres cover cropped is about one acre while

[7] Similar to MT, a set of nested questions was also asked about households' use of cover crops. In the context of the 2014 THS, cover cropping was *broadly* defined as growing crops to help cover and protect the soil. The second season of 2013 is used as the reference point for the cover crop questions since the period for planting cover crops in the first season of 2014 was still ongoing in some areas at the time of the data collection. For households that reported having planted cover crops in the second season of 2013, supplementary follow-up questions asked about the type of crops planted as a cover crop and the households' reasons for cover cropping.

the average number of years practicing cover cropping is approximately 14. Although mucuna was the specific cover crop being tested on the SANREM experimental plots, none of the sampled adopting households listed mucuna as one of their planted cover crops. Groundnuts, beans, and sweet potatoes were the most common crops planted as cover crops by the households that practiced cover cropping in some form in the second season of 2013. The main cited reasons by this group of households for planting cover crops were that they help improve soil fertility and increase yields while also providing additional food for home consumption and sale. To reduce soil erosion and to control weeds were also cited as reasons by a minority of households in this group (about 34% and 13% respectively). Of the households that used to practice cover cropping but did not do so in the last season, the main cited reason was limited land. Given these responses, widespread planting of mucuna as a cover crop may be constrained by its limited desirability as a food source and little opportunity for sale.

3.2. Small Area Estimation Poverty Estimates

Small Area Estimation Regression Results

This section describes the SAE regression results. A technical, detailed description of SAE is available in Section 2.7. The estimated alpha coefficients from the OLS regression of (2.16) are listed in Table 3.1. The purpose of this regression is to predict the heteroskedastic variance of the household specific random effect. The adjusted R^2 of this variance component model is 0.09. The value of $\hat{\sigma}_{\varepsilon}^{2}$ for each rural Eastern Region household sampled in the 2011/2012 UNPS is predicted via these estimated coefficients and (2.14). The average estimated value of $\hat{\sigma}_{\varepsilon}^{2}$ is 0.0367. The homoskedastic variance of the cluster-specific effect, $\hat{\sigma}_{\eta}^{2}$, is estimated as 0.0148 using

(2.12). The estimated values of $\hat{\sigma}^2_{\varepsilon_{ch}}$ and the estimated value of $\hat{\sigma}^2_{\eta}$ are used to build the Ω matrix in (2.18) for the FGLS estimation.

The estimated betas from the FGLS regression of logged household consumption in (2.7) are listed in Table 3.2.[8] The included variables are based on past SAE of poverty applications (Cuong 2011; Daniels 2011; Okwi et al. 2003). To reduce prediction "noise," the vast majority of the selected variables are significant at the five percent level or less. These regressors achieve a high R^2 while keeping the model relatively parsimonious, reducing the risk of over-fitting. The model's adjusted R^2 of 0.455 is within the range of other applications of SAE of poverty to the rural portion of Uganda's Eastern Region. The adjusted R^2 of the logged household consumption model of the rural portion of the Eastern Region in Okwi et al. (2003) is 0.34; the associated model in Daniels (2011) is 0.247. Although the primary purpose of the regression of (2.7) is prediction and any interpretation of the parameter estimates should be done tentatively, the signs of the estimated coefficients are intuitive. For instance, the estimated coefficients of cell phone and motorcycle ownership indicate that a household's ownership of these assets is associated with higher levels of household consumption. Similarly, the coefficients on the education-related variables suggest that formal education is positively correlated with household consumption. The magnitude of the correlation also appears to increase at higher education levels. This estimated regression model is combined with the SAE of poverty methods described in Section 2.7. to predict the rural FGT poverty indices for the Tororo District.

[8] One outlying observation was omitted from the regression; its consumption per capita was 2.4 times the second largest estimated consumption per capita value, resulting in undue influence on the fitted regression line.

Table 3.1. Regression Results for the Alpha Coefficients in the Heteroskedastic Variance Model of $ln\left(\frac{\hat{\varepsilon}_{ch}{}^2}{A-\hat{\varepsilon}_{ch}{}^2}\right)$ from Equation (2.16)

Variables	**Coefficient Estimates**
Household size	-0.212*** (0.052)
Household's main source of drinking water is an unprotected well, spring, river, or lake (yes=1; no=0)	0.874** (0.345)
Number of household members whose highest education level completed is primary school	0.376* (0.204)
Constant	-3.443*** (0.369)
N	559
R^2	0.095
Adjusted R^2	0.090

Note: Coefficients were estimated by OLS with individual sampling weights. Cluster robust standard errors are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by one, two, and three asterisks respectively.

Table 3.2. Regression Results for the Beta Coefficients in the FGLS Model of Logged Household Consumption Expenditure per Capita from Equation (2.7)

Variables	Coefficient Estimates
Household size	-0.078*** (0.008)
Proportion of household members under 16 years	-0.195 (0.177)
Household has an improved (non-mud) floor (yes=1; no=0)	0.166** (0.066)
Household's main source of drinking water is an unprotected well, spring, river, or lake (yes=1; no=0)	-0.385*** (0.141)
Number of cell phones owned	0.094*** (0.022)
Number of motorcycles owned	0.312*** (0.081)
Household has electricity (yes=1; no=0)	0.542*** (0.125)
Number of household members whose highest education level completed is *primary school*	0.017 (0.031)
Number of *male* household members whose highest education level completed is *some secondary* school	0.150*** (0.049)
Number of *female* household members whose highest education level completed is *some secondary* school	0.060 (0.047)
Number of *male* household members whose highest education level completed is *secondary school or above*	0.233** (0.094)
Number of *female* household members whose highest education level completed is *secondary school or above*	0.275** (0.109)
Number of agricultural acres owned	0.021*** (0.003)
Number of pigs owned	0.058*** (0.012)
Constant	13.611*** (0.096)
N	559
R^2	0.469
Adjusted R^2	0.455

Note: Coefficients were estimated by FGLS with individual sampling weights. Village-level cluster robust standard errors are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by one, two, and three asterisks respectively.

Poverty Analysis Results

This section reports the estimated rural poverty rates for the Eastern Region and the Tororo District. Based on the 2011/2012 UNPS, the mean annual household consumption per capita for rural households in the Eastern Region is approximately 623,070 Ugandan Shillings. Using the official 2012 Ugandan Shillings (UGX) to U.S. Dollar (USD) annual exchange rate, which is 2,504.56 UGX per USD, the estimated mean annual consumption per capita is approximately 248.77 USD (World Bank 2015).[9] This estimated mean annual consumption per capita is slightly above the adjusted international poverty line of 567,475 UGX (226.58 USD). The Eastern Region's rural poverty estimates, their associated standard errors, and their 95% confidence intervals are listed in Table 3.3. The rural headcount, depth, and severity poverty indices for the Eastern Region are estimated to be 0.5627, 0.1758 and 0.0751 respectively. That is, more than half of the rural population of the Eastern Region is estimated to fall below the international poverty line. The estimated rural poverty depth index translates to an average poverty gap among the rural population of the Eastern Region of approximately $0.22 per day at 2005 PPP.

The Tororo District's rural poverty estimates, their associated standard errors, and their 95% confidence intervals are also listed in Table 3.3. The rural headcount, depth, and severity poverty indices for the Tororo District are estimated to be 0.5649, 0.2148 and 0.1116 respectively. Figure 3.1. graphs the empirical cumulative distribution function (CDF) for the rural Tororo District's household consumption per capita predictions. This CDF provides a visualization of the 4.8 million simulated consumption

[9] The official 2012 annual average exchange rate is used to convert from UGX to USD throughout this study.

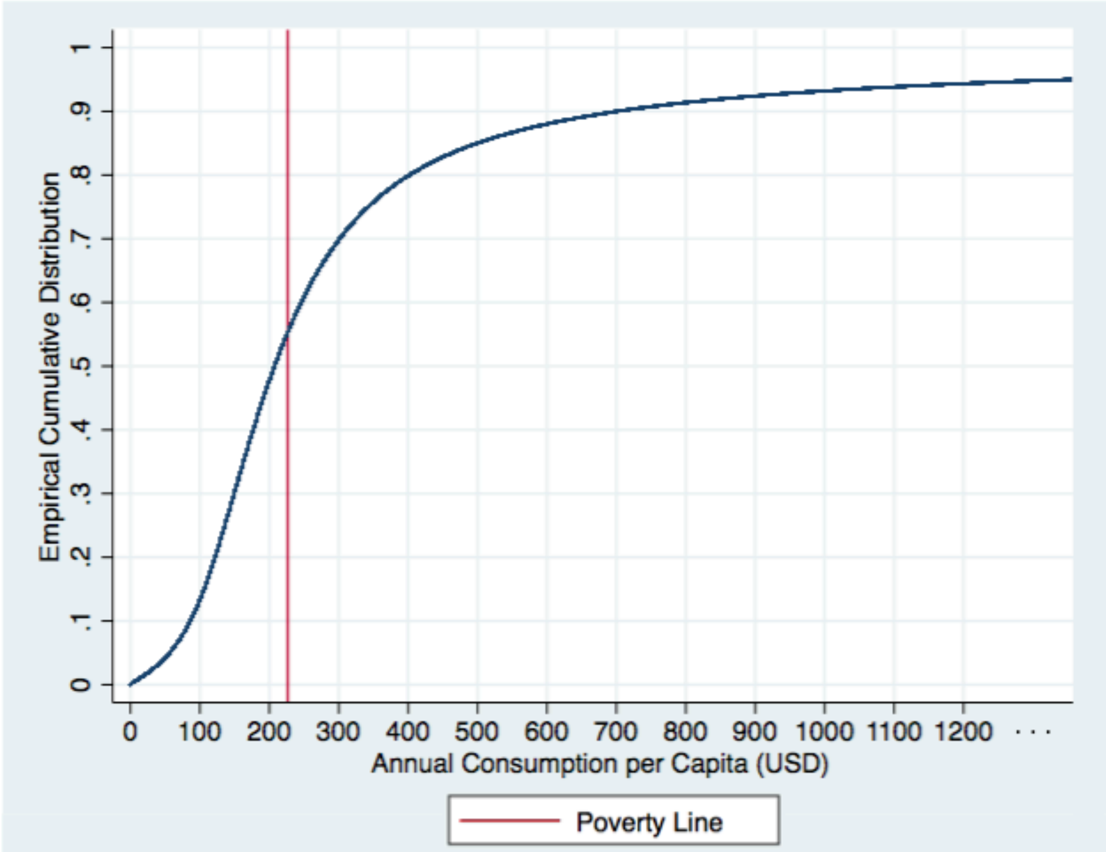
values (10,000 predictions for each of the 480 sampled rural Tororo District households). The majority of the household consumption predictions fall below the international poverty line, resulting in the Tororo District's estimated rural poverty incidence of 56.49%. This rural poverty incidence estimate is within half a percent of the corresponding estimate for the Eastern Region as a whole. Despite similar estimated headcount indices, the poverty depth point estimates suggest that the rural population in the Tororo District is farther below the poverty line on average. The Tororo District's estimated rural poverty depth index translates to an average poverty gap among its rural population of approximately $0.27 per day at 2005 PPP. The two estimated rural severity indices further indicate that the poorest rural segment of the Tororo District falls farther below the international poverty line on average than the poorest rural segment in the overall Eastern Region. These differences in the estimated depth and severity indices signify that increases in the household consumption of poor households in the Tororo District will affect households in a more extreme state of poverty than identical efforts in the region as a whole.

Table 3.3. Estimates of the Rural FGT Poverty Indices

FGT Poverty Index	Eastern Region				Tororo District			
	Estimate	Std. Error	95% Confidence Interval		Estimate	Std. Error	95% Confidence Interval	
			Lower	Upper			Lower	Upper
Headcount	0.5627	0.0340	0.4946	0.6308	0.5649	0.0445	0.4762	0.6508
Depth	0.1758	0.0189	0.1379	0.2137	0.2148	0.0248	0.1684	0.2644
Severity	0.0751	0.0123	0.0505	0.0997	0.1116	0.0163	0.0826	0.1457

Note:
The Eastern Region's rural poverty indices are estimated using the household consumption per capita aggregates from the 2011/2012 UNPS as described in Section 2.4., the adjusted international poverty line as described in Section 2.6., and Stata's svy estimation commands for survey data.
The Tororo District's rural poverty indices are estimated by applying the SAE of poverty technique described in Section 2.7. to the 2014 THS.
The poverty line is $1.25 per capita per day (at 2005 PPP) adjusted to 2012 Ugandan shillings

Figure 3.1. Empirical Cumulative Distribution Function of the Rural Tororo District's SAE Household Annual Consumption per Capita Predictions



Note:
Consistent with other currency conversions in this study, UGX are converted to USD using the official 2012 annual exchange rate of 2,504.56 UGX per USD.
The adjusted international poverty line is 226.58 USD.

3.3. Estimated Poverty Reductions from Consumption Changes

This section describes the estimated reductions in the Tororo District's rural FGT poverty indices at different levels of per acre profit increases to poor households, where poor households are defined as those whose predicted consumption per capita is below the poverty line in more than 70% of the 10,000 simulations.[10] The characteristics of this subpopulation of poor households relative to the non-poor are summarized in Table 3.4.

[10] The contrasting group of households whose predicted consumption per capita is below the poverty line in 70% *or less* of the 10,000 simulations is referred to as "non-poor." This distinction is made for ease of reference.

On average, poor households tend to have more household members and less education; the average household size among poor households is 8.70 compared to 6.22 for non-poor households. Despite having more household members, poor households own fewer assets on average; the average number of cell phones owned by poor households is less than one compared to an average close to 1.5 for non-poor households. Similarly, the average number of motorcycles owned is approximately three times higher among non-poor households. Poor households also own less land on average; the average number of agricultural acres owned is 1.79 acres and 3.65 acres for poor and non-poor households respectively; Relatively few poor households rent out land, give out land for free, or borrow land for free. Possibly due to their limited land endowments, poor households do, however, rent in more land on average than non-poor households. Living conditions also differ predictably between the two groups; only 7% of poor households have an improved floor compared to 24% of non-poor households. These differences are associated with lower predicted consumption per capita levels for poor households. The average estimated poverty depth for poor households was 0.3478 compared to 0.1328 for non-poor households.

Table 3.4. A Comparison of Mean Descriptive Characteristics Between Groups	Poor Households		Non-Poor Households		Adjusted Wald Test Statistic of Mean Diff.
Variables	**Mean**	**Std. Error**	**Mean**	**Std. Error**	
Household size	8.70	0.17	6.22	0.18	94.44***
Proportion of household members under 16 years	0.61	0.01	0.43	0.01	121.98***
Household has an improved (non-mud) floor (yes=1; no=0)	0.07	0.02	0.24	0.03	42.94***
Household's main source of drinking water is an unprotected well, spring, river, or lake (yes=1; no=0)	0.34	0.10	0.13	0.04	9.44***
Number of cell phones owned	0.83	0.08	1.43	0.08	27.91***
Number of motorcycles owned	0.03	0.01	0.09	0.02	11.14***
Household has electricity (yes=1; no=0)	0	-	0.03	0.01	8.80***
Number of household members whose highest education level completed is *primary school*	0.58	0.07	0.61	0.05	0.17
Number of *male* household members whose highest education level completed is *some secondary school*	0.23	0.04	0.70	0.06	32.46***
Number of *female* household members whose highest education level completed is *some secondary school*	0.19	0.03	0.40	0.05	14.21***
Number of *male* household members whose highest education level completed is *secondary school or above*	0.01	0.01	0.11	0.02	15.41***
Number of *female* household members whose highest education level completed is *secondary school or above*	0	-	0.05	0.02	12.01***
Number of agricultural acres owned	1.79	0.14	3.65	0.27	38.57***
Number of acres cultivated	2.85	0.14	3.16	0.09	5.72**
Number of acres rented out to others for money	0.04	0.02	0.42	0.17	4.70**
Number of acres given out to others for free	0.05	0.03	0.38	0.09	13.15***
Number of acres rented in for money	1.08	0.09	0.48	0.07	41.68***
Number of acres borrowed for free	0.28	0.05	0.38	0.07	1.70
Number of acres left fallow	0.19	0.06	0.52	0.07	9.50***
Number of goats owned	1.30	0.15	1.60	0.21	1.16
Number of pigs owned	0.37	0.09	1.10	0.21	13.76***
Number of cows owned	0.54	0.08	1.06	0.20	4.98**
Number of oxen owned	0.20	0.07	0.18	0.03	0.09

Note:
Land characteristics refer to the first season of 2014. The means are calculated with household weights. The standard errors are cluster-robust at the village-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by one, two, and three asterisks respectively.

As detailed in Section 2.8., this study applies consumption changes to poor households and assesses the effects on the estimated FGT indices for the rural portion of the Tororo District. The results of the analysis based on consumption changes to land cultivated and land owned are summarized in Table 3.5. and Table 3.6. respectively. The results indicate that an increase in the per acre profit on cultivated land of 5,000 UGX (2.00 USD) per season for poor households would decrease the incidence of rural poverty

Table 3.5. Estimated Reductions in the FGT Rural Poverty Indices for Different Levels of Per Acre Profit Changes to Land Cultivated by Poor Households During the First Season of 2014

Per-Acre Profit Change UGX (USD)	Estimated Reduction in FGT Rural Poverty Indices:		
	Headcount	Depth	Severity
5,000 (2.00)	0.0127	0.0157	0.0119
7,500 (2.99)	0.0203	0.0232	0.0170
10,000 (3.99)	0.0287	0.0304	0.0217
15,000 (5.99)	0.0479	0.0436	0.0298
20,000 (7.99)	0.0685	0.0552	0.0363
25,000 (9.98)	0.0894	0.0653	0.0417

Table 3.6. Estimated Reductions in the FGT Rural Poverty Indices for Different Levels of Per Acre Profit Changes to Land Owned by Poor Households

Per-Acre Profit Change UGX (USD)	Estimated Reduction in FGT Rural Poverty Indices:		
	Headcount	Depth	Severity
5,000 (2.00)	0.0085	0.0105	0.0080
7,500 (2.99)	0.0134	0.0155	0.0115
10,000 (3.99)	0.0188	0.0203	0.0147
15,000 (5.99)	0.0305	0.0293	0.0204
20,000 (7.99)	0.0432	0.0376	0.0252
25,000 (9.98)	0.0569	0.0449	0.0292

in the Tororo District by about one percentage point. If CAPS is only adopted on owned land, the per acre profit of poor households would need to increase by nearly 7,500 UGX (2.99 USD) per season for a one percentage point decrease in rural poverty incidence. Appendix C, Table C.6. lists the focus group discussion's median costs and yield estimates for one acre of maize production. Based on these estimates, the median profit per acre for one season of maize production in the district is approximately 58,500 UGX (23.36 USD). Thus, profit per acre increases of 5,000 UGX and 7,500 UGX represent median increases of roughly nine percent and 13% respectively.

As the per acre profit change is increased, the estimated effects on the rural poverty indices for a given per acre profit change continue to be greater if CAPS is adopted by poor households on all cultivated land rather than only on owned land.
The kernel density plots in Figure 3.1. and Figure 3.2. illustrate the simulated effects on the Tororo District's rural poverty headcount estimates for per acre profit changes of 5,000 UGX (2.00 USD) and 20,000 UGX (7.99 USD) respectively. These plots show how the magnitude of the shift in the empirical distribution of the 10,000 simulated poverty headcount estimates is affected by the size of the per acre profit change and the acres on which poor households adopt the CAPS. The size of the estimated reduction in poverty incidence increases as the per acre profit change increases and as households choose to adopt CAPS on all cultivated land, regardless of ownership status. To see a four to five percentage point reduction in the incidence of rural poverty, per acre profit on cultivated land would need to increase by 15,000 UGX (5.99 USD) to 20,000 UGX (7.99 USD) per season. Based on median estimates from the focus group discussions, profit per acre increases of 15,000 UGX and 20,000 UGX represent percent changes in median

profit per acre of 26% and 34% respectively. To observe a four to five percentage point reduction in poverty incidence based on adoption only on owned land, per acre profit would need to increase by more than 20,000 UGX (7.99 USD) per season.

Figure 3.2. The Shift in the Empirical Distribution of the Tororo District's SAE Poverty Estimates after Simulating a Profit Per Acre Change of 5,000 UGX (2.00 USD) to Poor Households

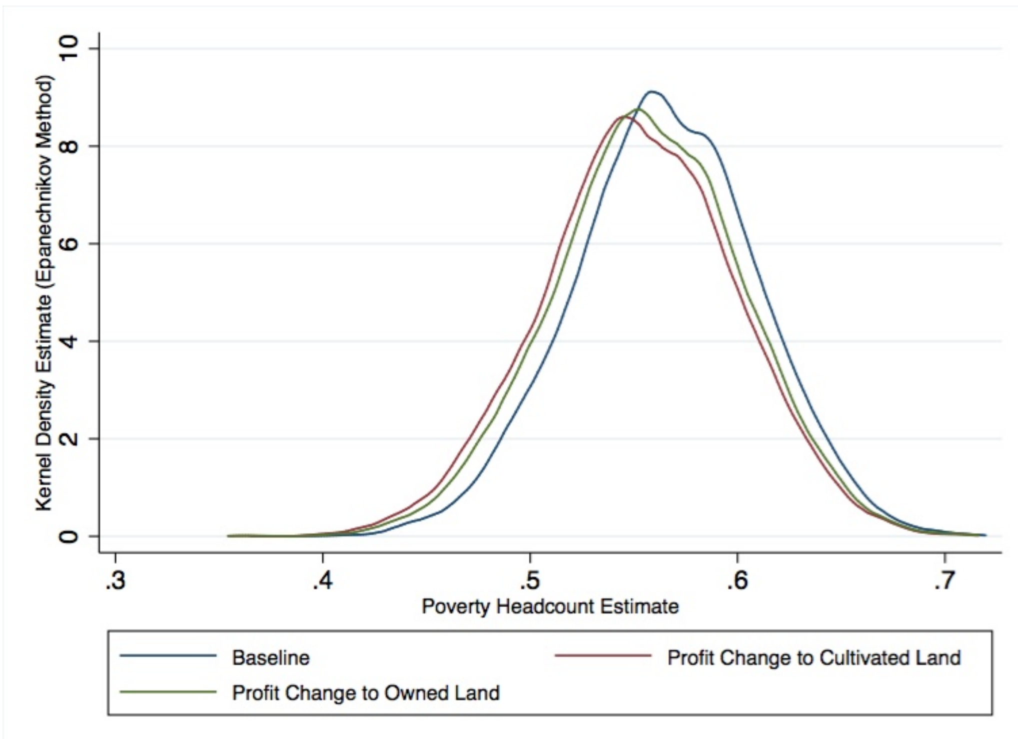
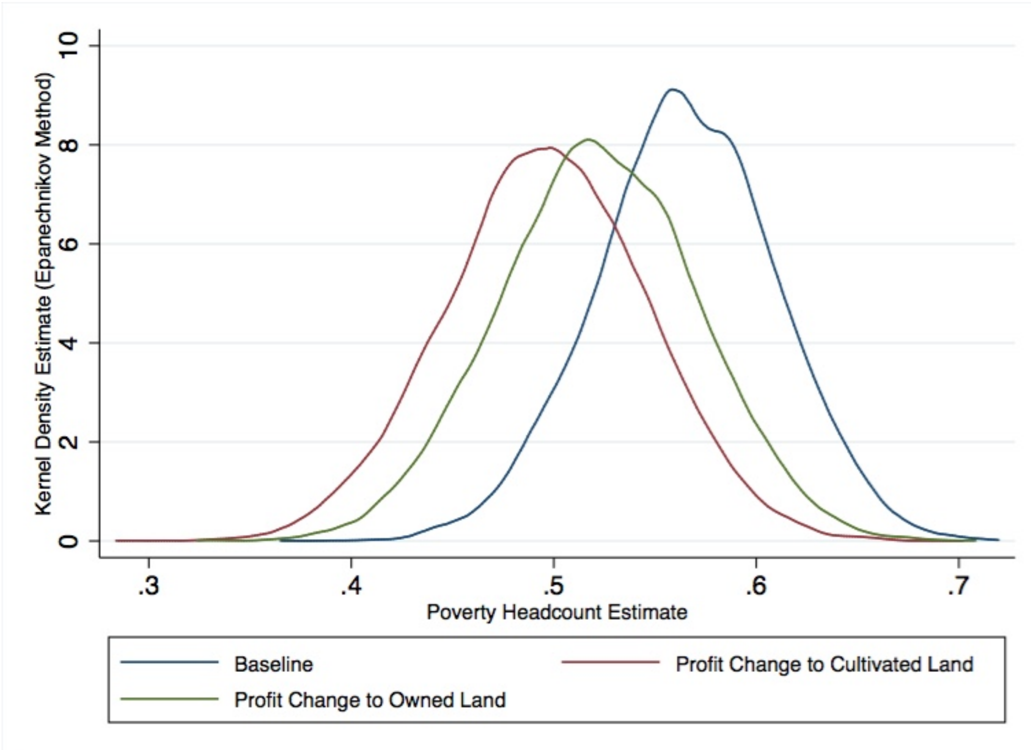


Figure 3.3. The Shift in the Empirical Distribution of the Tororo District's SAE Poverty Estimates after Simulating a Profit Per Acre Change of 20,000 UGX (7.99 USD) to Poor Households



3.4. Sensitivity Analysis

This study conducts a sensitivity analysis of the Tororo District's SAE rural poverty estimates using OLS with village-level cluster robust standard errors. Unlike FGLS, this estimation framework does not attempt to explicitly model Ω, the variance-covariance matrix of the nested error term. An OLS model with village-level cluster robust standard errors is estimated using Stata's *svy* estimation commands for survey data. This Stata package uses Taylor-linearized variance estimation to take into account the multistage sampling design of the 2011/2012 UNPS when calculating the standard errors of the estimated OLS coefficients (StataCorp 2013). The results from the OLS regression of (2.7) are listed in Table 3.7. The estimated coefficients from OLS are similar, but not identical to those from FGLS. As both estimation frameworks are consistent, the two sets of estimated coefficients should converge as the sample size increases. The Tororo District's SAE poverty indices were re-estimated using the OLS coefficients, their associated variance-covariance matrix, the same random number seed in Stata, and the previously described simulation procedure. The SAE point estimates of the poverty indices based on OLS are within 0.005 of the FGLS results. This suggests that, at least for this application, the SAE rural poverty estimates are robust to whether OLS or FGLS is chosen to estimate the given regression model.

Along with a sensitivity analysis around the choice of estimator, this study also assesses the effect of omitting the user cost of durable goods from the household consumption aggregate. As detailed in Section 2.4., this study applies the method of estimating the user cost of durable goods employed by Deaton and Zaidi (2002) when detailed data were scarce. Given the large number of assumptions required for this method, a sensitivity analysis without the user cost of durable goods could indicate the degree of influence these assumptions have on the final results. In this application, omitting the user cost of durable goods had a negligible effect on the rural poverty estimates. Among the rural households sampled in the Eastern Region in the 2011/2012 UNPS, the estimated user cost of durable goods is less than 1% of the consumption aggregate on average. Excluding it from the consumption aggregate and rerunning the SAE analysis increased the point estimates of the Tororo District's rural poverty indices by approximately 0.003. That is, the incidence of poverty expressed as a percent of the rural population in the district increased by a third of a percentage point.

Table 3.7. Regression Results for the Beta Coefficients in the OLS Model of Logged Household Consumption Expenditure per Capita from Equation (2.7)

Variables	Coefficient Estimates
Household size	-0.072*** 0.010
Proportion of household members under 16 years	-0.329* 0.185
Household has an improved (non-mud) floor (yes=1; no=0)	0.205** 0.085
Household's main source of drinking water is an unprotected well, spring, river, or lake (yes=1; no=0)	-0.304*** 0.111
Number of cell phones owned	0.097*** 0.025
Number of motorcycles owned	0.220** 0.083
Household has electricity (yes=1; no=0)	0.446*** 0.140
Number of household members whose highest education level completed is *primary school*	0.046 0.031
Number of *male* household members whose highest education level completed is *some secondary* school	0.088* 0.052
Number of *female* household members whose highest education level completed is *some secondary* school	0.107 0.071
Number of *male* household members whose highest education level completed is *secondary school or above*	0.275** 0.105
Number of *female* household members whose highest education level completed is *secondary school or above*	0.374*** 0.124
Number of agricultural acres owned	0.012*** 0.004
Number of pigs owned	0.057*** 0.019
Constant	13.604 0.090
N	559
R^2	0.482
Adjusted R^2	0.468

Note: Coefficients were estimated by OLS with individual sampling weights. Village-level cluster robust standard errors are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by one, two, and three asterisks respectively.

3.5. Comparison to Net Returns from Conservation Agriculture

This section synthesizes data from the on-station and on-farm SANREM conservation agriculture trials in the Tororo District and findings from the focus group discussions conducted during the 2014 THS to assess the net returns from a locally adapted conservation agriculture production system (CAPS). As shown in equation (2.4), which describes the change in farm profits from conservation agriculture adoption, these net returns will be a function of the value of the change in output minus the total change in the variable costs of production. A SANREM analysis of the on-station and on-farm maize and bean yield data for Tororo across the first two years (four seasons) of the agricultural trials showed no significant difference in yields from CAPS compared to the conventional practice. The report notes, however, that "…based on observed maize and bean yields, participating farmers made general observations that minimum tillage was less costly and produced yields that were comparable to those in conventional tilled plots" (SANREM 2013). Given these SANREM yield findings, this analysis will assess the net returns from conservation agriculture by examining available data on the change in the costs of production from CAPS adoption.

A simplified summary of the costs of production for the on-station SANREM trials in the Tororo District is listed in Table 3.8. The shaded line items differ between CAPS and the conventional practice; this partial budget framework focuses the analysis on the costs of production that change between the two systems. A naïve first reading of the differences in the on-station costs of production figures would suggest a decrease in costs of approximately 83,000 UGX (33.14 USD) per acre for CAPS relative to the conventional practice. Even with no yield change between the two systems, this

Table 3.8. Simplified Per Acre Costs of Production for On-Station SANREM Trials in the Tororo District, Uganda

	CA Production System				Conventional Practice			
	Units	No. Units	Unit Price (UGX)	Total (UGX)	Units	No. Units	Unit Price (UGX)	Total (UGX)
Land (rent per season)	Acres	1	60,000	60,000	Acres	1	60,000	60,000
				60,000				**60,000**
Seed/Chemical Inputs								
Maize seed	kgs.	10	5,000	50,000	kgs.	10	5,000	50,000
Beans seed	kgs.	25	4,500	112,500	kgs.	25	4,500	112,500
Mucuna seed	kgs.	25	1,500	37,500	kgs.			
DAP	kgs.	50	2,200	110,000	kgs.	50	2,200	110,000
CAN	kgs.	50	1,800	90,000	kgs.	50	1,800	90,000
TSP	kgs.	25	2,200	55,000	kgs.	25	2,200	55,000
Dual Gold	Litres	0.7	72,000	50,400	Litres			
Glyphosate	Litres	1.7	17,000	28,900	Litres			
Pesticides	Litres	1	15,000	15,000	Litres	1	15,000	15,000
Fungicides	Litres	1.5	40,000	60,000	Litres	1.5	40,000	60,000
				609,300				**492,500**
Labor								
Land preparation (1st)	Acres				Acres	1	120,000	120,000
Land preparation (2nd)	Acres				Acres	1	120,000	120,000
Herbicide application (1st)	Acres	1	10,000	10,000	Acres			
Herbicide application (2nd)	Acres	1	10,000	10,000	Acres			
Planting + fertilizer application	Acres	1	120,000	120,000	Acres	1	120,000	120,000
Weeding (1st)	Acres	1	120,000	120,000	Acres	1	120,000	120,000
Weeding (2nd)	Acres	1	120,000	120,000	Acres	1	120,000	120,000
Pest control (1st)	Acres	1	10,000	10,000	Acres	1	10,000	10,000
Pest control (2nd)	Acres	1	10,000	10,000	Acres	1	10,000	10,000
Top dressing	Acres	1	30,000	30,000	Acres	1	30,000	30,000
Harvesting beans	Acres	1	30,000	30,000	Acres	1	30,000	30,000
Threshing beans	Acres	1	30,000	30,000	Acres	1	30,000	30,000
Relaying mucuna	Acres	1	20,000	20,000	Acres			
Harvesting maize	Acres	1	72,000	72,000	Acres	1	72,000	72,000
Threshing maize	Acres	1	50,000	50,000	Acres	1	50,000	50,000
				632,000				**832,000**
Season Total				**1,301,300**				**1,384,500**

Source: (Grace Tino, personal communication, April 2015).

Notes: Conventional practice is conventional tillage with a maize-beans intercrop.
The representative CA production system is min./no tillage with a maize-beans intercrop and a mucuna relay.
Shaded line items differ between the two systems.
These costs are based on those recorded on the 10x10 meter on-station trial plots.
The labor rates are higher than what would be observed in a non-research setting.
The official 2012 annual exchange rate is 2,504.56 UGX per USD (World Bank 2015).

cost of production difference would be more than enough for a substantial decrease in rural poverty in the Tororo District if it were representative of the cost difference faced by poor households and they adopted CAPS. The subsequent analysis assesses whether this is the case.

The partial budget framework shows that the estimated cost savings from CAPS compared to the conventional practice is primarily driven by the land preparation cost savings. The estimate of the on-station conventional practice land preparation costs extrapolated to one acre is 240,000 UGX (95.83 USD) for two ploughings or a cost of 120,000 UGX (47.91 USD) per acre per ploughing. The 2014 THS focus group discussions suggest that these on-station land preparation costs are higher than what would be observed in a non-research setting. Although the 2014 THS focus group discussions revealed substantial heterogeneity in typical land preparation costs, the estimates were generally lower than the on-station figure. In a majority of the villages, the discussion groups indicated that the main method of land preparation in their village was oxen. As ownership of oxen and ox ploughs is scarce, this land preparation is primarily done by hired labor. Across the 24 sampled villages, the estimated cost of hiring laborers with an ox plough and oxen to plough non-virgin land ranged from 30,000 UGX (11.98 USD) to 120,000 UGX (47.91 USD) per acre per ploughing. The discussion groups noted that the realized land preparation cost depends on a multitude of factors including a field’s soil type and weed cover, the timing of the request, and the local availability of oxen for hire. An estimate near 120,000 UGX (47.91 USD) was rare and tended to be for low-lying, swampy fields such as those typically used for rice cultivation. A majority of the cost estimates for land preparation by oxen on land typically used for maize cultivation were within a range of 30,000 UGX (11.98 USD) to 100,000 UGX (39.93 USD) per acre per ploughing. The focus group discussions' median land preparation cost estimates were 65,000 UGX (25.95 USD) and 45,000 UGX (17.97 USD) per acre for the first ploughing and second ploughing respectively, for a total of 110,000 UGX (43.92 USD).

Taking the on-station costs of production specific to CAPS as given (i.e. the costs of buying and applying the herbicides and buying and planting mucuna) and assuming no change in yield between the two systems, a household would need to face a typical land preparation cost of approximately 157,000 UGX (62.69 USD) in order to breakeven with CAPS. If a household typically ploughs its land twice before planting, this corresponds to a cost of about 78,500 UGX (31.34 USD) per acre per ploughing. Assuming the mucuna seed is initially supplied for free and then saved each season thereafter, the necessary typical land preparation cost for a household to breakeven from a switch to CAPS falls to approximately 119,000 UGX (47.51 USD) or about 59,500 UGX (23.76 USD) per acre per ploughing. This lower, subsidized-mucuna breakeven point is just above the focus group discussions' median land preparation estimate of 110,000 UGX (43.92 USD).

Under no yield change from CAPS adoption, the cost of production breakeven point of 157,000 UGX (62.69 USD) suggests that the change in farm profits from switching to CAPS could range from a decrease in profits of 97,000 UGX (38.73 USD) per acre to an increase in profits of 43,000 UGX (17.17 USD) per acre depending on whether a household faces land preparation costs of 30,000 UGX (11.98 USD) per acre for each of two ploughings or 100,000 UGX (39.93 USD) per acre for each of two ploughings respectively. If a household typically only ploughs once before planting, the cost savings and associated change in profits from switching to CAPS would decrease; for example, if a household only ploughs once before planting at a cost of 100,000 UGX (39.93 USD) per acre, the cost of production figures suggest that a switch to CAPS would decrease profits by 57,000 UGX (22.76 USD) per acre (under no change in yields).

These results emphasize that the potential for a locally adapted CAPS to reduce rural poverty in the Tororo District depends in part on the costs currently being incurred under the conventional practice, particularly those from land preparation. If land preparation costs faced by poor households are high, the estimated change in profits from CAPS adoption is well within the range necessary to generate a substantial reduction in the Tororo District's FGT rural poverty indices. If land preparation costs are low, however, these households may incur a reduction in per-acre profits from CAPS adoption. The potential for CAPS to measurably reduce rural poverty is further complicated by the heterogeneity in land preparation costs revealed by the 2014 THS's focus group discussions in each of the 24 sampled villages. Although the SAE results suggest that relatively modest increases in poor households' per-acre profits would measurably reduce the rural poverty indices, the available data on the net returns to conservation agriculture in the Tororo District suggest that these modest increases may only be achievable for adopting households that face high land preparation costs.

3.6. Chapter References

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Chapter 4: Conclusions

4.1. Implications

The results from the SAE analysis can be used as a benchmark to assess development progress. This study's assessment of "best case" scenarios suggests that measurable rural poverty reduction in the Tororo District could be achieved via relatively modest increases in the profit per acre of poor households. Profit increases of 5,000 UGX (2.00 USD) per acre per season on the cultivated land of the bottom 30% of households could reduce the rural incidence of poverty by about one percentage point. The effect on poverty, however, is reduced if poor households only adopt CAPS on owned land; in such a case, a profit increase of 7,500 UGX (2.99 USD) per acre per season would be needed to generate a one percentage point reduction in poverty incidence. Based on median estimates from the focus group discussions, profit per acre increases of 5,000 UGX and 7,500 UGX represent median profit per acre increases of approximately nine percent and 13% respectively. The potential for measurable poverty reduction via these relatively small increases in the farm profits of poor households should be encouraging to the district's researchers and project implementers whose work aims to reduce poverty.

While these district targets could be achieved by a locally adapted CA production system, the technology's current ability to reduce poverty is constrained by the lack of significant short-term yield gains from the system and the heterogeneity in land preparation costs faced by households; in the absence of short-term yield gains, the profit increases from CAPS adoption may be most readily available to households that face high land preparation costs. Furthermore, although the evidence from the 2014 THS suggests that households are generally aware of MT practices, the adoption of MT appears to be constrained by a lack of information on the practice and the cost and availability of herbicides. The widespread adoption of mucuna, the specific cover crop tested on the Tororo District SANREM experiment plots, may be constrained by the crops limited desirability as a food source and little opportunity for sale. These results suggest that there is more work to be done if CA development in the Tororo District is to achieve its aim of poverty reduction. At the present state of CAPS development, achieving rural poverty reduction in the Tororo District from CAPS may require policy incentives that improve the technology's short-term profitability relative to current farmer practices.

Along with these context-specific insights, the method applied in this study could easily be adapted to other settings. The collection of detailed consumption data for welfare analyzes may be outside the budget and time constraints of many researchers and project implementers. Detailed datasets of household-level consumption data, however, are available from the World Bank's Living Standards of Measurement Study (LSMS). By utilizing these publically available datasets and applying the Elbers, Lanjouw, and Lanjouw (2002; 2003) small area estimation of poverty method to survey data, researchers can conduct welfare analyzes of their small geographic area of interest without the expense of collecting detailed consumption data. Although the method is somewhat computationally intensive, the covariates used in the welfare analysis can be collected relatively easily in a low-cost survey of household characteristics. This allows researchers to conduct detailed welfare analyzes while focusing their efforts (and budget) on other research questions of interest.

4.2. Opportunities for Future Research

The methods applied in this study provide several opportunities for improvement in future research: (i) the present analysis assumes that spatial variation in prices does not affect the Tororo District's rural poverty measures. This assumption could be directly examined by building a price index to adjust household consumption for spatial variation in prices and assessing the effect on the estimated poverty indices; (ii) this study focuses on the changes in profits to poor households that could lead to short-term rural poverty impacts. Future research could examine the temporal effects of CAPS adoption on rural poverty; (iii) it may be possible to build a model that better predicts household consumption per capita by incorporating formal statistical methods for selecting covariates. Cross-validation methods, for example, could select the subset of available covariates that minimize the mean squared prediction error of out-of-sample forecasts; (iv) the methods described in this paper would benefit from a more rigorous assessment of the accuracy of applying the method outlined in ELL (2002; 2003) to survey data rather than a census. This could be achieved by drawing a sample of households from a census dataset for a small geographic area of interest, estimating the poverty indices using SAE and the sampled households, and comparing the estimated poverty indices from the sample to the SAE results using the full census of observations.

4.3. Chapter References

Elbers, C., J.O. Lanjouw, and P. Lanjouw (ELL). 2002. "Micro-Level Estimation of Welfare." Policy Research Working Paper No. 2911. Washington D.C.: World Bank.

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Appendices

Appendix A: Survey Questionnaire

Respondent ID: ______________________

Sub County:_______________ Parish: _________________ Village:___________________

Name of Enumerator: ___________________________ Date: ____________

Hello, my name is _________, and this is ______________ and __________. We are conducting research for the SANREM Project, which has many institutions involved, including Makerere University, Appropriate Technology, and universities in the United States. We would like to ask you questions about your household, housing conditions, and farming practices. Would you be willing to participate in this survey? Participation in this survey is voluntary and the answers that you provide will be anonymous and confidential.

We have a series of questions which will take approximately 1 hour. Do you agree to participate in this survey? YES NO

**[This survey must be answered by an adult member of the household.
If none is present, go on to the next household]**

Name of respondent	Sex 1=M 2=F	Is the respondent the household head? 1=Yes 0=No	**If no:** What is the relationship of the respondent to the household head? 1=Spouse 2=Brother/Sister 3=Parent 4=Other (specify)	How many months in the past 12 months has the respondent stayed away from his/her household?

Section 1A: Marriage Status

1) What is the present marital status of [NAME OF HOUSEHOLD HEAD]?

a) MARRIED MONOGAMOUS b) MARRIED POLYGAMOUS [**If b) specify number of wives**: ____]

c) DIVORCED/SEPARATED d) WIDOW/WIDOWER e) NEVER MARRIED

Section 1B: Household Roster

We would like to identify all persons who are members of this household. **The household roster must be filled out with greatest care.** Note that other members can help by adding information or details in the questions concerning them.

Household members include:

- All persons who **normally** live in this dwelling and share food expenses or take meals together, even if they may not have blood relationship with the household head or are not present on the date of the interview
- Members who are away for school or seasonal work and are coming back.
- Infants and small children

The following persons are NOT to be listed:

- Guests/visitors present on the date of the interview
- Persons who have left the household permanently (such as children who have left to start their own families)

Section 1B: Household Roster

Person ID	We would like to make a complete list of household members. ***WRITE COMMON NAMES ONLY AND ASK IF ALL MEMBERS ARE LISTED BEFORE CONTINUEING***	Sex 1=M 2=F	What is the relationship of [NAME] to the head of the household? 1=Head 2=Spouse 3=Son/daughter 4=Grand child 5=Parent of head or spouse 6=Brother/Sister of head or spouse 7=Nephew/Niece 8=Other relatives 9=Non relatives	How old is [NAME] in completed years? ***IF LESS THAN ONE YEAR, WRITE 0***	**For persons 5 years and above** Has [NAME] ever attended any formal school? 0= Never attended 1= Attended school in the past 2= Currently attending school	**For persons who have attended school in the past:** What is the highest grade/class that [NAME] has completed? **For persons who are currently attending school:** What grade/class is [NAME] currently attending? (If necessary, see additional schooling codes below)	**For persons who are currently attending school:** Who owns the school that [NAME] attends? 1=Government 2=Private 3=Other (specify)
01							
02							
03							
04							
05							
06							
07							
08							
09							
10							
11							
12							
13							
14							
15							
Additional Schooling Codes: V= Vocational; C= College; U= University							

Section 1C: Other Information about Household Members

1) Income Sources

In the past 12 months, has your household received income from **remittances** (domestic or abroad)? 1=YES 0=NO	In the past 12 months, has your household had any other **non-farm** income? 1=YES 0=NO	In the past 12 months, was your household's income from remittances and non-farm sources greater than your farm income? 1=YES 0=NO

2) Farmer Groups and Extension Visits

		If yes:	
Currently, is anyone in your household a member of any farmer groups? 1=YES 0=NO	In the last 12 months, has your household received training or information from an agricultural extension specialist (includes NAADS, other government, NGO, etc.)? 1=YES 0=NO	How many times in the past 12 months was your household in contact with an agricultural extension specialist?	Who did the agricultural extension specialist work for? **Write all that apply** 1=Government 2=NGO 3=Other (specify)

3) Access to Loans

	If yes:		
In the past 5 years, has your household ever accessed loans to finance your agricultural production? 1=YES 0=NO	What was the most recent year that your household accessed a loan?	How much did your household access? *Answer in Ugandan Shillings*	What was the source of the loan? **See Credit Codes Below**
Credit Codes: 1=Local money lender; 2=Village Savings & Loan Assoc. (VSLA); 3=Relative; 4=Friend/neighbor; 5=Formal Bank; 6=Micro finance institution; 7=Savings & Credit Cooperative (SACCO) ; 8=Other (specify)			

4) Does every member of your household have at least two sets of clothes? [do **not** count heavily worn clothes with holes or school uniforms] YES NO

5) Does every member of your household (excluding infants) have at least one pair of shoes? [do **not** count slippers or "tire" shoes] YES NO

Section 2: Housing Conditions

1) What is the **major** construction material of the **roof** of the main house? [If more than one material, record the predominant one]

a) THATCHED/MUD/STRAW b) IRON/TIN SHEET c) TILES/CEMENT/CONCRETE d) OTHER (specify) ______________

2) What is the **major** construction material of the external **wall** of the main house? [If more than one material, record the predominant one]

a) MUD b) BURNT BRICKS WITH MUD c) BURNT BRICKS WITH CEMENT/CEMENT BLOCKS d) OTHER (specify) ______________

3) What is the **major** construction material of the **floor** of the main house? [If more than one material, record the predominant one]

a) MUD b) CEMENT/CONCRETE c) TILES d) OTHER (specify) ______________

4) What is the **main** source of drinking water for your household? [An unprotected well is one that is not sheltered from outside contamination]

a) RIVER/STREAM/LAKE b) UNPROTECTED WELL/SPRING c) PROTECTED WELL/SPRING

d) BORE-HOLE e) OTHER (specify) ______________

5) What type of toilet is **mainly used** in your household? [A covered pit latrine has a wall AND a roof]

a) BUSH b) UNCOVERED PIT LATRINE c) COVERED PIT LATRINE d) FLUSH TOILET

e) OTHER (specify)___________

6) Which of the following types of stoves are used by your household? **[Circle all that apply]**

a) THREE STONES/OPEN FIRE b) CHARCOAL c) IMPROVED CHARCOAL/IMPROVED WOOD BURNING (LORENA)

d) GAS/KEROSENE e) ELECTRIC f) OTHER (specify)________________

7) Which stove is used **most often** by your household? **[Write corresponding letter from above question]** ____________________

8) What is the **main** source of lighting in your household?

a) FIREWOOD b) TADOOBA c) PARAFFIN LAMP d) BATTERY LAMP e) SOLAR LAMP

f) ELECTRICITY (GRID, GENERATOR, OR SOLAR PANEL) g) OTHER (specify) ________________

9) Household Assets

Item Code	Item Name	Does any member of your **household** currently own a [ASSET]? 1=YES 0=NO	**If yes:** How many [ASSET] does your **household** currently own?	**If yes:** What is the total estimated value of this [ASSET]? [i.e. what would it be worth today if you tried to sell it?] **If more than one [ASSET] owned, add up total value**
1	Generator			
2	Solar Panel			
3	Television			
4	Radio			
5	Bicycle			
6	Motorcycle			
7	Mobile Phone			
8	Other House Assets (e.g. automobile) (specify)____________________			

Section 3: Farming Assets and Practices

1) Farm Implements

Item Code	Item Name	Does your **household** currently own any of the following farm implements? 1=YES 0=NO	**If yes:** How many [ITEM] does your **household** currently own?
1	Hoe		
2	Spray Pump		
3	Wheel Barrow		
4	Ox Plough		
5	Other Large Farm Assets (e.g. grinder, sheller) (specify)________________		

2) Livestock

Live-stock Code	Type of Livestock	Does your **household** currently own any of the following animals? 1=YES 0=NO	**If yes:** How many [ANIMAL] does your **household** currently own (present at your farm or away)?
1	Cows (including calves, heifers, cows, exotic, and bulls)		
2	Oxen		
3	Goats		
4	Sheep		
5	Pigs		
6	Turkeys		
7	Any Other Large Animals (e.g. donkeys, mules) (specify) ________________		

3) Land

How many acres does your household **own**? [ask for **all** the household members, not just the person being interviewed]	This season, how many acres did your household **cultivate**?	This season, how many acres did your household rent out to others **for money**?	This season, how many acres did your household give out to others **for free**?	This season, how many acres did your household hire from someone **for money**?	This season, how many acres did your household borrow **for free**?	This season, how many acres did your household **leave to rest**?

4) Does your household have a formal land title for any of your land? YES NO

5) Major Crops Planted this Season

Crop Ranking	In terms of **land area planted** this season, which of your crops took the **biggest** land? …**second biggest**? …**third biggest**? 1=Maize 2=Sorghum 3=Millet 4=Cassava 5=Sweet Potatoes 6=Rice 7=Groundnuts 8=Beans 9=Bananas 10=Other (specify)	Do you grow this crop **mainly** for home consumption or sale? 1= Home Consumption 2= Sale	This season, what was the main source of your seed for this [CROP]? 1= Saved from previous season 2=Given by relatives/neighbors 3=Given by NGO/Government 4= Bought from a local market/shop 5= Bought from an agro-input shop	Did you apply any manure, compost, or mulch on this [CROP]? 1=YES 0=NO	Did you apply any chemical fertilizer on this [CROP]? 1=YES 0=NO	Did you apply any pesticides or herbicides on this [CROP]? 1=YES 0=NO	**If seed was NOT bought:** When did you last buy seed for this [CROP]? **Record answer in years**
1							
2							
3							

7) Did your household hire any labor to work in your fields this season? YES NO

8) In this season was more than half of your land preparation done by hired labor? YES NO

9) In this season was more than half of your weeding done by hired labor? YES NO

10) Do you practice crop rotation on your fields? YES NO

11) Minimum Tillage

Minimum tillage means planting crops directly without ploughing or only slightly disturbing the soil. Have you ever heard of this before? 1=YES 0=NO **[If no, move on to question 12]**	Did you practice minimum tillage on any field this season? 1=YES 0=NO	**If yes:**			**If no:**	
		On how many acres did you practice minimum tillage this season?	How many years have you practiced minimum tillage?	Why do you practice minimum tillage? **[Write brief description and move on to question 12]**	Have you ever practiced minimum tillage in the past? 1=YES 0=NO	Why have you <u>stopped</u> practicing minimum tillage? **OR** Why have you <u>never</u> practiced minimum tillage? **[Write brief description and move on to question 12]**

12) Cover Crop

Cover crops, such as mucuna, are crops grown to protect the soil from direct sunshine, water erosion, and wind erosion, and to add nutrients to the soil (NOT mulching with crop residues). Have you ever heard of this before? 1=YES 0=NO **[If no, stop here]**	Did you plant a cover crop on any field **<u>last</u>** season? 1=YES 0=NO	**If yes:**				**If no:**	
		What crop(s) did you plant as a cover crop? **[Write crops]**	On how many acres did you practice cover cropping **<u>last</u>** season?	How many years have you practiced cover cropping?	Why do you practice cover cropping? **[Write brief description and stop here]**	Have you ever planted a cover crop in the past? 1=YES 0=NO	Why have you <u>stopped</u> cover cropping? **OR** Why have you <u>never</u> cover cropped? **[Write brief description and stop here]**

Appendix B: Discussion Questionnaire

Sub County:_______________ Parish: _________________ Village:___________________

Hello, my name is _________, and this is ______________ and __________. We are conducting research for the SANREM Project, which has many institutions involved, including Makerere University, Appropriate Technology, and universities in the United States. The purpose of this focus group is to get a more general picture of your village's farming practices as well as get some estimates of agricultural yields and prices for use in research. This discussion will take approximately 1 hour. Would you be willing to participate in this discussion? Participation in this survey is voluntary and the answers that you provide will be anonymous and confidential.

ID	Name	Sex 1=M 2=F	Role of [NAME] in this Village	Number of Years [NAME] has Lived in this Village
1				
2				
3				
4				

1	Estimate of the number of households in your village	Number of HHs	
2	Changes in the number of households in your village over the last 10 years	1=Increased substantially; 2=Light increase; 3=Remained same; 4=Decreased slightly; 5=Decreased substantially	
3	Estimate of the average acres owned per household in your village	Number of Acres	
4	Changes in the average acres owned per household in your village over the last 10 years	1=Increased substantially; 2=Light increase; 3=Remained same; 4=Decreased slightly; 5=Decreased substantially	
5	Distance from village center to the nearest **asphalt (tarmac) road**?	Answer in Kilometers	
6	Distance from village center to the nearest **market selling agricultural produce**?	Answer in Kilometers	
7	Distance from the village center to the nearest **market/store selling agricultural inputs**?	Answer in Kilometers	

	Are you aware of any of the following conservation agriculture practices?			Do you practice any of them?		
Person ID	Crop Rotation	Minimum Tillage	Cover Cropping	Crop Rotation	Minimum Tillage	Cover Cropping
1						
2						
3						
4						
5						

Earlier estimate of the number of households in your village:		
Out of all the households in your village, estimate the number of households that practice the following conservation agriculture practices:		
Crop Rotation	Minimum Tillage	Cover Cropping

Main Crops

Crop Ranking	In terms of **land area planted**, what are the five main crops in your village? 1=Maize 2=Sorghum 3=Millet 4=Cassava 5=Sweet Potatoes 6=Rice 7=Groundnuts 8=Beans 9=Bananas 10=Other (specify)	What is the average yield per acre for this [CROP] in your village?		What is the average price of [CROP] in your village in a period of **high** availability (peak season)? Answer in U.sh per most relevant unit (e.g per bag, per kilo, per 100 kg)		What is the average price of [CROP] in your village in a period of **low** availability (off-peak season)? Answer in U.sh per most relevant unit (e.g per bag, per kilo, per 100 kg)	
		QTY	UNIT	PRICE	UNIT	PRICE	UNIT
1							
2							
3							
4							
5							
	Unit Codes: 1= 100 Kg/Sac; 2= 50 Kg/Sac 3= One (1) Kg 4= 20 Kg Basin/Tin 5= Bunches 6= Other (specify)						

In your village, what is the average wage rate for agricultural laborers per day?

For what size of land cultivated?

How many hours does it typically take to finish such an area?

How does the wage rate vary by activity (e.g. ploughing vs. planting vs. weeding)?

How does the wage rate vary by crop (e.g. weeding maize vs. weeding beans)?

How do most households in your village plough their land (e.g. by hiring oxen? by hand?)

	Costs of Production per Acre of Maize			
	Quantity	**Unit**	**Unit Price**	**Total Cost/Value**
General Costs for One Acre of Maize				
Hire Land	1	Acre		
Ox Plough				
Oxen				
First Ploughing with Oxen				
Second Ploughing with Oxen				
Hoes				
Pangas				
First Ploughing with Manual Labor				
Second Ploughing with Manual Labor				
Home Saved Seed				
Improved Seed from an Agro-Input Shop				
Sowing/Planting labor				
First Weeding Labor				
Second Weeding Labor				
Home Saved Seed (no fertilizer)				
Average Yield				
Harvesting Labor				
Transporting				
Drying				
Threshing Labor				
Bags for Storage				
Bagging and Storage Labor				

	Quantity	Unit	Unit Price	Total Cost/Value
<u>Other Costs</u>				
Fertilizer				
Fertilizer Labor				
Spray Pump				
Herbicide				
Herbicide Labor				

Appendix C: Survey Descriptive Statistics

C.1. General Agricultural Practices

- These agricultural statistics are for the first season of 2014.
- "Major" crops are defined in terms of land area planted.
- Households are weighted by the inverse probability of their selection.
- Standard errors are cluster-robust at the village level.

Table C.1. Agricultural Landholding

Variable	Mean	Std. Err.	95% Confidence Interval		Min	Max
			Lower	Upper		
Owned	3.077	0.199	2.658	3.496	0	50
Cultivated	3.067	0.095	2.867	3.266	0.125	40
Rented Out	0.306	0.113	0.068	0.544	0	25
Given Out	0.277	0.066	0.138	0.416	0	22
Rented In	0.661	0.063	0.530	0.793	0	6
Borrowed	0.351	0.049	0.249	0.454	0	10
Fallow	0.418	0.050	0.314	0.522	0	10

Agricultural Landholding Variable Definitions

Variable Name	Units	Definition
Owned	Acres	The average number of acres *owned.*
Cultivated	Acres	The average number of acres *cultivated.*
Rented Out	Acres	The average number of acres *rented out* to others for money.
Given Out	Acres	The average number of acres *given out* to others for free.
Rented In	Acres	The average number of acres *rented in* for money.
Borrowed	Acres	The average number of acres *borrowed* for free.
Fallow	Acres	The average number of acres left *fallow.*

Table C.2. Land Ownership and Inputs				
Variable	Percent	Std. Err.	95% Confidence Interval	
			Lower	Upper
Formal Land Title	0.843%	0.293%	0.228%	1.458%
Hired Labor (HL)	66.287%	1.782%	62.542%	70.032%
Land Preparation HL	51.223%	1.787%	47.468%	54.977%
Weeding HL	42.167%	2.766%	36.356%	47.979%
Organic Fertilizer	12.028%	2.421%	6.942%	17.114%
Chemical Fertilizer	0.748%	0.460%	0%	1.714%
Pesticides or Herbicides	29.214%	3.152%	22.593%	35.836%

Land Ownership and Inputs Variable Definitions		
Variable Name	Units	Definition: The percent of households that…
Formal Land Title	%	...have a formal land title for any of their land.
Hired Labor (HL)	%	...hired agricultural labor to work in their fields.
Land Preparation HL	%	...hired labor for more than half of their land preparation.
Weeding HL	%	...hired labor for more than half of their weeding.
Organic Fertilizer	%	...applied manure, compost, or mulch on any of their top three major crops.
Chemical Fertilizer	%	...applied chemical fertilizer on any of their top three major crops.
Pesticides or Herbicides	%	...applied pesticides or herbicides on any of their top three major crops.

Table C.3. Farm Implements and Livestock Ownership				
Variable	Percent	Std. Err.	95% Confidence Interval	
			Lower	Upper
Hoe	99.695%	0.301%	99.063%	100.000%
Ox Plough	10.723%	1.403%	7.776%	13.671%
Wheel Barrow	8.555%	2.445%	3.419%	13.692%
Spray Pump	7.802%	1.600%	4.442%	11.163%
Goat	49.860%	2.758%	44.066%	55.655%
Pig	37.796%	4.063%	29.260%	46.331%
Cow	32.764%	2.303%	27.926%	37.602%
Turkey	20.955%	1.306%	18.212%	23.698%
Ox	8.958%	1.319%	6.186%	11.730%
Sheep	6.277%	1.784%	2.529%	10.024%
Ox Plough OR 2 Oxen	11.791%	1.600%	8.429%	15.153%
Ox Plough AND 2 Oxen	4.823%	0.619%	3.522%	6.125%

Farm Implements and Livestock Ownership Variable Definitions		
Variable Name	Units	Definition: The percent of households that currently own…
Hoe	%	…at least one working hoe.
Ox Plough	%	…at least one working ox plough.
Spray Pump	%	…at least one working spray pump.
Wheelbarrow	%	…at least one working wheelbarrow.
Goat	%	…at least one goat.
Pig	%	…at least one pig.
Cow	%	…at least one cow.
Turkey	%	…at least one turkey.
Oxen	%	…at least one ox.
Sheep	%	…at least one sheep.
Ox Plough OR 2 Oxen	%	…at least one working ox plough *or* at least *two* oxen
Ox Plough AND 2 Oxen	%	…at least one working ox plough *and* at least *two* oxen

Table C.4. Major Crops (in Terms of Land Area Planted)				
Most Common Crops Ranked #1	Percentage	Std. Err.	95% Confidence Interval	
			Lower	Upper
Cassava	42.299%	3.946%	34.009%	50.589%
Maize	32.006%	3.805%	24.011%	40.001%
Groundnuts	9.484%	1.659%	5.998%	12.970%
Rice	7.784%	1.443%	4.751%	10.816%
Millet	6.002%	2.026%	1.745%	10.259%
Other	2.425%	0.641%	1.078%	3.772%
	100.000%			
Most Common Crops Ranked #2	Percentage	Std. Err.	95% Confidence Interval	
			Lower	Upper
Maize	30.587%	2.055%	26.269%	34.905%
Cassava	22.976%	2.252%	18.245%	27.707%
Millet	11.171%	2.141%	6.674%	15.668%
Groundnuts	10.664%	1.741%	7.006%	14.321%
Rice	7.344%	1.330%	4.550%	10.139%
Beans	4.125%	0.864%	2.309%	5.941%
Sweet Potatoes	3.886%	1.161%	1.447%	6.324%
Sorghum	3.750%	0.851%	1.962%	5.538%
Other	2.882%	0.931%	0.927%	4.838%
Only One Crop Planted	2.615%	0.878%	0.771%	4.459%
	100.000%			
Most Common Crops Ranked #3	Percentage	Std. Err.	95% Confidence Interval	
			Lower	Upper
Cassava	13.765%	2.839%	7.800%	19.730%
Maize	13.162%	1.776%	9.431%	16.894%
Groundnuts	12.393%	1.219%	9.833%	14.953%
Millet	9.027%	1.807%	5.230%	12.824%
Rice	8.517%	1.209%	5.977%	11.058%
Sweet Potatoes	7.804%	1.772%	4.081%	11.526%
Beans	6.660%	1.408%	3.702%	9.618%
Sorghum	5.063%	1.254%	2.427%	7.698%
Other	6.841%	0.967%	4.810%	8.872%
Only Two Crops Planted	16.769%	1.559%	13.494%	20.044%
	100.000%			

The variables represent the estimated percent of households that planted [CROP] on the largest (rank one), second largest (rank two) or third largest (rank three) land area out of all the crops the household planted.

Table C.5. Farming Characteristics of Maize Producing Households[1]				
Main Purpose for Growing Maize	Percent	Std. Err.	95% Confidence Interval	
			Lower	Upper
For Home Consumption	72.487%	2.050%	68.181%	76.793%
For Sale	27.513%	2.050%	23.207%	31.819%
	100.000%			
Main Maize Seed Source	Percentage	Std. Err.	95% Confidence Interval	
			Lower	Upper
Saved from Previous Season	40.350%	3.544%	32.904%	47.796%
Local Market/Shop	39.873%	3.020%	33.528%	46.218%
Agro-Input Shop	11.271%	2.711%	5.575%	16.967%
Given by Friends/Neighbors	8.132%	1.491%	5.000%	11.264%
Given by NGO/Gov't	0.373%	0.392%	0%	1.197%
	100.000%			
Input Use on Maize	Percentage	Std. Err.	95% Confidence Interval	
			Lower	Upper
Organic Fertilizer	10.672%	2.337%	5.761%	15.582%
Chemical Fertilizer	0.413%	0.278%	0%	0.997%
Pesticides or Herbicides	3.358%	1.048%	1.155%	5.561%

[1]Defined as the subpopulation of HHs that grew maize as one of their three major crops (in terms of land area planted).

Farming Characteristics of Maize Producing Households Variable Definitions		
Variable Name	**Units**	**Definition: The percent of *maize producing* households that…**
For Home Consumption	%	…grew maize mainly for home consumption
For Sale	%	…grew maize mainly for sale.
Local Market/Shop	%	…bought most of their maize seed from a local market or shop.
Saved from Previous Season	%	…saved most of their maize seed from the previous season.
Agro-Input Shop	%	…bought most of their maize seed from an agro-input shop.
Given by Friends/Neighbors	%	…were given most of their maize seed from friends or neighbors.
Given by NGO/Gov't	%	…were given most of their maize seed from an NGO or the Gov't.
Organic Fertilizer	%	…applied manure, compost, or mulch on maize.
Chemical Fertilizer	%	…applied chemical fertilizer on maize.
Pesticides or Herbicides	%	…applied pesticides or herbicides on maize.

Table C.6. Simplified Median Costs and Yield for One Acre of Maize Production (Maize-Alone) in the Tororo District				
	Units	No. Units	Unit Price (UGX)	Total (UGX)
Land (rent per season)	Acres	1	100,000	100,000
				100,000
Seed/Other Inputs				
Maize seed	kgs.	10	3,500	35,000
Bags	Bag	8	1,000	8,000
				43,000
Labor				
Land preparation (1st)	Acres	1	65,000	65,000
Land preparation (2nd)	Acres	1	45,000	45,000
Planting	Acres	1	20,000	20,000
Weeding (1st)	Acres	1	55,000	55,000
Weeding (2nd)	Acres	1	50,000	50,000
Harvesting	Acres	1	24,500	24,500
Transport	Acres	1	11,000	11,000
Threshing	Acres	1	15,500	15,500
				286,000
Season Total Costs				**429,000**
Maize Yield	kgs.	750	650	**487,500**
Profit				**58,500**

C.2. Conservation Agriculture

Table C.7. Conservation Agriculture Awareness and Adoption				
Variable	Percent	Std. Err.	95% Confidence Interval	
			Lower	Upper
Heard of MT	58.319%	3.074%	51.862%	64.777%
Practice MT	0.543%	0.407%	0%	1.397%
Used to Practice MT	0.814%	0.471%	0%	1.803%
Heard of CC	61.314%	2.072%	56.962%	65.666%
Practice CC	48.857%	2.173%	44.292%	53.422%
Used to Practice CC	10.273%	1.423%	7.284%	13.262%
Practice CR	94.422%	0.916%	92.498%	96.347%

Conservation Agriculture Awareness and Adoption Variable Definitions		
Variable Name	Units	Definition: The percent of households that…
Heard of MT	%	…have heard of minimum tillage (MT). MT was defined within the context of the survey as using herbicides to prepare the land so that crops can be planted directly without ploughing or by only slightly disturbing the soil.
Practice MT	%	…practiced minimum tillage on any of their fields during the first season of 2014.
Used to Practice MT	%	…practiced minimum tillage in the past, but did *not* practice it during the first season of 2014.
Heard of CC	%	…have heard of cover cropping (CC). CC was defined within the context of this survey as growing crops specifically to help cover and protect the soil.
Practice CC	%	…practiced cover cropping on any of their fields during the second season of 2013. The second season of 2013 was chosen as the reference point since the time for planting cover crops in the first season of 2014 was still ongoing in some areas at the time of the data collection.
Used to Practice CC	%	…practiced cover cropping in the past, but did *not* practice it during the second season of 2013.
Practice CR	%	…practice some form of crop rotation on any of their fields.

Table C.8. Minimum Tillage Adopter Characteristics				
Variable	Mean	Std. Err.	95% Confidence Interval	
			Lower	Upper
Acres MT	1.265	0.315	0.495	2.036
Years MT	1.233	0.207	0.726	1.740

Table C.9. Cover Crop Adopter Characteristics				
Variable	Mean	Std. Err.	95% Confidence Interval	
			Lower	Upper
Acres CC	1.193	0.096	0.992	1.394
Years CC	13.659	0.690	12.209	15.109

Minimum Tillage and Cover Crop Adopter Variable Definitions		
Variable Name	Units	Definition:
Acres MT	Acres	The average number of acres adopting households cultivated with minimum tillage in the first season of 2014.
Years MT	Years	The average number of years adopting households have practiced minimum tillage.
Acres CC	Acres	The average number of acres adopting households cultivated with cover crops in the second season of 2013.
Years CC	Years	The average number of years adopting households have practiced cover cropping.

Appendix D: Institutional Review Board (IRB) Approval Letter

VirginiaTech

Office of Research Compliance
Institutional Review Board
North End Center, Suite 4120, Virginia Tech
300 Turner Street NW
Blacksburg, Virginia 24061
540/231-4606 Fax 540/231-0959
email irb@vt.edu
website http://www.irb.vt.edu

MEMORANDUM

DATE: July 16, 2014

TO: George W Norton, Jarrad Farris

FROM: Virginia Tech Institutional Review Board (FWA00000572, expires April 25, 2018)

PROTOCOL TITLE: Assessing the Potential of Conservation Agriculture to Reduce Poverty in Tororo, Uganda

IRB NUMBER: **14-610**

Effective July 16, 2014, the Virginia Tech Institution Review Board (IRB) Chair, David M Moore, approved the Amendment request for the above-mentioned research protocol.

This approval provides permission to begin the human subject activities outlined in the IRB-approved protocol and supporting documents.

Plans to deviate from the approved protocol and/or supporting documents must be submitted to the IRB as an amendment request and approved by the IRB prior to the implementation of any changes, regardless of how minor, except where necessary to eliminate apparent immediate hazards to the subjects. Report within 5 business days to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

http://www.irb.vt.edu/pages/responsibilities.htm

(Please review responsibilities before the commencement of your research.)

PROTOCOL INFORMATION:

Approved As:	**Exempt, under 45 CFR 46.110 category(ies) 2,4**
Protocol Approval Date:	**June 9, 2014**
Protocol Expiration Date:	**N/A**
Continuing Review Due Date*:	**N/A**

*Date a Continuing Review application is due to the IRB office if human subject activities covered under this protocol, including data analysis, are to continue beyond the Protocol Expiration Date.

FEDERALLY FUNDED RESEARCH REQUIREMENTS:

Per federal regulations, 45 CFR 46.103(f), the IRB is required to compare all federally funded grant proposals/work statements to the IRB protocol(s) which cover the human research activities included in the proposal / work statement before funds are released. Note that this requirement does not apply to Exempt and Interim IRB protocols, or grants for which VT is not the primary awardee.

The table on the following page indicates whether grant proposals are related to this IRB protocol, and which of the listed proposals, if any, have been compared to this IRB protocol, if required.

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Date*	OSP Number	Sponsor	Grant Comparison Conducted?
06/09/2014	05001607	US Agency International Development	Not required (Exempt approval)

* Date this proposal number was compared, assessed as not requiring comparison, or comparison information was revised.

If this IRB protocol is to cover any other grant proposals, please contact the IRB office (irbadmin@vt.edu) immediately.