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Sustainable Land Management and its Effects on Water Security and Poverty

Evidence from a Watershed Intervention Program in Ethiopia

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ABSTRACT

This paper investigates the impacts of sustainable land management (SLM) on water security and poverty based on an evaluation of a watershed level SLM program promoted in Amhara regional state of Ethiopia. A household survey was conducted in two WLRC watersheds with SLM programming as well as complementary support and two adjacent watersheds without such programming. Our findings show that the SLM program significantly increased plot-level adoption of SLM practices, particularly of soil bunds and stone terraces. We also find that SLM contributes to water security for both crop and livestock production. Households in SLM-supported learning watersheds have more access to groundwater for irrigation and have higher crop yields for maize, mango and millet; have experienced improving water availability for livestock production in the past five years; and have higher income from livestock products than households in control watersheds. The positive impacts of SLM and complementary interventions on livestock income is attributed to the improved water security conditions in the learning watersheds, access to better animal forage planted along the SLM constructed structures, and animal vaccination and artificial insemination services that were part of the broader set of interventions. These findings further show that although SLM impacts were limited, the potential to improve welfare of smallholders across several livelihoods is enhanced when SLM is combined with other multifaceted complimentary interventions.

Keywords: Sustainable Land Management, Water Insecurity, Learning Watersheds, Propensity Score Weighted Regression, Bias Corrected Matching.

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ACRONYMS

IFPRI	International Food Policy Research Institute
LW	Learning Watersheds
NN	Nearest Neighbor (Estimator)
PSM	Propensity Score Matching
SLM	Sustainable Land Management
WLRC	Water and Land Resources Center

1. INTRODUCTION

Land degradation is a pressing global challenge with three billion people residing in degraded landscapes. The annual global cost of land degradation is estimated to be about $300 billion (Nkonya et al. 2016a). Sub-Saharan Africa accounts for 26% of the total global costs of land degradation due to land use and land cover changes (Nkonya et al. 2016b). Thus, investments in sustainable land management (SLM) both to revert already degraded land to productive uses and to proactively reduce future land degradation is considered vital for rural development in many parts of the world. This is particularly true in Ethiopia, where over 85% of the land is estimated to be moderately to severely degraded at an estimated cost of $4.3 billion annually (Gebreselassie et al. 2016).

To halt land degradation and support land restoration through sustainable land management investments and practices in Ethiopia, the Water and Land Resource Center (WLRC) and the consortium of development partners it brings together, established six Learning Watersheds (ranging from 220-900 hectares) in the Central and North-Western parts of Ethiopia in 2012.

The selected watersheds were used to pilot sustainable land and water management activities with participation of communities, extension agents, researchers, and policy-makers, to restore degraded soils and improve crop and livestock productivity. The SLM activities promoted include both traditional SLM approaches, such as physical soil and water conservation measures on cultivated lands, gully land, and degraded hillsides; biological soil and water conservation measures such as grasses, forages, and trees; and water harvesting for multipurpose use; as well as other rural development support, such as poultry development and cattle variety improvement through artificial insemination; establishment of saving and credit cooperatives; the provision of agricultural farm machineries and improved crop varieties, the promotion of cash crops, such as fruit trees and support to groundwater development. While the main objectives of the SLM program focused on land restoration, a linkage to the University of Oxford-led REACH program added an additional objective to WLRC SLM activities related to water security. REACH focuses on reducing water poverty through a variety of initiatives, and operates through three observatories in Ethiopia that address water-related poverty through more accessible and better managed water supply in small towns; better water management at the basin scale, including through improved irrigation management; and through better SLM investments and practices, respectively.

Using data collected from two learning watersheds where the SLM activities have been undertaken and two adjacent control watersheds with similar biophysical characteristics, this paper investigates the effects of SLM on smallholder livelihoods through changes in water availability and use. The following sections provide an overview on linkages between SLM and water security, describe the data and methodology used in the analysis, summarize the results and conclude.

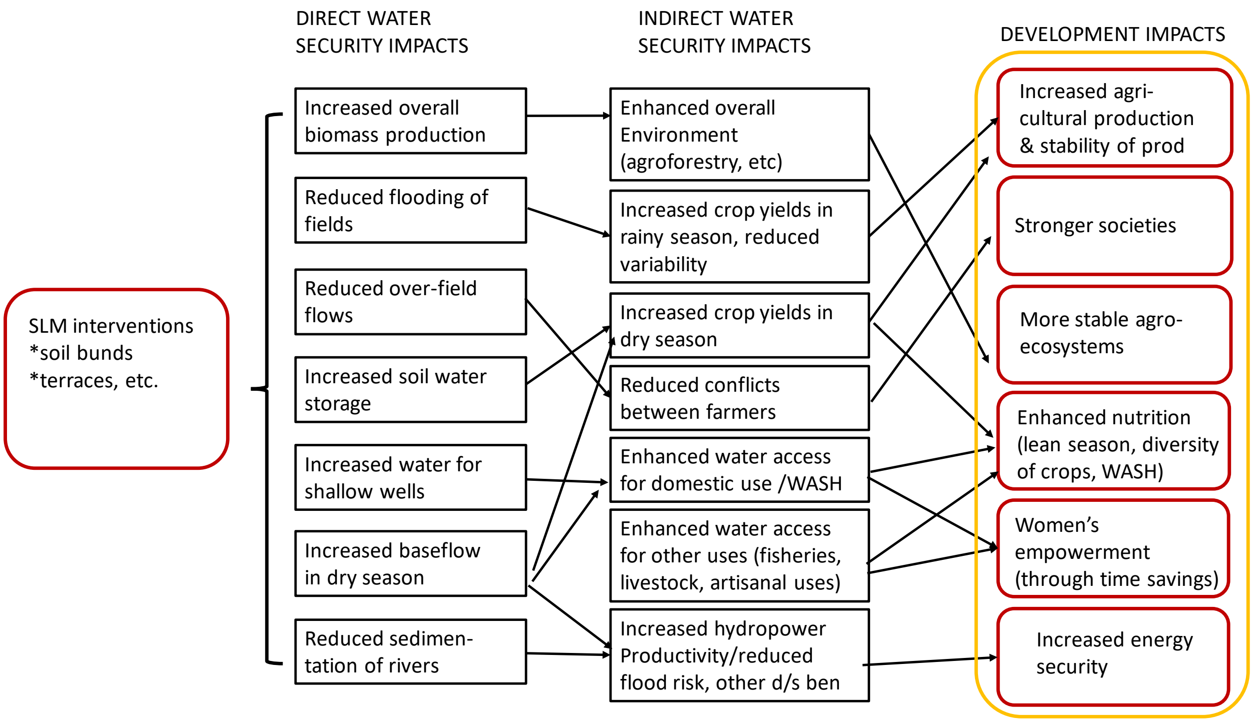
2. LINKAGES BETWEEN SLM AND WATER SECURITY

SLM is traditionally promoted to address land degradation due to soil erosion, nutrient imbalances and other factors adversely affecting soil productivity. This is of particular importance in Sub-Saharan Africa, where soil erosion constitutes more than 80% of land degradation, affecting about 22% of agricultural land and all countries in the region (FAO ITPS 2015). However, SLM also has important benefits for water conservation and improving water security.

UN-Water proposes the following definition of water security: "The capacity of a population to safeguard sustainable access to adequate quantities of and acceptable quality water for sustaining livelihoods, human well-being, and socio-economic development, for ensuring protection against water-borne pollution and water-related disasters, and for preserving ecosystems in a climate of peace and political stability" (UN Water 2013, p. vi).

Key linkages between SLM and elements of water security are described in Figure 2.1. SLM has both direct and indirect linkages to water security. Direct linkages include increased overall biomass production, reduced flooding and improved soil water storage which, in turn, contribute to higher crop yields and reduced variability of yields in the dry and rainy seasons; as well as an overall enhanced environment. Reduced over-field flows due to SLM can also reduce conflicts and tensions between farmers of adjacent fields as such flows can adversely affect young crops or destroy field structures, such as soil bunds.

Figure 2.1: Linkages between SLM and Water Security



Source: Authors.

Importantly, SLM has broader benefits and can contribute to increased water availability for wells that can be used for drinking water and other domestic uses. SLM can also contribute to increased baseflow in the dry season and reduced sedimentation in rivers which, in turn, contribute to many other productive and environmental uses of water, including fisheries, hydro-electricity production, enhanced crop production and reduced flooding. Through all these mechanisms, SLM can contribute to various development goals, such as food security, energy security, and water security.

In our study, we focused on certain domains of water security that we believe are affected by sustainable land management investments and practices at the household level. As will be discussed below, the most common SLM practices in the study area are soil bunds and stone terraces, which are expected to reduce average runoff from farms, increase soil water storage, and increase water infiltration. To reflect these benefits of SLM practices, we use access to groundwater for irrigation purposes as a measure of water security when we analyze crop productivity. Given expected improvements in underground hydrological conditions from SLM that can improve livestock access to drinking water, we also asked respondents to rate their perception of availability of water for livestock in 2012 (before the SLM program) and in 2017 after the SLM program had been well established.

3. DATA USED IN THE STUDY AND SLM PROGRAM INTERVENTIONS

3.1 Data

The data for this study were derived from a cross-sectional household survey conducted in the Amhara Region of Ethiopia within the Awash basin in 2017, with a few retrospective questions for 2012. The SLM program started in the AWASH basin in 2012, but no socioeconomic baseline data collection was undertaken at that time. Thus, we used recall questions for certain outcomes for which recall bias would not be a serious concern. The data were collected by a joint effort of three institutions, including the International Food Policy Research Institute (IFPRI) leading the study design, the Water and Land Resource Center of Addis Ababa University (WLRC) contributing to the design and leading field data collection, and the University of Oxford's REACH program. Data were collected in four watersheds, with two watersheds receiving support for SLM and associated measures, also called learning watersheds (LW) (Aba Gerima and Debre Yacob watersheds), and two nearby watersheds (the control watersheds) without promotion of SLM practices, but with otherwise similar characteristics. Each selected learning watershed was matched with one control watershed with relatively similar agro-ecological conditions, topography, land degradation conditions, farming system, level of infrastructural development and biophysical conditions. The selection of the study watersheds was done by a group of natural and social scientists at WRLC who are involved in promoting the SLM approaches in partnership with international and local development partners. A total of 561 households with 2900 plots were interviewed from the four watersheds. The sample size of households was determined and guided by sample size power calculations and differential levels of SLM adoption in the learning and control watersheds. We therefore had an optimum sample size with enough statistical power to detect significant differences in water security and poverty if they really existed between the two groups of watersheds.

The survey covered several modules and questions on household demographic characteristics, plot level land characteristics and tenure, plot-level crop production, livestock production, plot-level SLM practices, local institutions in water governance, water use and access, household assets, and shocks. On water security, separate questions were included for crop production and livestock production. A typical household head in the study area is about 44 years old, lives in a household with five members, is likely illiterate—more than 70% of household heads do not have any formal education-- operates about 5 plots, and keeps livestock integrated into his or her farming livelihoods (more than 90% of households hold livestock). We did not find statistically significant differences in socio demographic and socio-economic characteristics between households in learning watersheds and control households (Table 3.1), implying that these variables are less likely to drive differences in adoption or impact of the SLM interventions between learning and control watersheds, although unobserved social-economic differences could still be a concern. However, our key outcomes of interest in this paper are based at plot level and we see significant differences in plot level characteristics (Table 3.1). Plots in learning watersheds appear to be nearer to the homesteads and have better soil quality in terms of perceived soil depth and soil quality than plots in control watersheds. The caveat here is that these plot characteristics are not pre-project baseline measurements for 2012, but measurements from 2017 and conditions could have been improved by SLM investments promoted by the SLM program in learning watersheds. The econometric identification approach we have used for SLM impacts corrects for this source of confoundedness bias as explained later in the methods section.

Table 3.1: Demographic, Socio-Economic and Plots Profile of Survey households 2017

	Learning Watersheds	Control Watersheds	Equality of Mean Test: Learning=Control
Age of Family head	44.1	44.4	0.8027
% female headed households	2.3	3.7	0.1830
% family head without any formal education	72.1	74.9	0.4718
% family head with Primary education	21.2	16.7	0.1997
% family head with Secondary education	0.9	0.8	0.8588
% family head with Post-Secondary education	4.7	3.9	0.6566
Number of Land Parcels	3.9	4.1	0.1433
Family size	5.4	5.3	0.6745
Number of oxen	1.8	1.7	0.6313
% with livestock	97.2	91.6	0.0029***
Plot Characteristics:			
Plot Access:			
% plots adjacent to the household	29.7	21.5	0.000***
% plots less than 5 minutes from household	24.1	25.1	0.5634
% plots less than 15 minutes from household	23.5	29.1	0.0009***
% plots less than 1 hour from household	18.6	20.1	0.3600
% plots More than 1 hour from household	3.1	2.9	0.8333
Plot Soil Depth:			
% plots with deeper soils	42.0	35.2	0.0004***
% plots with medium deep soils	42.5	45.4	0.1418
% plots with shallow soils	0.9	0.8	0.7482
% plots with unknown soil depth	13.6	17.3	0.0070***
Plot Soil Quality:			
% plots with good soil quality	40.6	34.4	0.0011***
% plots with moderate soil quality	48.8	52.5	0.0542**
% plots with poor soil quality	9.6	11.8	0.0686*

Source: IFPRI, WLRC & REACH survey 2017

3.2 SLM Program Interventions

During the implementation phase of the SLM program, WLRC along with other stakeholders initiated several concurrent integrated watershed development activities. Some of the major activities include construction of different physical soil and water conservation measures (e.g. stone terraces, soil bunds), runoff control structures (e.g. check dams , ditches, grass strips and trenches), degraded hillside rehabilitation, area closures, and soil-improving agronomic practices. Soil bunds are embankments made by ridging soil on the lower side of a ditch along a slope contour. They can be constructed by hand digging or plowing. Stone terraces are constructed walls that retain embankments of soil. Their construction involves preparing a base for the wall, transporting construction rocks and carefully layering them. Stone terraces are more effective than soil bunds in preventing soil erosion on steep slopes prone to heavy runoff but building stone terraces requires considerably more time and inputs than soil bunds. Finally, a check dam is a small, often temporary structure constructed across gully lines to reduce soil erosion by minimizing runoff velocity thereby inducing infiltration.

The SLM program further supported the physical soil and water conservation structures mentioned above with biological measures. The biological measures included planting forage trees on soil bunds around cultivated lands and as part of gully rehabilitation activities. Water harvesting structures were introduced, water lifting devices were installed and hand dug wells for multipurpose use and for drinking supply to humans and animals were developed. Additionally, income generating activities such as homestead development were introduced where farmers were encouraged to produce fruits and vegetables. Apart from the above technologies, crops and livestock improvement technologies were given to farmers, such as improved crop varieties (cereals, pulses, and fruit crops), sheep breeds, forage breeds, and livestock health services. The SLM program also introduced energy saving stoves in the program watersheds. All these activities have been gradually introduced since 2012. In the initial years the physical measures were given more attention as the areas were highly degraded and these interventions were followed by biological measures, homestead development, and other complementary interventions.

4. METHODS

The study examines whether there are significant differences in water security outcomes and poverty proxy outcomes (crop income and livestock income outcomes) between SLM supported learning watersheds (LW) and Non-SLM supported control watersheds. We therefore analyze cross-sectional differences in LW and control watersheds on water security indicators for livestock production and crop production, differences in SLM adoption rates, differences in crop yields (crop income), and differences in livestock income and we then test the direct effects of SLM on crop income. We use descriptive statistics and econometric methods in the analysis. Econometric approaches are used to account for differences in household characteristics and plot characteristics in learning and control watersheds so that we minimize statistical biases in our estimates of impacts of SLM which could arise from not controlling for these confounders. The econometric analysis uses a matching methods estimation approach (Propensity Score Matching-PSM and Bias Corrected Matching) and the doubly robust regression method approach (PSM Weighted Regression and Non-PSM weighted Regression).

4.1 Matching Methods

We used matching methods to select households and plots in LW that are like households and plots in control watersheds in terms of being similar in household characteristics and plot characteristics before comparing the means of outcomes in both watersheds. Matching is intended to overcome the widely acknowledged statistical problem of selection bias in program evaluation studies (Rosenbaum and Rubin 1983; Dehejia and Wahba 2002; Heckman et al. 1998; Caliendo and Kopeinig 2005; Smith and Todd 2005). Selection bias in this study would arise if we compare outcomes of households in LW with outcomes of control watersheds when the two groups of households differ systematically in several observed characteristics and these differences are correlated with participation in the SLM program and outcomes. We used two matching estimators in our analysis, namely propensity score matching (PSM) (Rosenbaum and Rubin 1983) and the Bias-corrected nearest neighbor matching estimator (NN estimator, developed by Abadie, et al. (2004). Both methods use a distance metric based on observed covariates to select comparable "treatment" vs. "control" observations for comparison. PSM uses the predicted probability of an observation being in the "treated" vs. "control" category as the distance metric. Bias corrected matching uses a distance metric based on the magnitudes of differences in the values of the covariates, weighted by the inverse of the variance matrix, which accounts for differences in the scale of the covariates.

Each of these methods has advantages and disadvantages. An advantage of PSM is that its distance metric gives greater weight to factors that influence the selection process, which are the factors that are most important to match to reduce potential selection bias in comparing the "treated" vs. "control" groups. By contrast, the distance metric of the Bias-corrected nearest neighbor matching (NN estimator) is more arbitrary. Two disadvantages of PSM relative to the NN estimator are (1) that the estimated impacts are biased to the extent that perfect matching is not achieved (i.e., there are still differences in the covariates among the matched samples), and (2) that the estimated standard errors are not correct because the propensity scores are estimated (Abadie and Imbens 2006). Analysts often use bootstrapping to estimate standard errors with PSM, but this has been shown to be invalid in the case of PSM with NN selection (Ibid.). By contrast, the NN estimator with bias correction corrects for bias using auxiliary regressions, and the estimated standard errors are correct (Abadie et al. 2004). Since each method has advantages and disadvantages, we use both and check the robustness of our conclusions to the choice of method.

4.2 Doubly robust regression methods:

The second econometric approach we have used to check the robustness of our impact estimates of SLM and findings is the doubly robust regression approach which has the advantage of further reducing bias beyond the PSM matching methods through both weighting (the first robust correction of bias) and, at the same time conditioning on differences in observable characteristics (the second robust correction of bias) between LW households and control watershed households. Regressions can be weighted by propensity scores to reduce bias (e.g. Hirano and Imbens 2001; Kang and Schefer 2007; Robins et al. 2007; Wooldridge 2010). Details of the statistical theory underlying double robust regression estimators can be found in the literature (e.g.; Leon, Tsiatis, and Davidian 2003; van der Laan and Robins 2003; Lunceford and Davidian, 2004; Neugebauer and van der Laan 2005; Tsiatis 2006; Wooldridge, 2007). Following Woodridge (2010), we estimate doubly robust regressions in a three-step procedure, with the first step estimating a discrete choice probit regression for being in SLM supported LW versus being in Non-SLM supported control watersheds. In the second step, we predict the probabilities (propensity scores) of participating in LW versus control watersheds from the probit regression, and in the third step apply the predicted propensity scores as weights in the regressions estimating impacts of the SLM program on SLM adoption, crop income, crop yields, and livestock income. In the results section, we report both the impact estimates of propensity score weighted regressions (PSM Weighted Regressions) and the impact estimates of the same regressions without applying propensity score weights (Non-PSM weighted regressions) to see if the results substantially differ as a result of possible bias in the latter unweighted regression. In all the estimations, the weighted regression estimates, and un-weighted regressions estimates appear very similar in magnitude and significance levels indicating that selection bias is not a major concern in this analysis.

5. RESULTS

In this section, we present several of our findings based on both descriptive analysis and econometric analysis on (1) whether the SLM program promoted in the two LW in Amhara region of Ethiopia was successful in increasing greater adoption of SLM practices and investments, and (2) the implications of these SLM investments and practices on proxy measures of water security and poverty.

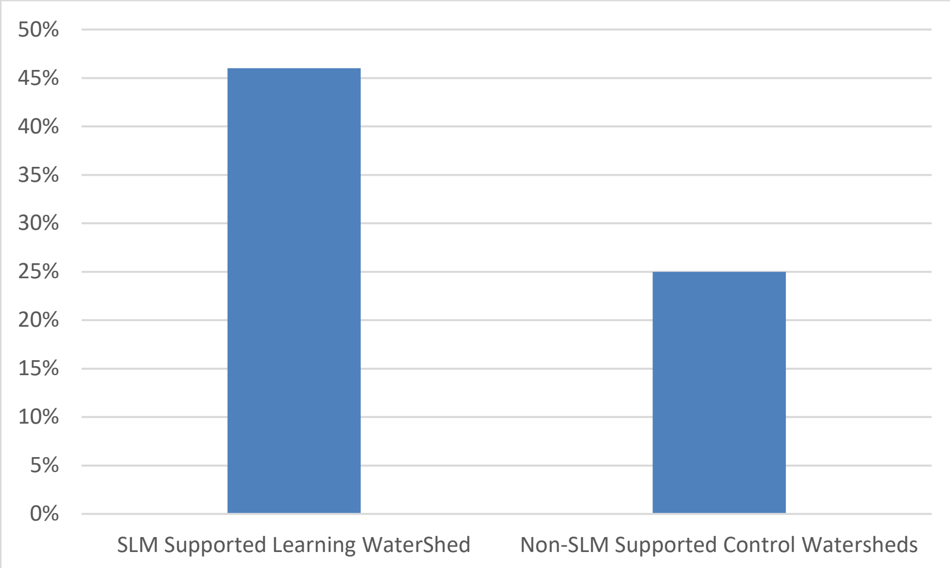
5.1 Impacts of the Watershed SLM program on adoption of SLM

We report on the levels of adoption of different SLM investments and practices between SLM supported LW and Non-SLM supported control watersheds in Figure 5.1.1, Figure 5.1.2, and Table 5.1.1 and impacts of the SLM program on SLM adoption in Table 5.1.2.

The results in Figure 5.1.1 show higher adoption rates in SLM supported LW than in the Non-SLM supported control watersheds, with particularly higher adoption of stone terraces, soil bunds, drainage ditches, trees and to a lesser extent check dams and drainage trenches (Figure 5.1.2). These descriptive results in Figures 5.1.1, and 5.1.2, and Table 5.1.1 are supported by the econometric results in Table 5.1.2 where we estimate the actual impacts of the SLM program on adoption of these SLM investments using various rigorous econometric estimators. The econometric results show significant impacts of the SLM program in increasing adoption rates of SLM investments (Table 5.1.2) across several practices with the highest impacts on soil bunds (19.4%) and stone terraces (4.8%), consistent with the results in Figure 5.1.1.

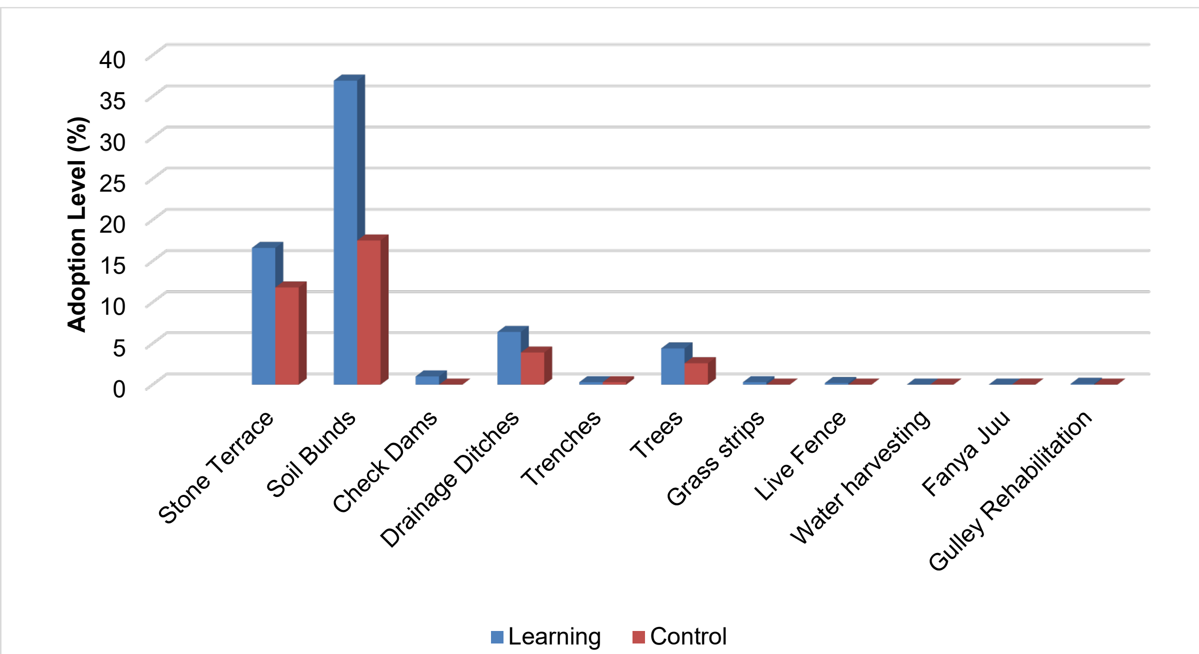
Overall, SLM adoption in SLM supported LW (46%) is nearly twice the adoption rate in Non-SLM supported control watersheds (25%). These findings are statistically significantly different from zero and robust across the four semi-parametric and parametric econometric approaches. The higher impacts on adoption of soil bunds and stone terraces suggest that soil erosion, land degradation, and water-conservation are key welfare challenges for the smallholder farmers in the study area. From these results, it can be concluded that the Watershed SLM program approach promoted in the learning watersheds was effective in increasing adoption and use of sustainable land management investments and practices.

Figure 5.1.1: Plot level Adoption rates of SLM investments



Source: IFPRI, WLRC & REACH survey 2017

Figure 5.1.2: Plot level Adoption rates of individual SLM investments



Source: IFPRI, WLRC & REACH survey 2017

Table 5.1.1: Plot level Adoption of Sustainable land management Investments in the Watersheds

% of Plots	Learning Watersheds (N=1,838)	Control Watersheds (N=1,047)	Test of Equality of Means: Learning=Control
% With Stone Terrace	16.6	11.8	0.001***
% With Soil Bunds	36.9	17.5	0.000***
% With Check Dams	1.0	0.0	0.004***
% With Drainage Ditches	6.4	3.9	0.005***
% With Trenches	0.3	0.3	0.943
% With Trees	4.4	2.6	0.019***
% with Grass strips	0.3	0.0	0.032**
% With Live Fence	0.2	0.0	0.096*
% With Water harvesting	0.0	0.0	-
% with Fanya Juu	0.0	0.01	0.1852
% With Gulley Rehabilitation	0.1	0.0	0.1429

Source: IFPRI, WLRC & REACH survey 2017

Table 5.1.2: Impacts of SLM Program on Adoption of SLM Practices

	Adoption Levels			SLM Program Impacts on Adoption Levels:			
	SLM Supported Learning Watersheds (% Adopters)	Non-SLM Supported Control Watersheds (% Adopters)	Difference in Adoption (Leaning-Control)	Propensity Score Matching	Bias Corrected Matching	PSM Weighted Regression	Non-PSM Weighted Regression
Stone Terraces	16.6%	11.8%	4.8%***	4.9%*** (0.0135)	4.6%*** (0.0193)	5.0%*** (0.0137)	5.0%*** (0.013)
Soil Bunds	36.9%	17.5%	19.4%***	19.6%*** (0.0165)	17.8%*** (0.0206)	19.4%*** (0.0169)	19.0%*** (0.017)
Check Dams	1%	0%	1%***	1%*** (0.0026)	1%*** (0.0032)	1.2%*** (0.0031)	1.0%*** (0.003)
Drainage Ditches	6.4%	3.9%	2.5%***	2.5%*** (0.0088)	3.7%*** (0.0111)	3.0%*** (0.0092)	3.0%*** (0.008)
Trees	4.4%	2.6%	1.8%***	1.7%*** (0.0033)	1.1 (0.0097)	1.6%*** (0.0062)	1.7%*** (0.0073)
Grass Strips	0.3%	0.0%	0.3%***	0.3%*** (0.0012)	0.2% (0.00162)	0.4%*** (0.0017)	0.3%* (0.0017)
Overall SWC Investments	46%	25%	22%***	22.1%*** (0.0171)	19.0%*** (0.0231)	22.3%*** (0.0184)	21.8%*** (0.0184)

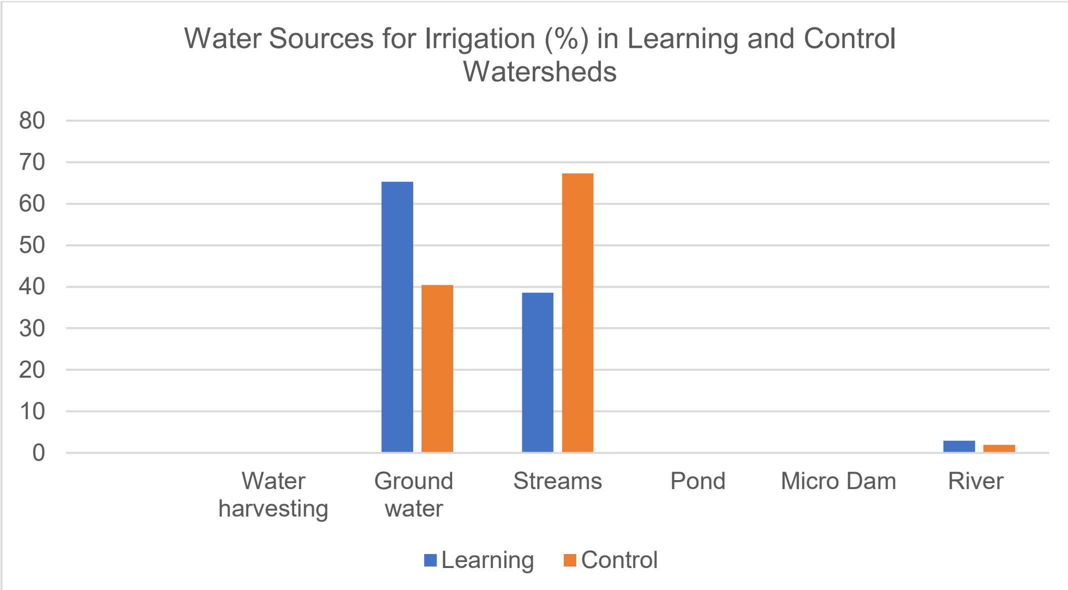
Source: Authors' computation using IFPRI, WLRC & REACH survey 2017.
SWC refers to Soil and Water Conservation investments.
***, **, * represent significance at 99%,95% and 90% confidence intervals.

5.2 SLM and Water Security for Crop Production

As discussed in the previous section, soil bunds are the single most important SLM investment that is widely adopted in learning watersheds, a 19% difference in adoption between learning and control watersheds that is both statistically significant and meaningful from an economic point of view. An experimental study in the northern highlands of Ethiopia by Adimassu et al. (2014) showed that soil bunds reduce the average runoff from plots by 28%. Stone terraces are the second most widely used SLM investment in the learning watersheds, with a 5% difference in adoption between learning and control watersheds. Klik et al. (2018) found that stone bunds in the Northern Highlands of Ethiopia increase soil water content along the hillslope by interrupting hillslope hydrology and therefore increasing time for infiltration, especially near the stone bunds. In the mid-phase of the rainy season, zones above and below the stone bund show a soil moisture increase of 15% compared with the center zones and by almost 20% compared with tracts of the land without stone bunds (Klik et al. 2018). Thus, the hydrological expectation from these SLM practices is for soil moisture and groundwater recharge to improve in the learning watersheds. From an observational study of this type one would expect to see more use of groundwater in SLM supported learning watersheds than in Non-SLM supported control watersheds. In this section, we investigate whether there is an association between SLM use and groundwater access.

Figure 5.2.1 presents different sources of irrigation water sources between learning watersheds and control watersheds. Consistent with our expectation, we see a significantly higher access to groundwater use in SLM supported learning watersheds than in Non-SLM supported control watersheds, while Non-SLM Control watersheds appear to have more access to stream water for plot level crop irrigation and other water uses. This could be due, in part, to the promotion of groundwater use as a component of the SLM program in the learning watersheds. We recommend further analyses to understand increased groundwater use in learning watersheds to assess the hydrological impact of SLM as well as the promotional impact from the program.

Figure 5.2.1: Plot level Sources of Irrigation Water



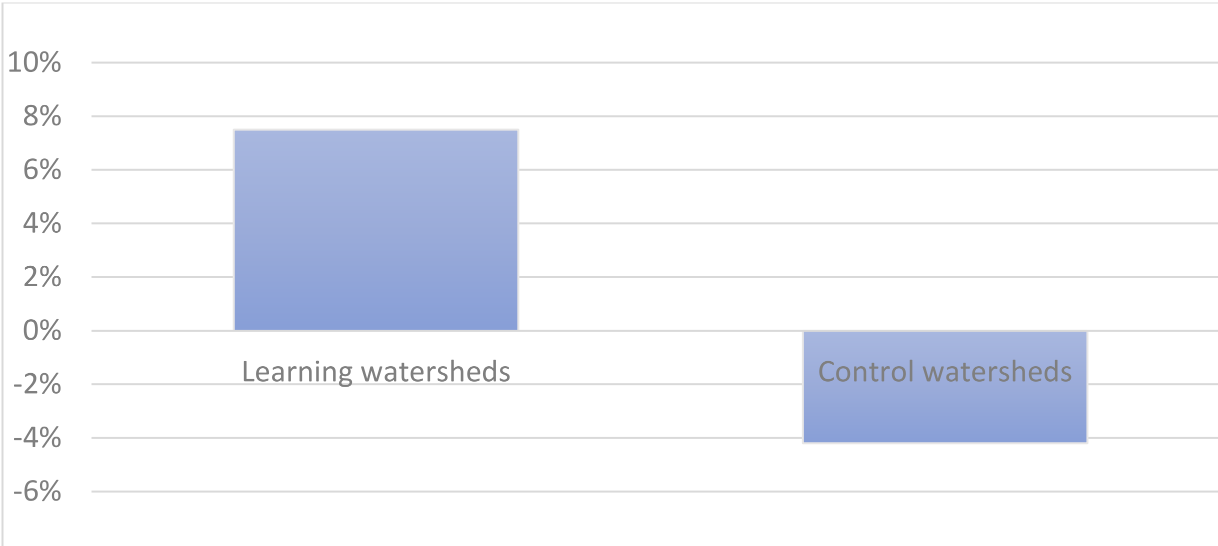
Source: IFPRI, WLRC & REACH Survey 2017.

5.3 Sustainable Land management and Water Security for Livestock Production

We examine how SLM relates to water security for livestock production using a perception outcome indicator. Respondents were asked whether they felt they had enough water for livestock use in 2012 and a similar question was asked for 2017. We then computed the percentage of respondents who felt they had enough water in 2012 (share reporting Yes) and again computed a percentage of respondents who reported to have enough water for livestock use in 2017.

With these two percentages in 2012 and 2017, we computed a change in percentages which provides the average change in perception between 2012 and 2017, which is reported in Figure 5.3.1. We find that smallholder farmers in SLM supported learning watersheds experienced an improvement of more than seven percentage points over the 5-year period (2012-2017), implying improved water access for livestock production, while their counterparts in Non-SLM supported control watersheds perceived a worsening of water access. These results suggest improved water security for livestock production in SLM supported watersheds and deteriorating water security in Non-SLM supported watersheds. The results imply a relationship between SLM adoption and better water security for livestock production, which is consistent with what we found earlier on SLM adoption and higher groundwater use for crop productivity.

Figure 5.3.1: Change in Perception among respondents on availability of enough water for livestock (between 2012-2017)



Source: IFPRI, WLRC & REACH Survey 2017.

5.4 Sustainable Land management and Poverty

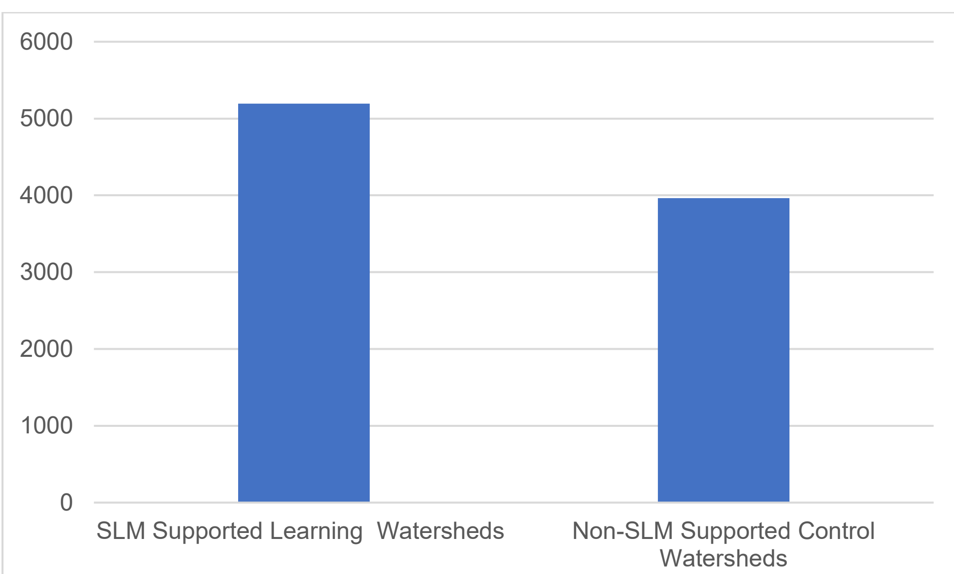
We investigate SLM linkages with poverty alleviation through its direct effects on crop productivity (crop income) and its indirect impacts on livestock productivity (livestock income). There are two possible pathways through which SLM could influence livestock productivity or livestock income. The first pathway is through increased production of cereal crop residues for use as livestock feeds and the second pathway is through improved access to livestock watering. In the sections below, we compare livestock income and crop yields between the SLM supported learning watersheds and Non-SLM supported control watersheds using descriptive statistics. In addition, we estimate multivariate regressions to investigate the direct individual effects of each SLM practice on crop yields after controlling for several plot and household characteristics.

Livestock Income and SLM

The analysis in this paper has shown higher use of groundwater in SLM supported learning watersheds and based on this evidence, we further test whether SLM supported watersheds earn significantly higher livestock income since we hypothesize that groundwater could also be used in livestock production activities. Figure 5.4.1 presents significantly higher livestock income for smallholder farmers in SLM-supported learning watersheds than households in Non-SLM supported control watersheds. Households in SLM-supported watersheds earned livestock incomes of 1230 birr (about 50 dollars) above households in Non-SLM supported watersheds. This evidence is consistent with the econometric analysis in Table 5.4.1 where we find significant impacts of the SLM program on livestock income of about 66%, which is robust under different econometric estimators. This impact on livestock production suggests that water security might be a substantial constraint for livestock production in the study areas. Adequate access to safe water and a large volume of crop residues for animals is important for milk production, the main income source from livestock.

Another pathway through which the SLM program could have led to positive impacts on livestock income is because the program directly provided livestock-production related complimentary support to farmers. The SLM program provided livestock extension services on husbandry practices (vaccination, disease control, AI) and distributed seeds of improved pasture legumes to farmers for enhancing animal feed quality and raising productivity. The strong impacts we find on livestock income in SLM treatment supported watersheds suggests a potential for SLM programs to boost farmers' income if packaged with other complimentary interventions relevant to the livelihoods in a given context.

Figure 5.4.1: Livestock Income levels in SLM-supported Learning Watersheds and Non-SLM supported Control Watersheds (in Birr)



Source: IFPRI, WLRC & REACH Survey 2017.

Table 5.4.1: Livestock Income Differences between SLM supported Learning Watersheds and Non-SLM Supported Control Watersheds

	Livestock Income Levels			SLM Program Impacts on Livestock Income Levels			
	SLM Supported Learning Watersheds (% Adopters)	Non-SLM Supported Control Watersheds (% Adopters)	Difference in Adoption (Leaning-Control)	Propensity Score Matching (PSM)	Bias Corrected Matching	PSM-Weighted Regression	Non-PSM-Weighted Regression
Livestock Income (Birr)	5193	3962	1230**	1633*** (227)	980*** (326)	1751*** (285)	1570*** (244)
Log Livestock Income (Birr)	6.87	6.19	0.67***	0.66*** (0.1341)	0.46*** (0.1634)	0.67*** (0.1251)	0.67*** (0.1217)
% Impacts			67%***	66%***	46%***	67%***	67%***

Source: Authors' computation using IFPRI, WLRC & REACH Survey 2017.

Crop Yields and SLM

We find statistically significant differences in crop yields between SLM supported learning watersheds and Non-SLM supported control watersheds in three of the ten crops we analyzed (Table 5.4.2), specifically for maize, mangos and finger millet. Further econometric analysis (Table 5.4.3) on maize and finger millet shows SLM impacts on yields of about 18%-19%. These results indicate that SLM can have significant impacts on crop yields although these impacts are limited to a sub-set of the crops in our sample. Limited yield gains from SLM, particularly soil bunds – the main SLM practice in the learning watersheds, is to be expected as yield increases from soil bunds would partly be compensated by lack of cultivated area, which is a serious problem given the small average plot size in the area. Using an experimental study in the highlands of Ethiopia, Adimassu et al. (2012) found that soil bunds decrease crop yields by about 7%, which is entirely explained by the reduction of the cultivable area by 8.6% due to the soil bunds.

Crop Income and SLM

Aggregating all crops produced on a farm plot, we find slightly higher crop incomes per hectare in SLM supported learning watersheds compared to Non-SLM supported control watersheds. The difference in crop income is about 238 Birr per hectare (approx. 12 dollars per ha). It is therefore not surprising that the econometric analysis (Table 5.4.4) shows an overall impact of SLM on crop income of only 9%. This finding is consistent with our earlier results which showed that crop yields were significantly higher for a small set of crops (3 of the 10 crops reported) in SLM supported watersheds. Therefore, the poverty effects of SLM plus complementary investments on crop income is small compared to its effect on improving livestock productivity.

Table 5.4.2: Plot level Crop Yields across Watersheds

Crop Yields Kgs/ha	SLM Supported Learning Watersheds	Non-SLM Supported Control Watersheds	Mean Difference
Maize (N=788)	3074	2765	309**
Mango (N=40)	1664	823	841*
Teff (N=294)	906	869	37
Sorghum (N=35)	1449	1237	211
Wheat (N=36)	1276	1603	-327
Gesho (Aroma Hops) (N=230)	1446	1590	-144
Dagussa (Finger Millet) (N=523)	1784	1372	411**
Coffee (N=69)	548	526	21
Chat (N=276)	2243	1774	469
Barley (N=67)	1679	1705	25

Source: Authors' computation using IFPRI\WRLC\REACH Survey 2017.

***, **, * significance at 1%,5% and 10% respectively.

Table 5.4.3: Impacts of SLM on Crop Yields

Impact on Yields (Kgs/Ha)	Propensity Score Matching	Propensity Score Matching	Bias Corrected Matching	PSM Weighted Regression	Non-PSM Weighted Regression
Maize Yield	268**	268**	253*	278**	268**
	(134)	(130)	(138)	(130)	(126)
Log Maize Yield	0.18***	0.18***	0.18***	0.18***	0.18***
	(0.055)	(0.065)	(0.068)	(0.067)	(0.061)
Impact %	18%***	18%***	18%***	18%***	18%***
Dagussa (Finger Millet) Yield	413**	413**	235	404**	411**
	(192)	(208)	(192)	(167)	(203)
Log Dagussa (Finger Millet) Yield	0.19***	0.19***	0.08	0.19***	0.19***
	(0.069)	(0.070)	(0.076)	(0.074)	(0.067)
Impact %	19%***	19%***	8%	19%***	19%***

Source: Authors' computation using IFPRI\WRLC\REACH Survey 2017.

Table 5.4.4: Impacts of SLM on Crop Income

Impact on Crop Income (Birr/Ha)	Propensity Score Matching	Propensity Score Matching	Bias Corrected Matching	PSW Weighted Regression	Non-PSW Weighted Regression
Crop Income Per ha (Birr/Ha)	238 (378)	238 (423)	126 (375)	202 (360)	259 (363)
Log Crop Income Per ha (Birr/Ha)	0.09* (0.045)	0.09* (0.053)	0.11** (0.054)	0.09* (0.053)	0.09* (0.049)
% impact	9%*	9%*	11%**	9%*	9%*

Source: Authors' computation using IFPRI\WRLC\REACH Survey 2017.

6. CONCLUDING REMARKS

In this paper we investigated empirically the effect of SLM on water security and poverty. We test these relationships using Ethiopia as a case study drawing on a 2017 household survey data assessing a comprehensive watershed-level SLM program implemented in the Amhara region since 2012. SLM programs have gained in importance in Ethiopia in response to the national recognition of widespread land degradation, water insecurity and poverty in the highlands of Ethiopia. The SLM program was implemented in learning watersheds which we compare with control watersheds to see if there are differences in outcomes on SLM adoption, water security, and poverty indicators.

We find that the SLM program substantially increased adoption of SLM investments in the learning watersheds (46%) with adoption rates twice the levels observed in the control watersheds (25%). These adoption differences may not be surprising given that the stated objective of the program has been to introduce SLM interventions in the learning watersheds. The SLM program increased adoption rates by 19% for soil bunds and 5% for stone terraces, with statistically significant but small impacts on adoption of trees (2%), check dams (1%), drainage ditches (3%), and grass strips (0.3%). We find better water security for livestock production and crop production in SLM supported learning watersheds compared to Non-SLM supported control watersheds using proxies of water security. In SLM supported watersheds, farmers are more likely to use groundwater in crop irrigation and have experienced improvements in water for livestock production.

We find higher yields for maize, mango, and finger millet in SLM supported learning watersheds as compared to control watersheds. We also find significantly higher livestock income in SLM supported learning watersheds than Non-SLM supported control watersheds. Important to note is that the impacts on livestock income (66%) were substantially larger than those for crop income (9%). This could be partly because of the specific livestock intervention package (such as poultry development and cattle variety improvements through artificial insemination) that accompanied the traditional SLM measures and partly because the SLM practices increased drinking water for livestock through improved groundwater recharge.

In conclusion, sustainable land management using a comprehensive, learning-watershed approach is strongly associated with greater access to groundwater, better access to adequate livestock watering, significant impacts on yields on a limited crops - hence weaker impacts on overall crop income, but strong impacts on livestock income.

We recommend hydrological studies to be conducted to better understand what drives groundwater use in the learning watersheds to validate our findings of SLM and groundwater linkages which are based on observational household data.

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