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Analysis of farm-household adoption and choice of natural resource management innovation (Soil and Water Conservation Technologies) in Ethiopia: The role of poverty

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The study examined factors that determine adoption and choice of SWC technologies under CGIAR-related agricultural innovations in Ethiopia, using data from Ethiopian Socioeconomic Survey (ESS4). Specifically, the study assessed the effect of poverty, socioeconomic and plot level factors on adoption and choice of SWC technologies. Poverty is found as an important factor in adoption and choice of SWC technologies by farm households. Household characteristics like head age, active labor, education, and head sex also significantly affected the likelihood of adopting and choice of SWC technologies by land owners. Similarly, plot level characteristics (size, slope, average annual rainfall) have significant effect on farm households' adoption and choice decision. Conversely, cultivated land as compared to other land use types is positively associated with adoption of SWC technologies. Regarding choice of conservation technology, terracing followed by plough along the contour are most practiced method of soil erosion prevention by farm households. Adoption of terracing is positively associated with increased annual consumption per adult equivalence (poverty). The study emphasized that efforts targeting to increase adoption of NRM in general and SWC technologies in particular need to be augmented by policies that mitigate poverty both at household and community level.

Key words: Adoption, poverty, soil and water conservation, farm household, binary logit, multinomial logit.

INTRODUCTION

The economies of most sub-Saharan Africa countries, including Ethiopia, are agro-based, which smallholder farmers are major producers (De La O Campos et al., 2018). In these countries, the agricultural sector plays a major role in economic development, food security, poverty alleviation and social welfare (Kosmowski et al., 2020). The importance of the sector is even more conspicuous, especially in rural areas, where families depend heavily on agriculture alone to make a living (Angelsen et al., 2014). The major concern however is that the degradation of land, water, and soil resources adversely affects agriculture productivity and production

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(FAO-UNCCD, 2019). Without taking appropriate soil, water, and land management measures, degradation will persist and yields decline thereby increasing recurrence of food insecurity and extreme poverty (Barbier, 2000; Gerber et al., 2014; Scott and Conacher, 2018).

Fortunately, both government and non-governmental organizations have consistently promoted and provided Sustainable Land Management (SLM) technologies (Kosmowski et al., 2020). Increased agricultural productivity through the diffusion of innovations has the potential to contribute to economic growth, food security, and poverty alleviation in developing countries like Ethiopia (Global Mechanism of the UNCCD, 2019). Despite efforts to promote various Natural Resource Management Innovations (NRMI), their adoption is still low and land degradation continues to be a major limitation to agricultural productivity, in Ethiopia (Asrat and Simane, 2017b; Gebreselassie et al., 2015). Hence, understanding adoption of new NRMI in the agricultural sector and its determinants is a topic that continues to receive attention by the academic community. Particularly, understanding the effect of poverty on adoption decision and choice of conservation technologies is worth investigation both from academic and practical perspective.

Actually, quite a number of studies (Kirui, 2017; Lalani et al., 2016; Mekuriaw et al., 2018; Soule et al., 2000) have investigated about the decision to adopt and choice of SLM technologies. However, there has always been a new innovation with a promise to bring about high agricultural productivity and possible positive wellbeing impacts (Kosmowski et al., 2020). Accordingly, adoption of these innovations by farm households and the effect of certain policy variables like poverty is still worth investigating.

Moreover, the study by Kosmowski et al. (2020) has provided a detail analysis on adoption and diffusion of CGIAR-related Innovations in Ethiopia. The paper would then complement this study, which is mostly descriptive in nature, by investigating the effect of poverty on adoption, and choice of NRMI (SWC practices) in Ethiopia. Thus, policy makers and interventionists can have a comprehensive picture about NRMI in Ethiopia and possible elsewhere.

Research questions

(1) Which factors determine the adoption and choice of NRMI (SWC technologies) in Ethiopia?
(2) What is the effect of poverty on adoption and choice of NRMI (SWC technologies) in Ethiopia?

Objective of the study

The main objective of the study is to examine the factors that determine the adoption and choice of Natural Resource Management Innovations (NRMI[1]) [Soil and Water Conservation technologies] under CGIAR-related agricultural innovations in Ethiopia, using data from Ethiopian Socioeconomic Survey (ESS4). In addition, the study specifically attempts to assess effect of poverty, socioeconomic and plot level factors on adoption and choice of SWC technologies in Ethiopia.

REVIEW OF EMPIRICAL STUDIES

Land degradation, poverty, and SLM nexus

Because of its adverse impact on agricultural productivity, food security, and people's quality of life (poverty), land degradation has become a global issue, but to take effective action, it must be assessed at the local level (ELD Initiative, 2014). Moreover, the economic consequences of land degradation are not the same for all people or countries. Studies indicate that land degradation is severe especially for poorer societies that do not have the available means to compensate for the loss of land productivity (Cordingley et al., 2015) and suffer from loss of livelihood, food insecurity, and poverty (Jouanjean et al., 2014). The majority of the poor, who heavily depend on surrounding natural resources, live on degraded land (Castañeda et al., 2018). Land degradation, thus, poses a challenge on efforts to eradicate extreme poverty and enhance food security (Kirui, 2017; Kirui and Mirzabaev, 2014).

Commonly, adoption of SLM, the likes of SWC technologies are advised to reverse land degradation (Liniger et al., 2019). However, such measures are successful if land managers have the means, commitment, and control to restore, maintain, or improve the quality of land (Verburg et al., 2019). Unfortunately, the poor mostly reside in a remote and marginal area, where they are highly vulnerable to geographical poverty traps (De La O Campos et al., 2018; FAO-UNCCD, 2019; Kissinger et al., 2013). Such traps may occur because production on such land is subject to low yields and soil degradation, while lack of access to markets and infrastructure may constrain their ability to improve farming systems and livelihoods (De La O Campos et al., 2018). Moreover, the positive effects of adopting SLM may also occur over time, which will result in a short-term loss of livelihood and reduced income (UNEP, 2015). For these people, the short-run opportunity cost of switching to SLM might be higher than the expected benefit of SLM (Falco et al., 2019). They, therefore, need to be motivated economically to secure the benefits of SLM.

Previous studies on land degradation, have largely concentrated on the estimation of its economic cost, drivers, and identification of hot spot areas. Only few

[1]There are other Natural Resource Management Innovation reported by CGIAR (see Kosmowski et al., (2020)). However, the current study focused only on Soil and Water Conservation Technologies.

attempted to study the relationship between poverty and land degradation (Etongo et al., 2016; Hopkins et al., 1999; Mirza et al., 2019). However, arguments remain inconclusive about the direction of causality-whether poverty creates or is a result of land degradation. Apart from macro-level studies of mapping land degradation and patterns of the poor, little evidence is provided on the causality of land degradation and poverty.

On the other hand, Masron and Subramaniam (2018) attempted to show how poverty is associated with lower environmental quality in developing countries. However, their study failed to show the association at the household level and instead checked the existence of the Environmental Kuznets Curve (EKC) between the environment and level of poverty at the national level. Manh et al., (2014) on the other hand, analyzed the socio-economic and bio-physical determinants of land degradation in Vietnam, at a district level. However, the decision to engage in degrading activity and reverse degradation is made at the household level. Hence, analyzing factors of land degradation at a higher administrative level than the household level may not give us the true picture of the problem. Accordingly, there still exists a knowledge gap as to the nexus between poverty and land degradation at household level.

Natural resource management: Determinants and impact

In recent times it is observed that the agriculture and development literature is dominated by studies of NRM adoption, choice of innovation, productivity change, food security, poverty, and ecosystem services. This due to the fact that new NRMI are consistently being introduced to farmers, with varying level of adoption, and possible impact on productivity and wellbeing. Subsequently, a short review of studies on adoption, determinants, and impact on wellbeing is presented. Almost all the studies are focused on Ethiopia, making the review relevant to the current study based on ESS data.

Quite a number of studies (Asfaw and Neka, 2017; Gebreselassie et al., 2015; Liniger et al., 2019; Deressa et al., 2009) have provided a strong evidence for increased NRM investments by farm households in Ethiopia. The main NRM technologies includes soil and water conservation technologies (physical construction of bunds, terraces, dams, ditches, etc.), various agronomic and vegetative practices (planting edible trees, green cover, etc.), and adoption of new land management (area enclosure, early and late planting, changing land use type) approaches. Conversely, level of education, gender, age, and wealth; access to extension and credit; and information on climate, social capital, and agroecological settings, influence farmers' choices of NRMI (Beyene et al., 2017; Mekuriaw et al., 2018). Other scholars (Adgo et al., 2014; Ayele and Tahir, 2015; Benin and Pender, 2001; Gorfu, 2016; Nantongo, 2011) have also emphasized the role tenure security in adoption of various NRMI in Ethiopia.

With regard to welfare impacts of Natural Resource Management Innovations, an opposing result was obtained. For example Schmidt and Tadesse, (2019) evaluated the impact of Sustainable Land Management Program (SLMP) on the value of agricultural production, across six regions of Ethiopia. Using a panel survey from 2010 to 2014, they found no significant association between the SLMP with increases in household-level agricultural value of production. However, SLM investments and agricultural value of production increased significantly in both treatment and nontreatment areas between 2010 and 2014, demanding further investigation as to the sources of such increases.

In contrast, Kassie et al. (2007) found that SWC technologies like stones bunds have increased agricultural productivity in Ethiopia. Similarly, Asrat and Simane (2017b), investigated the impact of SLM practices on crop productivity at household and plot level in Dabus Sub-basin, Blue Nile River. In their study, it is found that SLM practicing households experienced a 24% higher value of production compared to non-users over a period of five years. In their plot level analysis, plots that received SLM measures within the period (2004-2009) experienced a 28.6% increase in value of production in 2016. Actually, such variation in the impact of NRMI is one of the reasons, which justifies continues investigation in the area. Accordingly, it is the sated knowledge gap that required the need to investigate the factors (specifically poverty) that determine farm households' adoption and choice of SWC technologies in Ethiopia.

METHODOLOGY

Data type, and data source

The current study is based on the data from 2018/2019 Ethiopian Socioeconomic Survey (ESS4)[2] collected by a collaboration of the Central Statistics Agency of Ethiopia (CSA) and the World Bank (WB). It is financially supported by the Bill and Melinda Gates Foundation (BMGF) through the Living Standards Measurement Study Integrated Surveys on Agriculture (LSMS-ISA) project. ESS is a nationally representative household survey with a strong focus on agriculture. It covers a nationally representative sample of over 6,700 households living in both rural and urban areas. The sample is also regionally representative. The 2018/2019 ESS (ESS4) is a new panel, not a follow-up to previous ESS waves. The survey covers all nine regional states and two cities, Addis Ababa and Dire Dawa from 565 EAs, of which 316 are rural and 219 are urban.

The ESS4 survey consisted of five questionnaires. The household questionnaire was administered to all households in the sample. The community questionnaire was administered to a group of community members to collect information on the socioeconomic indicators of the EAs where sample households reside. The agriculture questionnaires (consists of three questionnaires: Post-Planting, Post-Harvest, and Livestock Questionnaires) were

[2]A detail discussion about the survey design is reported in (CSA-WB, 2020)

administered to all members of households engaged in agricultural activities.

The ESS4 agricultural questionnaire is administered at the holder level. A holder, in CSA surveys, is a person who exercises management control over the operations of the agricultural holdings and makes the major decisions regarding the utilization of the available resources. S/he has technical and economic responsibility for the holding. Because households may have more than one holder, where appropriate the agriculture modules were administered to each holder in the household.

The current study combined information from household questionnaire (demographic, and socioeconomic variables), agricultural questionnaire (NRMI, land ownership and use; farm labor; GPS land area measurement), and community questionnaire (information on infrastructure access) to answer the specific research questions raised in the paper.

Sampling procedure and sample size

Since the study is based on a secondary data, the sample is directly adopted from ESS4-2019 data (CSA-WB, 2020). ESS4 is the first wave or baseline of a new panel data collected in 2018/2019 after three waves of ESS surveys. The survey used the 2018 CSA pre-census enumeration areas (EAs) for selecting samples. A two-stage stratified sampling procedure was adopted in the survey. Rural ESS4 EAs are a sub-sample of Annual Agricultural Sample Survey (AgSS) EA sample. In the first stage simple random sampling was employed to select EAs from the 2018 AgSS EA sample in rural Ethiopia. In the second stage ESS4, adopted a systematic random sampling technique to select households to be surveyed in each EA. From the rural EAs, a subsample of 10 agricultural households was selected from the households selected for the AgSS4, and 2 nonagricultural households were selected from the non-agriculture households in each EA. Actually, in ESS_4, 10 agricultural households per EA were sampled even if there was only one non-agriculture household or none.

A total of 19,339 plot or land holders were reported in ESS4-2019. However, only 15,636 plots or land holders answered a question which asks if the land is prevented from erosion through the adoption of any SWC technology. Accordingly, the current study used this variable to classify adopters and non-adopters of SWC technology. In the next stage the paper identified the type of SWC technologies practiced in the plot, to examine the effect of poverty on choice of technology. This part basically refers to those 8,916 plots who reported to practice any one of the SWC technologies available in the area.

Method of analysis

The study employed both descriptive and econometric analysis. The objective of the descriptive analysis is to compare adopters and non-adopters of SWC technologies, where focus is the land plot not the household. The econometric analysis would help investigate the effect of explanatory variables on the adoption and choice of SWC technology in Ethiopia, with poverty at the heart of the analysis. The choice of the econometrics method adopted here is based on the objective of the study, which is examining factors (specifically poverty) that determine farm level adoption and choice of SWC technologies in Ethiopia.

Adoption could either be categorical (Gebreselassie et al., 2016), continuous variable, or count variable. In the former case farm households could be differentiated based on the type of SWC measures they adopted on their plot (Beyene et al., 2017). Here the dependent variable is a categorical value of adopters and none-adopters, ordered values, or choice of SLM practices on plot of a given farm. Other studies (Adjepong et al., 2019; Sileshi et al., 2019) defined adoption of SWC as a count variable, where farmers are differentiated based on the number of SWC technologies they practiced on their plot. Here, they assumed that each SWC technology is independent of the other, hence, requires independent decision to adopt it.

In the case of ESS4-2018/2019 data land holders adopted a single SWC measure on their plot from a list of eight main SWC measures. Accordingly, we can make two types of analysis as far as adoption is concerned. First farm households could be differentiated simply as adopters and non-adopters irrespective of the type of SWC practiced in their plot. Second, those farm households who practiced SWC technologies on their plot could be differentiated based on the type of SWC they adopted. Hence, the Binary Logit Model (effect of poverty on adoption of SWC technologies) and Multinomial Logit Model (MNL) (effect of poverty on choice of SWC technology) could best capture the relationship between the dependent variable and poverty (the interest variable).

Theoretical models

Both Binary Logit Model (BL) and Multinomial Logit Model (MNL) are discrete choice models built on theoretical ground of random utility maximization. In this case, a holder is assumed to face utility maximization problem where the holder is assumed to have preferences defined over a set of SWC technology alternatives: The logit model can be used to estimate a utility maximization problem where the farm household is assumed to have preferences defined over a set of technology alternatives (Gujarati, 2004):

$$U_j=\beta_j X_i + \varepsilon_j \tag{1}$$

where U_j is the utility of technology j, X_i a vector of attributes of the plot and the farm household, β_j a parameter to be estimated and ε_j the disturbance term. The disturbance terms are assumed to be independently and identically distributed. If the farmer's choice is alternative j on a particular plot, it is assumed that the utility from alternative j is greater than the utility from other alternatives, that is

$$U_{ij}>U_{ik},\ \forall k\neq j$$

where U_{ij} is the utility to the i_{th} farm household of SWC technology j, and U_{ik} the utility to the i_{th} farm household of technology k. When each technology is thought of as a possible adoption decision by farm household, the farm household will be expected to choose the technology that has higher expected utility among the alternatives considered (Gujarati, 2004). The i^{th} individual's decision may, therefore, be modeled as maximizing the expected utility from a given plot by choosing the j^{th} technology from among J discrete technologies, that is:

$$\text{MaxjE } (U_{ij})\_fj\ (X_i)+\varepsilon_{ij},\ j=0\ldots,\ J \tag{2}$$

where E(Uij) is the expected utility of alternative j to the i_{th} farm household, and fj is a function of $X_i = (X_{i1}, \ldots, X_{in})$, a (1×n) vector of attributes of the plot and the farm that potentially affect the choice of a technology. The probability of choosing alternative j from among J alternative choices is equal to the probability that the expected utility from alternative j is greater than the expected utility from any other alternative, that is:

$$\Pr(C=j) = P\ [E(U_j) - E(U_k) >0]\ \forall k\neq j \tag{3}$$

where C denotes the choice.

Binary logit model

As indicated earlier the study employed the Binary Logit Model to examine the factors (specifically poverty), farm household adoption of SWC measures in Ethiopia. Here, the objective of the Logit model is to ensure that the predicted probability of the event occurring given the value of explanatory variable remains within the [0, 1] bounds (Gujarati, 2004). That means,

$$0 \leq Pr(Y = 1|X) \leq for\ all\ X$$

Assuming a nonlinear functional form for the probability, the error term (U_i) follows a cumulative distribution function. This is given by Cumulative Density Function (CDF) as:

$$Pr(Y_i = 1|X_i) = P_i = G(\beta_0 + \beta_1 X_i) = G(Z_i), 0 \leq Z_i \leq 1$$

where G is a function taking values strictly between 0 and 1, for all real numbers Z_i and this ensures that the predicted probability (P_i) strictly lies between 0 and 1. Hence, $G(Z_i)$ is defined as follows:

$$G(Z_i) = P_i = \frac{exp^{Z_i}}{1 + exp^{Z_i}} = \frac{e^{Z_i}}{1 + e^{Z_i}} = \frac{1}{1 + e^{-Z_i}} = \frac{1}{1 + e^{-(\beta 0 + \beta 1 Xi)}} = \frac{e^{(\beta 0 + \beta 1 Xi)}}{1 + e^{(\beta 0 + \beta 1 Xi)}}$$

Therefore,

$$P_i = \frac{e^{Zi}}{1 + e^{Zi}},$$

where $Zi = \beta_0 + \beta_1 X_i$.

If Pi is the probability of SWC adoption, then 1-Pi will the probability of not adopting SWC practices, Thus,

$$P_i = \frac{e^{Zi}}{1 + e^{Zi}}$$

$$1 - P_i = \frac{1}{1 + e^{Zi}}$$

Taking the ratio of the probability of SWC adoption (P_i) to the probability of not adopting SWC $(1-P_i)$ the resulting ratio is called odds ratio.

$$\frac{Pi}{1 - Pi} = \frac{\frac{e^{Zi}}{1 + e^{Zi}}}{\frac{1}{1 + e^{Zi}}} = e^{Z_i}$$

Taking the natural log of the odds ratio and the resulting equation is called logit.

$$\ln\left(\frac{Pi}{1 - Pi}\right) = L_i = Z_i$$

$$L_i = Z_i = \beta_0 + \beta_1 X_i \quad (4)$$

where Li is called the Logit, and it is linearly related with X_i explanatory variables.

Based on the theoretical model discussion of the Logit model earlier, the empirical model for the factors determining SWC adoption, is given by:

$$L_i = \beta_0 + \beta_1 X_I + Ui \quad (5)$$

where Li is the logit, the β are parameters and xi are a set of explanatory variables where poverty is the interest variable for the current study (Table 1).

The multinomial logit model

After examining the effect of poverty on the adoption of SWC measures and identify the determining factors, the paper further investigated the choice of specific SWC measures by land owners.

The multinomial logit model is basically an extension of the binary logit model, with more than two responses. This model makes it possible to study the determination of the factors influencing SWC in the context of individually specific data on multiple choices. In the multinomial logit analysis plots are classified according to practiced SWC technology in the ESS4-2019.

Following Greene (2003), the Multinomial Logit form for a multiple-choice problem is:

$$Pr(y = j) = \frac{e^{\beta j X i}}{e^{\beta 0 X i} + e^{\beta 1 X i} + \dots e^{\beta j X i}} \quad (6)$$

The alternative SWC technologies are the following: terracing, water catchments, afforestation, plough along the contour, moving livestock in the field, water canal, and other SWC groups (Table 1).

RESULTS AND DISCUSSION

Descriptive analysis

Characteristics of adopters and non-adopters

A descriptive statistic of the variables analyzed in the study is presented in Table 2. Here, the study focused more on the difference between adopters and non-adopters of SWC technologies rather than the general characteristics of the sample in the data. Accordingly, there is no statistically significant difference with regard to household size, household active labor, and household average education of adopters and non-adopters of SWC technology. However, household age of adopters is slightly higher than non-adopters. Additional variations are also observed between the two groups, with regard to total field/plot size ($P<0.01$), proportion of household income from non-farm activities ($P<0.05$), slope of the land, average annual rainfall, percentage of crop land and distance to nearest main road. On average adopters own smaller plot size, steeply sloped land, and large proportion of crop land. On the other hand, non-adopters generate more income from non-farm activities and their plot received high average rainfall than adopters.

Adoption and types of SWC technologies practiced by farm households

According to the ESS4/2019 data, at least one SWC

Table 1. Description of explanatory variables and hypothesis in both Binary and Multinomial Logit Models.

Variable	Variable type	Expected sign	Description of the variable
Poverty status (ACPAE)	Continuous	Positive	Annual consumption per adult equivalence (an indicator of poverty)
Demography			
HH Sex	Dummy	Positive	Sex of Household Head (1 Male, 2 Female)
HH Age	Continuous	Positive/Negative	Age of the household head
HH Size	Continuous	Negative	The size of the household
HH Act. Labor	Continuous	Positive	Total Number HH members age between 12 and 60 inclusive
HH Ave. Edu	Continuous	Positive	Average education of HH years of schooling
Information access			
TV and Fixed Line tele	Dummy	Positive	Availability of TV and fixed line Tele in the HH (Yes=1, No=2)
% HH Inc. NFE	Continuous	Negative	Proportion of HH income from non-farm enterprise
Access to infrastructure			
D_N_M_Road	Continuous	Positive	Distance in km to the nearest main road
Dis. Reg Capital	Continuous	Positive	Distance in km to regional capital
Land tenure			
Private Ownership	Dummy	Positive	The plot is owned by the Farm HH (Yes=1, No=0)
Rented	Dummy	Negative	The plot is rented by the Farm HH (Yes=1, No=0)
Free Use	Dummy	Positive	The plot used by the Farm HH free of rent (Yes=1, No=0)
Total Field Size	Continuous	Positive	The size of plot measured in m^2
Slope Land	Continuous	Positive	The slope of the plot
Field use			
Cultivated	Dummy	Positive	Plot is cultivated by crop (Yes=1, No=0)
Pasture	Dummy	Negative	Plot is used for pasture (Yes=1, No=0)
Fallow	Dummy	Negative	Plot is used for fallow (Yes=1, No=0)
Forest	Dummy	Positive	Plot is allotted for forest (Yes=1, No=0)
Homestead	Dummy	Positive	Plot is used for homestead (Yes=1, No=0)
% Crop Land	Continuous	Positive	Proportion of total land cultivating crop
Dependent variable	Categorical		
Farm level			Plot Adopted SWC (1), Plot non-adopted (0) Binary Logit Model

Table1. Contd.

Adoption SWC technologies introduced by CGIAR program	Alternatives in Multinomial Logit Model: terracing, water catchments, afforestation, plough along the contour, moving livestock in the field, water canal, and other SWC groups.

Source: Authors

Table 2. Characteristics of Adopters and Non-Adopters.

Variable	Adopters N=8711*	Non-Adopters N=6433	Combined N=15,144	P-Value
Average field size	3714.267	4302.862	3967.232	0.000
Poverty status (CPAE)	13521.4	13324.25	13437.65	0.335
Slope of the land	17.2%	16.33%	16.8%	0.000
Percentage of cropped land	38.5%	30%	34.9%	0.000
Average annual RF	832.8 mm	951.4 mm	883.2 mm	0.000
HH Age	47.2 years	46 years	46.7 years	0.000
HH Size	5.18	5.21	5.19	0.375
HH active labor	3.36	3.4	3.38	0.159
HH Ave. Edu.	3.75 years	3.8 years	3.76 years	0.695
% HH Inc. NFE	3.11%	3.6%	3.31%	0.024
Distance N_M_Road	17.8 km	19.7 km	18.6 km	0.000
Dis. Reg Capital	0.135	0.153	0.142	0.1345

*The sample size is based on the minimum number of HH who have responded to the listed variables.
Source: Authors computation based on ESS4-2019 data.

technology has been adopted on 57% of the plots (Table 3). Household level adoption is reported to be 72% (Kosmowski et al., 2020), which is significantly higher than plot level adoption of SWC technology. This is because all plots owned by a household may not practice SWC technologies but the same household could report adopting a conservation technology on a single plot, while owning multiple plots.

Among adopters terracing is practiced by about 42.5%[3] of the plot as a soil and water conservations technology, while 30% of the plot practiced ploughing along the contour to prevent soil erosion. The remaining land owners adopted water catchment (10.3%), constructing water canals (about 10%) and other SWC technologies in their plot as a way protection from soil erosion (Table 4). .

[3]A slight difference is observed from the report by Kosmowski et al., (2020) and (CSA-WB, 2020). The reason could be the omission of SWC technologies from their analysis, which have adoption rate of less than 5% of the sample.

Factors determining farm households' adoption of SWC technologies (Logistic regression)

The study first investigated factors that determine plot level adoption of SWC technological innovations by CIGAR in Ethiopia. The main interest here is to examine the effect of poverty on adoption of SWC by land holders. In addition to the land owner's status of poverty, the paper included a set of household level characteristics, socioeconomic, and plot level characteristics to evaluate their effect on adoption decision (Table 5).

As can be seen from the Binary Logit Model (Table 5) that, poverty measured by total consumption per adult equivalence significantly (*P<0.01*) affects plot level adoption of SWC technologies in Ethiopia. Adoption of SWC by land owners is positively associated with increased total consumption per adult equivalence. The result obtained in the current study is at odds with the findings of Kosmowski et al. (2020) where they found adopters of SWC on average to be poor. Their result somehow contradicts the notion that farm households need to have financial capability to invest on SWC technologies, which most poor lacks (Tadesse and Belay, 2004). Yesuf and Pender, (2007) clearly indicated that the adoption of SWC investments is undermined by high discount rates, which are generally higher for poorer households in Ethiopian. Kosmowski et al. (2020) also reported that adopters had larger agricultural holdings, and owned more productive assets. If that is the case it is less likely for these households to be poor with such endowments. The fact that, the study used similar survey data and similar indicator for poverty (ACPE) with the current study requires more investigation into the stated relationship.

Proportion of household income from off-farm activities is found to have a statistically significant negative association with adoption of SWC technologies by farm households in Ethiopia (Table 5). The finding is consistent with a claim that households would likely abandon their farm as they engage more on non-farm activities. Similarly, Mekuriaw et al. (2018) and Asfaw and Neka (2017) found that households practicing off-farm activities like selling firewood and use of free grazing systems (communal land) influenced the adoption of SWC practices negatively.

Household level characteristics like head age, size of household active labor, household average education, and head sex has significantly affected the likelihood of adopting SWC technologies at plot level by land owners. Accordingly, age of the household head is found to have a positive and significant (*P=0.01*) association with adoption of SWC technologies (Table 5). Similar results of positive association between age and adoption of SWC technology is found by Mango et al. (2017). However, the positive relationship is observed only to certain extent, and replaced by a significant *(P=0.01*) negative association as measured by the square-root of age. With regard to sex households with male (*P<0.05*) heads are more likely to adopt SWC technologies in their plot. The result is consistent with the findings of Asfaw and Neka (2017) and Beyene et al. (2017).

An interesting result is observed with regard to literacy and availability of active labor. It is expected and true from previous studies (Asfaw and Neka, 2017; Sileshi et al., 2019; Zeweld et al., 2018) that literate households are more likely to adopt SWC technologies as they are assumed to be aware of the benefits. In this study however, it is found that literacy, which is measured by household average education is negatively *(P<0.05*) associated with adoption of SWC at plot level. There is no a convincing explanation for this apart from educated individuals will tend to get job somewhere else than at their farm. Some scholars (Tesfahunegn, 2017) argued that educated people can have alternative livelihood than farming, which decrease the probability of adopting any type of SWC technology. Though not given a reason (Alufah et al., 2012) has also reported a negative association of education and SWC technology adoption in Kenya.

Similarly, farm households with more active labor found to have negative association with adoption of SWC technologies at plot level. This might be due to the fact that active household members would tend to find their own earning than cooperate on exiting farm production. There is also a potential for a diseconomy of scale for households with large number of active labors given limited land holding.

The study also examined the effect of access to information on adoption of SWC technologies, assuming that land holders would gain more awareness and potential success stories of NRM by others. Studies indicated that Information in the form training or accessing it via television and radio has a positive association with the adoption of NRM technologies (Adjepong et al., 2019; Bekele and Drake, 2003; Mekuriaw et al., 2018). However, the current study found that availability of television in the house is negatively associated with the adoption SWC technology (*P<0.05*) (Table 5).

Plot level characteristics which include plot size, field status, and slope of the land are found to have significant effect on farm households' adoption of SWC technologies (Table 5). Accordingly, a positive and significant association is found between plot size and adoption of SWC technologies. The result indicates that, land holders are more likely to adopt SWC technologies with increased size of their plot. This is true as there exists an economies of scale advantage of investing on SWC technologies with increased plot size and is also supported by other studies (Adjepong et al., 2019; Tadesse and Belay, 2004) too. Contrary to the finding of the current study, Etsay et al.(2019) reported a negative relationship between plot size and adoption of SLM, as larger plots demand more labor and time to conserve.

The study also investigated the effect of field status on application of SWC measures on the land. This is because the status of the land determines the type of SWC investment by land owners. If the land is to be

Table 3. Proportion of plots adopted SWC technology.

Plots adopted SWC	Freq.	Percent	Cum.
Non-adopters	6,720	42.98	42.98
Adopters	8,916	57.02	100.00
Total	15,636	100.00	-

Source: Authors computation based on ESS4-2019 data.

Table 4. Types of soil and water conservations practiced by land owners.

SWC type	Freq.	Percent	Cum.
Terracing	3,786	42.46	42.46
Water Catchments	919	10.31	52.77
Afforestation	301	3.38	56.15
Plough Along the Contour	2,703	30.32	86.46
Moving livestock in the field	203	2.28	88.74
Water Canal	880	9.87	98.61
Other	124	1.39	100.00
Total	8,916	100.00	-

Source: Authors computation based on ESS4-2019 data.

cultivated, it has to be protected and conserved. Majority of the plot in the previous year are actually cultivated by crop, followed by homestead, pasture, and forest. In comparison to crop (cultivated) land, pasture, fallow, forest, and land prepared for Belg-season is negatively and significantly associated with adoption of SWC technologies in Ethiopia. However, homestead plots are found to be positively and significantly associated with adoption of SWC technologies (Table 5). The reason might be that people would tend to build terraces, plant trees, and dig water canals around their home with the objective of abating flooding or for simple ecstatic value.

On the other hand, slope of the land has positively and significantly (*P=0.001*) affected land holders' decision to adopt SWC technologies. It is not unusual for farmers to invest on SWC practices where their farm plots are located in steeper slopes. This is because soil erosion would be more visible to the farmers and high in steeper slopes than plots located at flat areas. Another interesting finding is that land holders tend to decrease adopting SWC technologies with increased average annual rainfall. This actually raises important question as to land owners' perception of rainfall effects on erosion. If they think rainfall increases erosion, then probably adoption of SWC should increase with increased rainfall.

Land tenure is a commonly cited factor that significantly affects the decision of land holders to invest in SWC technologies (Kirui, 2017; Holden et al., 2013; Ayele and Tahir, 2015; Benin and Pender, 2001). The general consensus is that there should be a secure property right for land cultivators if they are to invest in soil and water conservation work in anticipation of long-term benefits. Hence, it would be important to examine, which tenure types are more likely result in increased probability of SWC adoption. It is evident from the Binary Logit Model that compared to privately owned land, land obtained free of rent and rented land is positively and significantly associated with adoption of SWC measures at plot level.

The result earlier is against the notion that farm households with private land (secured property right) are highly likely to adopt SWC technologies. The potential explanation is farm households who rented land or obtained free of rent are the ones that engage in cultivation of the land. If they are to increase productivity, there is need to conserve the land. This, however, depends on the contractual agreement of land owners and land users. If it is a long-term contract, it could result in increased adoption of SWC technologies and the opposite is true it the contact is a short term one. All the aforementioned reasoning actually depends on the fact that tenure security increases with private ownership of the land. In fact, the type of ownership does not necessarily guarantee a secured tenure, especially in Ethiopia as farm households have only usufruct right (Mekuriaw et al., 2018). Accordingly, it requires a measure of tenure security so as to assess the exact effect it has on adoption of SWC technologies.

Two variables were included in the binary logit model with regard to access to certain infrastructure, that is, distance from main road and distance to regional capital, with the assumption of variation in access to certain infrastructural facilities to affect adoption decision. The

Table 5. Results of Binary Logit Model and Marginal effect after logit for determinants of SWC adoption.

Log likelihood	-9122.1418	
Number of obs.	15,142	
LR Chi^2(25)	2403.58	
Prob > Chi^2	0.0000	y = Pr(prevent) (predict)
Pseudo R2	0.1164	= 0.58463564

Variable	**Logit**			**Marginal effect after logit**			
	Coef.	**Std. Err.**	**P>Z**	**Coef.**	**Std. Err.**	**P>Z**	**X**
Poverty (TCPAE)	0.1998	0.0285	0.000	0.0485	0.007	0.000	9.25298
Total Field Size	0.0592	0.0204	0.004	0.0144	0.005	0.004	7.84648
% HH Inc. NFE	-0.0049	0.0014	0.000	-0.0012	0.00033	0.000	3.30722
Access to information							
Fixed Line tele*	-0.0468	0.0619	0.450	-0.0113	0.015	0.448	.900542
Television*	0.3034	0.131	0.021	0.075	0.033	0.022	.981046
Demographic characteristics							
HH Sex*	-0.1272	0.0503	0.011	-0.0311	0.012	0.012	0.1655
HH Size	0.0178	0.0121	0.139	0.0043	0.003	0.139	5.19403
HH Active Labor	-0.0387	0.0151	0.010	-0.0094	0.004	0.010	3.37644
HH Age	0.0248	0.0081	0.002	0.0060	0.002	0.002	46.6422
HH Age^2	-0.0002	0.00008	0.010	-0.00005	0.00002	0.010	2386.84
HH Ave. Edu.	-0.0059	0.0029	0.041	-0.0014	0.0007	0.041	3.76398
Field status and characteristics[C]							
Pasture*	-1.168	.0725	0.000	-0.282	.016	0.000	.068881
Fallow*	-.5874	.1149	0.000	-0.146	.028	0.000	.024105
Forest*	-1.45	.1085	0.000	-0.339	.021	0.000	.029983
Land for Belg Season*	-.4219	.1355	0.002	-0.105	.034	0.002	.017237
Home/Homestead*	.3066	.0436	0.000	0.0734	.01	0.000	.271034
Other (Specify)*	.326	.115	0.005	0.0765	.026	0.003	.027275
Slope Land	.0116	.0021	0.000	0.0028	.00052	0.000	16.8228
% Crop Land	.0394	.0014	0.000	0.0096	.00034	0.000	34.9005
Ave. Annual RF	-.0012	.00007	0.000	-0.00028	.00002	0.000	883.2
Land tenure type[p]							
Free of rent*	0.5433	0.1319	0.000	0.124	0.028	0.000	0.020869
Rented*	0.3041	0.1846	0.100	0.0715	0.042	0.087	0.009378
Others specify*	-0.6497	0.7688	0.398	-0.161	0.188	0.391	0.000462
Access to infrastructure							
Distance N_M_Road	0.0021	0.0011	0.052	0.0005	0.00027	0.052	18.5787
Dis. Reg Capital	-1.161	0.1807	0.000	-0.282	0.044	0.000	0.142247
Constant	-3.171	0.4086	0.000				

(*) dy/dx is for discrete change of dummy variable from 0 to 1. C-Crop Land is the comparison category. P-Private Land is the comparison category.
Source: Authors computation based on ESS-2019 data.

study found an opposing result with the two variables, where increased distance from the main road is positively and significantly associated with adoption of SWC technology (Table 5). On the other hand, distance from regional capital is negatively associated with adoption of SWC practices. Potential explanation for the observed relationship could be the fact that land holders would tend to participate in off-farm activity as opposed to farming as they are close to main road. If that is the case, the opportunity cost of investing labor time to conserve land is possibly higher than the gain from production increase as a result of conservation.

Yesuf and Pender (2007) also reported that households with better road access are associated with lower SWC investment, potentially because of higher opportunity costs of labor. In the latter case however, increased distance from the regional capital indicates a decreased access to potential consumer market. Hence, it would be rational for land owners to invest less on conservation technology. This result is consistent with the study by Asrat and Simane (2017b), where a 1 km increases in distance from market is associated with 3.1% decrease in the probability of adopting SLM practices.

Factors Determining Farm Households' Choice of SWC technologies (Multinomial Logistic Regression)

After examining the effect of poverty on land holders' decision to adopt SWC, the study further investigated its effect on the choice of a specific SWC technology by land holders in Ethiopia (Appendix Tables 1 and 2). A missing analysis from Kosmowski et al. (2020) report is the issue of choice of SWC technology and factors that determine it. In addition to the status of poverty, the study also included other demographic, socioeconomic, plot level characteristics and institutional variables to check their effect on choice of SWC technologies.

The MNL model result as shown in Appendix Tables 1 and 2, indicates that, apart from water catchment, the status of poverty has a statistically significant negative association with afforestation, ploughing along the contour, moving livestock in the field, constructing water canal, and other SWC technologies. Accordingly, land holders are more likely to choose terracing (the base outcome in MNL model) as a SWC technology with increased total consumption per adult equivalence, which is an indicator of poverty. This could be attributed to the fact that constructing terrace compared to other SWC technologies would require more labor, and land area, which mostly the wealthy can afford.

Another important finding with choice of SWC technology is that land holders would likely practice afforestation and ploughing along the contour with increased plot size. The finding of increased practice of afforestation with increased plot size is not surprising as it is rational for land owners to allocate a portion of land, when he/she owns a large size of land sufficient enough to cultivate crop and plant tree simultaneously (Bekele and Drake, 2003). On the contrary, the largely practiced terracing technology decreases with increased size of the plot. The reason could be the huge cost of construction and maintenance associated with terracing would be even bigger with increased size of the land. Accordingly, land owners are expected to switch to more affordable SWC technologies available to them. However, Etsay et al. (2019), found that households who poses larger plot choose physical conservation technologies than other SWC technologies.

Demographic characteristics like household size and sex are positively and significantly associated with choosing terracing and afforestation as a SWC practice (Appendix Table 1 and 2). Accordingly, large size households and male headed households would likely construct terraces and plant trees in their farm plot than their counter parts. Male headed households and large size households are more likely to have the needed labor to construct terraces.

Status of the plot (field use) has also affected the choice of SWC technology by farm households in Ethiopia. The study found that, relative to crop land, pasture land is positively and significantly associated with terracing (P=0.01) and afforestation (P=0.01). On the other hand, previously forested land would likely remain to be forest, practice water catchment, and move livestock along the field. Proportion of crop land from the total land is positively associated with only one SWC technology, which is the construction of water canal. In any of the other technologies, increased proportion of crop land has a negative coefficient, showing the trade-off between cultivating the land and conserving the land.

Slope the land is an important factor that exacerbates soil erosion unless mitigated by the adoption of appropriate SWC technology. Accordingly, the study included the variable to examine its effect on the choice of SWC technologies. It is evident from Appendix Table 2 that increased slope (steeper slopes) are positively and significantly associated with constructing terrace and water canal. In fact, the two SWC technologies are the most appropriate measures to mitigate soil erosion in plots with steeper slopes. Similar results are found in (Asrat and Simane, 2017a; Meseret and Amsalu, 2017).

As expected, average annual rainfall is positively and significantly associated with water catchment as a method of SWC technology. Similarly, there is a positive and statistically positive correlation between average annual rainfall and farm households' construction of water canal in their plot. The finding clearly depicts the fact that farm households collect water and construct water canal when there is an increased rainfall that would otherwise erode their land. The two SWC technologies are the potential prevention mechanism especially in the short term whenever there is an increased flow of water as a result of increased rainfall.

Conclusion

The study attempted to examine the factors that determine adoption and choice of SWC technology in

Ethiopia using the data from ESS4/2019. More importantly, the paper assessed the effect of poverty on farm households' adoption decision. It is found that poverty is important factor in adoption decision of SWC technologies by farm households. As can be seen from the current study annual consumption per adult equivalence, which is an indicator, poverty is positively and significantly associated with adoption of SWC technology. Similarly, capital and labor intensive SWC technologies like terracing are also positively associated with increased ACPAE.

Apart from poverty, the impact of other factors on adoption and choice of SWC technology is also investigated by the study. It is found that household level characteristics like head age, size of household active labor, household average education, and head sex has significantly affected the likelihood of adopting and choice of SWC technologies at plot level by land owners. Similarly, plot level characteristics (plot size, slope of the land, and average annual rainfall) are found to have significant effect on farm households' decision of adopting and choice of SWC technology in Ethiopia. On the other hand, cultivated land as compared to other land use types is positively associated with adoption of SWC technologies by land holders.

With regard to the choice of conservation technology, terracing followed by plough along the contour are the most practiced method of soil erosion prevention by farm households in Ethiopia. Adoption of terracing is positively associated with increased annual consumption per adult equivalence an indicator of poverty in the current study. Similarly, all other socioeconomic and plot level characteristics have significantly affected the choice of SWC technologies available for land holders. However, each variable in the study has a different effect on the choice of the conservation technology.

Recommendation

From the empirical evidence obtained from the current study it would be clear and logical that efforts targeting to increase adoption of NRM in general and SWC technologies in particular need to be augmented by policies that could mitigate poverty both at household and community level. The fact that adoption of SWC technology is negatively associated with poverty, tells us that the objective of achieving increased productivity and food security requires a twin policy set. This policy at one hand should encourage the adoption of SWC technologies and simultaneously increase the economic capability of farm households to invest on the technologies. The most important innovative policy in this regard could be the introduction of Payment for Ecosystem Service, which targets poverty and ecosystem conservation simultaneously.

The positive correlation observed between cultivated land and adoption of SWC technology clearly demonstrate the fact that farm households need to be promoted to engage more in production of farm outputs. Specially, devising effective policy that encourages farm households to be more market oriented could achieve the objectives of increased productivity, food security and poverty alleviation. It is a market-oriented farm household that would find it profitable to invest more on SWC technologies. This however, requires a significant land policy change in the country, where more efficient and profitable farmers can buy land and engage in production of agricultural goods for the market.

Another area is where policy makers and interventionist could work more to promote adoption of SWC technology by providing information and training. Though not supported by the empirical result farm household's adoption of SWC technology could be promoted via information access. This could significantly change the behavior of farm households by effectively communicating the benefits of SWC and success stories of adoption. Accordingly, it would be advisable for policy makers and interventionists to identify mechanisms, where farm households can have access to information and learn from success stories of SWC adoptions.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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APPENDIX

Table 1. Farm households' decision of SLM technologies (Multinomial Logit Model result).

SWC technologies (Terracing base outcome)	Log likelihood = -10947.22		Number of obs.= 8,709				LR Chi²(150) =3274		Prob >Chi²=0.0000		Pseudo R2=0.1301	
	Water Catchments		Afforestation		Plough A. Contour		Moving livestock in the field		Water canal		Other SWC	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Poverty status	-0.074	0.0643	-0.48	0.108***	-0.249	0.0464***	-0.386	0.122**	-0.333	0.08***	-0.41	0.162**
% HH Inc. NFE	-0.0055	0.0037	0.019	0.004***	0.003	0.0024	0.018	0.0042***	0.012	0.003***	-0.007	0.011
Total Field Size	-0.219	0.0462***	0.295	0.0843***	0.41	0.0354***	-0.346	0.0814***	0.144	0.059**	0.0033	0.12
Access to information												
Fixed Line tele	-0.116	0.135	-0.79	0.1999***	-0.46	0.09***	-0.521	0.234**	-0.163	0.14	-0.534	0.288*
Television	-0.822	0.234***	0.489	0.749	-0.166	0.214	-0.628	0.552	0.017	0.499	-0.573	0.75
Demographic characteristics												
HH Sex	-0.344	0.11112***	0.458	0.176***	-0.112	0.079	-0.558	0.237**	-0.047	0.129	-0.841	0.32***
HH Size	-0.096	0.0262***	0.079	0.044*	-0.067	0.0186***	0.049	0.0498	-0.158	0.0297***	-0.162	0.066**
HH Active Labor	0.0854	0.0314***	-0.059	0.057	0.0296	0.023	0.076	0.063	0.108	0.037***	0.094	0.08
HH Age	0.0715	0.0185***	-0.082	0.0273***	-0.0065	0.013	-0.01	0.0334	0.02	0.021	.052	0.048
HH Age^2	-0.00055	0.00018***	0.00087	0.00026***	0.000088	0.0001	0.0002684	0.00031	-0.00023	.0002	-0.00054	0.0005
HH Ave. Edu.	-0.0086	0.0066	-0.00007	0.013	0.011	0.0043***	-0.0022	0.016	0.0185	0.0063***	-0.028	0.022
Field status-*crop land is the comparison category*												
Pasture	-0.257	0.201	1.002	0.221***	-0.718	0.153***	0.264	0.33	-0.473	0.21**	1.498	0.27***
Fallow	-0.325	0.309	-1.75	1.016*	-0.113	0.199	0.258	0.48	-1.42	0.498***	1.04	0.452**
Forest	0.517	0.288*	2.53	0.26***	-0.487	0.273*	1.21	0.46***	0.104	0.31	0.534	0.74
Land (Belg Season)	-0.30	0.323	-0.41	0.54	-0.587	0.232**	-0.773	0.733	-0.57	0.34*	-0.605	1.02
Home/Homestead	0.035	0.084	-0.38	0.178**	0.236	0.061***	-0.955	0.21***	-0.438	0.0996***	-0.31	0.24
Other (Specify)	0.428	0.216**	1.09	0.299***	0.255	0.167	-0.232	0.447	0.314	0.22	-0.4	0.73
Slope Land	-0.025	0.0049***	-0.058	0.0084***	-0.055	0.0035***	-0.042	0.0095***	0.054	0.006***	-0.034	0.0122***
% Crop Land	-0.015	0.0034***	-0.026	0.0055***	-0.0088	0.0023***	-0.0513	0.0063***	0.134	0.005***	-0.024	0.0082***
Ave. Annual RF	0.00078	0.00016***	0.00074	0.00026***	0.00049	0.00011***	0.002	0.0003***	0.0042	0.00021***	0.0016	0.0004***
Land tenure type-*private land is the comparison category*												
Free of rent	-0.12	0.285	-0.88	0.61	0.133	0.181	1.43	0.365***	0.232	0.41	0.7	0.5
Rented	0.659	0.345*	-1.29	1.042	-0.141	0.29	-15.03	967.3	-1.08	0.75	-14.9	1300.5
Others specify	-17.4	3731.3	-17.02	6837.7	-17.01	2215.6	-16.5	7735	-15.4	3822.6	-15.9	10192.9
Distance N_M_Road	-0.012	0.00275***	-0.001	0.004	0.0086	0.00164***	0.0025	0.0045	0.0058	0.0025**	-0.0027	0.006
Dis. Reg Capital	2.46	0.381***	5.44	0.66***	2.94	0.289***	1.92	0.779**	4.48	0.547***	0.27	1.01
Constant	0.34	0.923	1.51	1.63	-0.1284	0.68	4.35	1.69**	-10.52	1.198***	0.91	2.35

Source: Authors

Table 2. Marginal effect after multinomial logit.

SWC technology	Terracing		Water Catchments		Afforestation		Plough A. Contour		Moving livestock in the field	
Variable	**Dy/dx**	**Std. Err.**	**Dy/dx**	**Std. Err.**	**Dy/dx**	**Std. Err.**	**Dy/dx**	**Std. Err.**	**Dy/dx**	**Std. Err.**
Poverty (ACPAE)*	0.054	0.0086***	0.0065	0.0055	-0.0096	0.003***	-0.028	0.008***	-0.0052	0.0026**
Total Field Size	-0.042	0.0063***	-0.033	0.00394***	0.00514	0.0023**	0.08	0.0059***	-0.0103	0.00174***
% HH Inc. NFE	-0.0008	0.00044*	-0.00078	0.00033**	0.00049	0.00011***	0.00017	0.0004	0.00035	0.00009***
Fixed Line tele	0.08	0.018***	0.0092	0.0114	-0.016	0.0055***	-0.066	0.015***	-0.0063	0.0049
Television	0.0595	0.041	-0.069	0.0196***	0.019	0.021	-0.0054	0.038	-0.01	0.012
HH Sex	0.035	0.015**	-0.0262	0.0096***	0.0164	0.0049***	-0.007	0.014	-0.01	0.0051**
HH Size	0.017	0.00344***	-0.0057	0.0023**	0.0036	0.0012***	-0.0065	0.0032**	0.002	0.0011*
HH Act. Labor	-0.0114	0.0043***	0.0059	0.0027**	-0.0026	0.0016*	0.00012	0.004	0.0011	0.0013
HH Age	-0.0025	0.0024	0.0068	0.0016***	-0.0026	0.00076***	-0.0032	0.0022	-0.00034	0.0007
HH Age^2	0.000014	0.00002	-0.000054	0.000016***	0.00003	7.20e^{-06}***	0.00003	0.00002	6.35e^{-06}	6.62e^{-06}
HH Ave. Edu.	-0.00134	0.00083	-0.0012	0.00057**	-0.00011	0.0003652	0.0021	0.00076***	-0.00011	0.00035
Field status										
Pasture	0.087	0.026***	-0.0048	0.018	0.0363	0.0062***	-0.134	0.027***	0.01	0.007
Fallow	0.087	0.041**	-0.012	0.027	-0.045	0.029	0.0334	0.0363	0.011	0.01
Forest	-0.014	0.045	0.048	0.024**	0.073	0.0072***	-0.145	0.047***	0.025	0.0095***
Land for B_Season	0.115	0.041***	-0.0011	0.028	-0.0023	0.015	-0.076	0.042*	-0.01	0.016
Homestead	0.00055	0.012	0.0039	0.0072	-0.011	0.005**	0.066	0.011***	-0.021	0.0046***
Other (Specify)	-0.0674	0.031**	0.027	0.018	0.027	0.0081***	0.021	0.028	-0.0095	0.0094
Slope Land	0.0069	0.00062***	-0.00072	0.00041*	-0.0011	0.00023***	-0.0099	0.00058***	-0.00045	0.0002**
% Crop Land	-0.0019	0.00041***	-0.0018	0.00026***	-0.00085	0.00014***	-0.0037	0.00035***	-0.0012	0.00014***
Ave. Annual RF	-0.00027	0.000021***	0.000014	0.000013	6.85e-07	6.77e^{-06}	-0.00006	0.000018***	0.00003	6.30e^{-06}***
Land tenure type										
Free of rent	-0.024	0.037	-0.0189	0.025	-0.028	0.017*	0.019	0.032	0.031	0.0078***
Rented	0.25	11.34	0.14	3.41	-0.01	1.3	0.16	8.65	-0.32	20.9
Others specify	3.7	352.1	-0.83	348.8	-0.198	196.3	-1.98	452.4	-0.14	168.6
D_N_M_Road	-0.0006	0.00032*	-0.0014	0.00024***	-0.00009	0.00011	0.0018	0.0003***	0.000023	0.000094
Dis. Reg Capital	-0.68	0.054***	0.079	0.032**	0.105	0.019***	0.31	0.048***	0.0014	0.0162

ACPAE=Annual Consumption Per Adult Equivalence.
Source: Own computation based on ESS-2019 data.

Table 2. Contd.

SWC measures	Water Canal		Other SWC	
Variable	**Dy/dx**	**Std. Err.**	**Dy/dx**	**Std. Err.**
Poverty (ACPAE)	-0.015	0.0053***	-0.0036	0.0022
Total Field Size	0.0016	0.004	-0.0014	0.0015
% HH Inc. NFE	0.00071	0.0002***	-0.00013	0.00015
Fixed Line tele	0.0037	0.009	-0.0043	0.0038
HH Sex	0.003	0.0087	-0.0103	0.00434**
Television	0.012	0.034	-0.0058	0.01
HH Size	-0.0087	0.002***	-0.0017	0.0009*
HH Active Labor	0.0061	0.0025**	0.0009	0.0011
HH Age	0.0012	0.0014	0.00065	0.00065
HH Age^2	-0.00002	0.000014	-7.14e-06	6.54e-06
HH Ave. Edu.	0.0011	0.00042***	-.00044	0.0003
Field status				
Pasture	-0.018	0.014	0.024	0.004***
Fallow	-0.091	0.034***	0.0175	0.0062***
Forest	0.0069	0.02	0.0064	0.0095
Land for Belg Season	-0.021	0.023	-0.0041	0.014
Homestead	-0.034	0.0066***	-0.0041	0.003
Other (Specify)	0.011	0.014	-0.008	0.01
Slope Land	0.0055	0.00039***	-0.0002	0.00016
% Crop Land	0.0098	0.0003***	-0.00036	0.0001***
Ave. Annual RF	0.00027	0.000014***	0.000013	5.06e-06***
Land tenure type				
Free of rent	0.013	0.028	0.0087	0.0067
Rented	-0.037	1.9	-0.19	17.7
Others specify	-0.45	274.2	-0.084	139.1
Distance N_M_Road	0.00029	0.00017*	-0.00006	0.00008
Dis. Reg Capital	0.21	0.036***	-0.021	0.0134

Source: Own computation based on ESS-2019 data