



Impact of soil and water conservation practices on household vulnerability to food insecurity in eastern Ethiopia: endogenous switching regression and propensity score matching approach

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Abstract

Governmental and developmental partners invest substantial resources to reduce land and water degradation in order to upgrade agricultural productivity, thus reducing food insecurity and related vulnerability in Sub-Saharan Africa. Understanding the impact of soil and water conservation on food insecurity outcomes would be a significant step toward improving environmental conditions, while ensuring sustainable and increased agricultural production. Therefore, this article analyzes the impact of adopting soil and water conservation on food insecurity and related vulnerability outcomes of farming households using a sample of 408 households selected using a multi-stage stratified sampling procedure from three districts in eastern Ethiopia. Vulnerability as expected poverty (three-step Feasible General Least Squares) is employed to analyze the vulnerability of sample households in the context of food insecurity. In addition, endogenous switching regressions with propensity score matching methods are combined to obtain consistent impact estimates. The study findings reveal that education and sex of household head, use of irrigation and fertilizer, source of information, and cultivated land are the main factors influencing the adoption of soil and water conservation practices. Moreover, the adoption of soil and water conservation not only positively impacts the per capita food consumption expenditure and net crop value, but it also significantly reduces the probability of farmers being food insecure, vulnerable to food insecurity, as well as being transient and chronically food insecure. Therefore, policymakers and development organizations should consider soil and water conservation as a main strategy to reduce land degradation and improve the livelihoods of the rural farm households.

Keywords Soil and water conservation · Endogenous switching regression · Vulnerability to food insecurity · Ethiopia

1 Introduction

Ethiopia is one of the fastest growing countries in sub-Saharan Africa, with double digit economic growth in most years since 2005. Between 2000 and 2015, the poverty level fell from 44 to 30% of the population (IFPRI 2015). However, the figure remains high and Ethiopia ranks 174 out of 188 countries on the 2015 UN Human Development Index and 104 out of 119 in the Global Hunger Index ratings (IFPRI 2017). IFPRI (2015) also reports that a large portion of the country's population, about 40%, consumes less than the recommended daily calories. Agriculture, which employs about 72% of the active population in Ethiopia, could have contributed significantly in reducing poverty and food insecurity in the country. However, the levels of poverty and food insecurity remain high, especially in the rural areas of Ethiopia (World Bank 2016).

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Food insecurity and poverty in Ethiopia is a long-term phenomenon caused by a combination of both natural and man-made factors; which include among others the limited opportunities for livelihood diversification, unreliable rainfall patterns, land degradation, poor infrastructure, poor access to agricultural inputs, and limited credit facilities (Dercon and Christiaensen 2011; Dercon and Krishnan 1998; Wisner et al. 2004; Wisner et al. 2004). Land and water degradation significantly affects household poverty, food insecurity, and related vulnerability. Empirical evidence shows that aggregate impacts of land and water degradation on food security are negative (see Berry et al. 2003; Demel 2001; Paulos 2001; Shibru and Kifle 1998; Demel 2001; Shibru 2010).

The available information further indicate that over 25% of the land in Ethiopia is degraded at moderate to very severe levels (Kirui and Mirzabaev 2016) and about 0.084 million km², or 9.5% of the country constitutes one of the most intensively eroded regions in the world (Borrelli et al. 2017). Erosion is more severe in the Ethiopian highland, where 85% of the country's human population lives, along with 77% of livestock population, and where there is intensive agriculture (Bewket 2007). Paulos (2001) and Berry et al. (2003) estimate losses caused by land degradation and unsustainable land management in Ethiopia to amount to billions of Birr.¹ Accordingly, Ethiopia loses at least 3 % of agriculture Gross Domestic Product (GDP) annually; which is equivalent to US\$ 162 million in 2007 agricultural GDP (Gebreselassie et al. 2015). Moreover, land and water degradation reduces agricultural productivity, thus contributing immensely to food insecurity and poverty (Shibru 2010). It is estimated that the amount of grain lost due to land degradation could feed more than 4 million people annually (Demel 2001).

Due to extensive land degradation, the natural resource base is deteriorating over time, directly resulting in food insecurity and related vulnerability (Barrett et al. 2002; Berhanu et al. 2010; Pender and Gebremedhin 2006). For instance, land and water degradation could affect all dimensions of food security in complex ways (food availability, accessibility, sustainability, and utilization). Land and water degradation has reduced agricultural production and productivity, while also affecting dietary diversity due to changes in the suitability of land for crop production (Pimentel and Burgess 2013; Sonneveld 2002; Demel 2001). This may directly affect household income and food availability. Lower yields could increase the prices of major crops due to reduced market supply at local and national levels (Slaymaker 2002). Under such circumstances, subsistence farmers, who already have high food expenditures, would have to sacrifice further to meet their adequate nutritional requirements and, in addition, would be unable to escape food insecurity in the near future (Stocking 2003).

¹ Birr is Ethiopia currency (1USD = 23.32 Birr).

Sustainable use of natural resources at household and community levels may improve the welfare of farming households and help them become food secure while escaping the vulnerability trap. Various studies (Hishe et al. 2017; Amare et al. 2014; Tenge et al. 2011; Keesstra et al. 2018) indicate that Soil and Water Conservation (SWC) practices help the reduced rainfall to be transformed into runoff that increases soil fertility and moisture content, improves soil health and function and restores and maintains the eco-system. In the long run, SWC will improve the ecology and environment as well as local climate, which is directly and indirectly associated with sustainable agriculture. Thus, adopting SWC could substantially impact not just crop production, but also the household income of smallholder farmers. According to Bogale and Shimelis (2009), and Mozumdar (2012), high production and household income increase farmers' purchasing power and consumption from own production. Moreover, as argued by Jenkins et al. (2003), Finnie and Sweetman (2003), and Devicienti (2002) households with high income are less likely to be food insecure and less vulnerable to external shocks.

The Ethiopian government has considerable investments in conserving the environment, with its main objective being the improvement of livelihood opportunities through improved environmental conditions that ensure sustainable and increased agricultural production. During the 1980s, the country started SWC campaigns, encouraging the implementation of SWC practices in drought prone and extremely land degraded parts of Ethiopia (Mekuriaw and Humi 2015). However, as farmers were forced to implement a conservation structure designed by experts, the program was not effective (Haregeweyn et al. 2015; Mekuriaw et al. 2018; Mekuriaw and Humi 2015; Wolka 2014). Since the Ethiopian People Republic Democratic Front (EPRDF) came to power in 1991, SWC has been a part of the agriculture extension package.

Since the beginning of the 2000s, under the SDPRP² framework launched in 2002 and the PASDEP launched in 2005, participatory watershed management has been recognized by the government. Given this strategy, different sustainable land management programs have been implemented throughout the country. Further, the country developed a national guideline known as Community Based Participatory Watershed Development Program (CBPWDP) in 2005 (MoARD 2005). Additionally, the integrated SWC implements different conservation technologies (such as Bench terracing, Soil bund, Stone bund, farm forestry, and so on) in

² "Two successive Poverty Reduction Strategic Papers (PRSP), i.e., the Sustainable Development and Poverty Reduction Program (SDPRP) launched in 2002 and the Plan for Accelerated and Sustained Development to End Poverty (PASDEP) were instituted in 2005. The two broad strategies of PASDEP are to reduce poverty by stimulating rural growth through agriculture and rural development, and to strengthen public institutions to deliver services" (Gelaw and Sileshi 2013).

selected areas. The main goal of this approach is to improve the living standards and welfare of the most vulnerable rural households and communities through SWC practices on individual farm plots and communal land. These consist of not only rainwater harvesting but also of promoting sustainable and income diversifying agricultural practices (Gebregziabher et al. 2016). In addition, the program also promotes and provides training for farmers on how to integrate SWC with live-stock fattening, improved poultry and apiculture production, and promotion of fruit tree planting.

Despite these efforts to improve livelihood opportunities, as well as increase farm productivity through improved environmental conditions, the impacts of conservation practices on food consumption expenditure, food insecurity, and related vulnerability outcomes are not yet systematically analyzed. Various studies have examined the impact of SWC on technical efficiency, crop productivity, and household income. A study on the impact of SWC in Rwanda and the Democratic Republic of the Congo shows that adopting SWC reduces technical efficiency (Judith et al. 2011). Kassie and Holden (2006) found that SWC in Ethiopia has yielded very low returns, with most smallholder farmers not receiving adequate incentive from their initial investment. In addition, Nyangena and Köhlin (2009), also revealed that plots under SWC practices generate lower yields than those without. In contrast, Adgo et al. (2013), in their study of the impact of SWC practices in Ethiopia, found that the adoption of these practices can significantly increase the productivity of *teff*, barley, and maize. In Zimbabwe, Zikhali (2008), also found that soil conservation technology enhanced productivity. The studies by Bekele (2003) and Yenealem et al. (2013) also found that plots under SWC practices significantly increased crop production compared to those without. In another study, Tesfaye et al. (2016) confirmed that SWC practices in Ethiopia increased grain productivity, thus benefiting farm communities.

However, most of these previous studies have focused their analysis on current production and household crop income (e.g., Adgo et al. 2013; Bekele 2003; Yenealem et al. 2013; Zikhali 2008), failing to address the effect of conservation measures on current and expected welfare problems (food insecurity and related vulnerability) as well as other food security categories (transient and chronic food insecurity). To the best of our knowledge, this is the first rigorous paper that examines the association between food insecurity and related vulnerability with adoption of SWC in Africa, in general, and Ethiopia, in particular. Impact assessment provides major inputs for policy makers and planners when designing and developing effective and sustainable conservation strategies to mitigate current and future food insecurity through increased farm productivity. This paper employs the standard Per Capita Food Consumption Expenditure (PCFCE) and the Vulnerability as Expected Poverty (VEP) approaches to measure food security and Vulnerability to Food Insecurity (VFI)

for farming households, respectively. This allows us to check the impact of adoption on current food insecurity as well as expected food insecurity after taking idiosyncratic shocks into account. Thus, the empirical premise of this article is to analyze the direction and magnitude of SWC effects on PCFCE, net crop value, food insecurity, and VFI in eastern Ethiopia. Moreover, the paper focuses on further disaggregated categories of food security among adopters and non-adopters, assessing the relationship between SWC adoption and food insecurity along with related vulnerability outcome variables by controlling for the effects of confounding factors.

The article is structured in five sections including the introduction part. The second section presents the sampling and data collection procedure, and a brief description of the study area. The third section describes the empirical methods and approaches used in the study. Specifically, we describe the analytical procedure for carrying out Endogenous Switching Regression (ESR), Propensity Score Matching (PSM), and VFI assessment. The fourth section discusses the results and the fifth section winds up the article by presenting some concluding remarks and policy implications that emanate from the study.

2 Study approach, methodology and description of the study area

2.1 Sampling procedure and data collection

The study was conducted in East Hararghe, Ethiopia, in August and September, 2017. A multi-stage sampling technique was employed to select districts, *kebeles*,³ and sample households. In the first stage, three districts (Deder, Gurugutu and Haramaya) were selected randomly from the program intervention area. In the second stage, three *kebeles* were selected purposively from each district based on the extent of soil degradation and program implementation. Thereafter, the households were stratified into two strata (control and treated villages). However, the two strata comprised the same social, infrastructural, agro-climatic, and economic characteristics. Finally, 208 households that did not adopt any SWC measures from control villages where no SWC interventions were made and 200 households that did adopt at least one SWC measures from treated villages with SWC interventions were randomly selected using proportionate probability sampling based on the size of each district and *kebele* (Table 1).

For the household survey, a structured questionnaire was designed and pretested before the actual survey. The survey covered a wide range of issues that influence SWC technology adoption, as well as food security and related vulnerability at

³ *Kebele* is usually a named peasant association and is the lowest administrative unit in the country.

Table 1 Sample districts, *Kebeles* and number of sample households

Districts	<i>Kebeles</i>	Adopters sample	Non- adopters sample	Total sample
Deder	Chafe Gurumu	28	27	55
	Gaba Gudina	34	30	64
	Walfaa Gabon	21	17	38
Gurugutu	Biftu Dirama	15	17	32
	Ifa Jalala	29	25	54
	Mauhasa Walfaa	16	22	38
Haramaya	Biftu Geda	17	24	41
	Amuma	15	20	35
	Ifa Oromiya	25	26	51
Total		200	208	408

household levels. The survey collected information on each household's socio-economic and institutional characteristics, SWC practices, different shocks and coping strategies, as well as the available relevant food security programs and activities. Furthermore, information on the types and amount of food consumed by each household from different sources was collected. This 'food basket' was valued at local prices to determine PCFCE of the households and food poverty line.

2.2 Description of the study area

The study area (East Hararge) is found in eastern Ethiopia. It is a zone in the regional state of Oromia located between latitudes 7°32'– 9°44' North and longitudes 41°10'– 43°16' East. East Hararghe is characterized by rugged, dissected mountains, deep valleys, plateaus, and plains, which are categorized into plateau, lowland, and transitional slope with altitudes ranging from 500 to 3405 m above sea level (PEDO, 2012). The zone has three agro-ecological zones namely the semi-arid (62.2%), semi-temperate (26.4%), and temperate tropical highlands (11.4%). This wide range of agro-climatic zone allows the area to produce a variety of products, including cereal crops such as sorghum, maize, wheat, and *teff*; vegetables such as potatoes, onions, shallots, and cabbage; as well as perennial crops such as coffee and *Khat* (*Catha adulis*). Livestock keeping is also an integral activity of farmers.

East Hararge is highly prone to regular droughts as well as serious degradation of land and other natural resources. Thus, the central and regional governments, along with other development partners, promote different policies and programs to reverse this situation. For instance, with the framework of the federal government's CBPWD, an integrated SWC program has been implemented since 2006 in selected districts. The main goal of this program is to improve the livelihood opportunities of rural communities and reduce food insecurity and

poverty through integrated natural resource management (Gebregziabher et al. 2016).

3 Econometric modeling strategy

3.1 Endogenous switching regression (ESR)

When making an accurate impact assessment of SWC adoption on food insecurity and the VFI of farm households, the observable and unobservable characteristics of the adopters (treatment group) and non-adopters (control group) must be captured. However, most impact assessment approaches using non-experimental data (not randomly assigned) fail to capture observable and/or unobservable characteristics that affect adoption and outcome variables. For instance, instrumental variables capture only unobserved heterogeneity, but the assumption is that the parallel shift of outcome variables can be considered as a treatment effect (Ahmed et al. 2017; Kabunga et al. 2012; Shiferaw et al. 2014). In contrast, using regression models to analyze the impact of a given technology using pooled samples of users and non-users might be inappropriate because it gives the similar effect on both groups (Ahmed et al. 2017; Kassie et al. 2010; Kassie et al. 2011b). A methodological approach that overcomes the aforementioned limitations is endogenous switching regression (ESR), which is the most frequently used common method to analyze the impact of a given technology (Abdulai and Huffman 2014, 2014; Ahmed et al. 2017; Asfaw et al. 2012; Di Falco et al. 2011; Jaleta et al. 2018; Kabunga et al. 2012; Kassie et al. 2011a; Shiferaw et al. 2014). In this paper, we employ parametric ESR with non-parametric PSM techniques to reduce the selection bias and assure consistent results by capturing both the observed and

unobserved heterogeneity that influence the outcome variable as well as the adoption decision.

The impact of SWC technology on food insecurity and related vulnerability under the ESR framework follows two stages. The first stage, adoption of SWC is estimated using a binary probit model as selection, while in the second stage both linear regression and binary probit models are employed to assess the association between outcome variable and adoption of SWC (Jaleta et al. 2018; Shiferaw et al. 2014). The detail of the econometric modeling framework used is specified below.

The study adopts the expected utility maximization theory for farmer adoption of SWC measures. Individual i adopts SWC on their farm plot if expected utility from adoption (U_{swc}) is greater than the expected utility from non-adoption (U_{nswc}), i.e. $U_{\text{swc}} - U_{\text{nswc}} > 0$.

$$I_i^* = \beta X_i + v_i \text{ where } I_i = \begin{cases} 1 & \text{if } I_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Where I_i^* is the latent variable capturing the unobserved preferences associated with the adoption of SWC determined by observed farm and socio-economic characteristics of the household (X_i) and the error term (v_i). I_i is the observed binary indicator variable that equals 1 if a farmer adopts SWC practices and zero otherwise, while β is a vector of parameters to be estimated.

In this article, adoption is defined as farmers using at least one of the introduced SWC technologies (soil bund, stone bund, and bench terracing) on one of their farm plots. However, according Jaleta et al. (2018), if the selection equation (first stage) is endogenous in the outcome equation (second stage), results would be biased and inefficient. Therefore, it is vital to use instrumental variable methods to identify the second stage equation from the first stage equation. The instrumental variable should affect the adoption of SWC but not the outcome variables, such as PCFCE, net crop value, food insecurity, VFI, as well as chronically and transient food insecure. While we acknowledge that the selection of instrumental variables is empirically challenging, we use sources of information (government extension (yes = 1) and farmers cooperatives (yes = 1)) as selection instruments. Adegbola and Gardebroke (2007) indicated that the source of information is a vital element in influencing adoption of a given agricultural technology. Shiferaw et al. (2014), Di Falco et al. (2011), and Khonje et al. (2015) use these variables as instruments to assess the impact of adopting improved seed and adaptation to climate change on household food security and welfare. Thus, these variables are more likely to be correlated with the adoption of SWC but not with the food insecurity and vulnerability outcome variables or correlated with the unobserved. Moreover, we also checked the validity of the instrument

variable using a falsification test. The test showed that the variable significantly affected the adoption decision but not our outcome variables.⁴

The outcome regression equations both for adopters (regime 1) and non-adopters (regime 2) can be written as an endogenous switching regime model:

$$\text{Regimes 1 : } Y_{1i} = \theta_1 Z_{1i} + \varepsilon_{1i}, \text{ if } I = 1 \quad (2a)$$

$$\text{Regimes 2 : } Y_{2i} = \theta_2 Z_{2i} + \varepsilon_{2i}, \text{ if } I = 0 \quad (2b)$$

where Y_i represents outcome variables (PCFCE, net crop value and a binary outcome variables such as food insecurity, VFI, chronically and transient food insecure status) of small-holder farmer i for each regime (1 = adopter of SWC practices and 0 = non-adopter of SWC practices), Z_i is a vector of farm and socio-economic characteristics of household that affects outcome variables, and θ_i is a vector of parameters to be estimated. The error terms in Eqs. (1) and (2) are distributed to be trivariate normal, with mean zero and a non-singular covariance matrix:

$$\text{cov}(\varepsilon_1, \varepsilon_2, v) = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{1v} \\ \sigma_{21} & \sigma_2^2 & \sigma_{2v} \\ \sigma_{v1} & \sigma_{v2} & \sigma_v^2 \end{pmatrix}, \quad (3)$$

where σ_1^2 , σ_2^2 , and σ_v^2 are the variance of the outcome function of regimes 1 and 2, as well as the selection equation, respectively, σ_{12} , σ_{1v} , and σ_{2v} represent the covariance of ε_{1i} , ε_{2i} , and v_i . The variance of selection question (σ_v^2) is assumed to be equal to 1 since the coefficients (β) are estimable only up to a scale factor. Maddala (1983), confirmed that the covariance of the error terms (ε_{1i} and ε_{2i}) is not defined since outcome variables (Y_{1i} and Y_{2i}) are not captured at the same time. The expected values of error term of the second stage are non-zero because the error term of the first stage (v_i) and second stage (ε_{1i} and ε_{2i}) are associated to each other. The expected value of error terms of question (2a) and (2b) can be expressed as follows:

$$E(\varepsilon_{1i} | Y_i = 1) = \sigma_{1v} \frac{\phi(\beta X_i)}{\Phi(\beta X_i)} = \sigma_{1v} \lambda_{1i} \quad (4a)$$

$$E(\varepsilon_{2i} | Y_i = 0) = \sigma_{2v} \frac{\phi(\beta X_i)}{1 - \Phi(\beta X_i)} = \sigma_{2v} \lambda_{2i} \quad (4b)$$

where $\phi(\cdot)$ is the standard normal probability density function, $\Phi(\cdot)$ is the standard normal cumulative density function, while $\lambda_{1i} = \frac{\phi(\beta X_i)}{\Phi(\beta X_i)}$ and $\lambda_{2i} = \frac{\phi(\beta X_i)}{1 - \Phi(\beta X_i)}$ are the inverse Mills ratios

⁴ Instrument variable are jointly statistically significant in the selection equation [$\chi^2 = 25.30$ ($p = 0.0000$)] but not outcome functions: for example binary food insecurity status of adopter [$\chi^2 = 1.11$ ($p = 0.5742$)] and non-adopter; [$\chi^2 = 1.04$ ($p = 0.5937$)] as well as the PCFCE for adopters [$F = 0.43$ ($p = 0.6520$)] and non-adopters [$F = 0.87$ ($p = 0.4188$)]. We also find similar results for other outcome functions (net crop value and binary chronic and transitory food insecurity, VFI).

(IMR) estimated from the first stage question. Then the variable included in the second stage questions captures both absorbed and unabsorbed heterogeneity in estimation procedure ESR (Jaleta et al. 2018). To address the heteroskedasticity arising from the generated regressors, the standard errors in questions (2a) and (2b) are bootstrapped (Ahmed et al. 2017; Jaleta et al. 2018; Shiferaw et al. 2014).

Based on the above context, comparing real and counterfactual scenarios of expected values of the outcomes of adopters, the average treatment effect on the treated (ATT) is obtained. Similarly average treatment effect on the untreated (ATU) also can be calculated by comparing the expected values of the outcomes of non-adopter in real and counterfactual scenarios (Khonje et al. 2015). Following Abdulai and Huffman (2014); Asfaw et al. (2012); Jaleta et al. (2018); Kabunga et al. (2012); Shiferaw et al. (2014), the expected values of the outcomes of both adopters and non-adopters in reality and the counterfactual are given as follows:

Adopters with adoption of SWC (real):

$$E[Y_{1i}|X, I = 1,] = \theta_1 X_{1i} + \sigma_{1v} \lambda_{1i} \quad (5a)$$

Non-adopters without adoption of SWC (real):

$$E[Y_{2i}|X, I = 0,] = \theta_2 X_{2i} + \sigma_{2v} \lambda_{2i} \quad (5b)$$

If adopted had non-adopted SWC (counterfactual):

$$E[Y_{2i}|X, I = 1,] = \theta_2 X_{1i} + \sigma_{2v} \lambda_{1i} \quad (5c)$$

If non-adopted had adopted SWC (counterfactual):

$$E[Y_{1i}|X, I = 0,] = \theta_1 X_{2i} + \sigma_{1v} \lambda_{2i} \quad (5d)$$

Hence, ATT of adopter is computed as the difference between (5a) and (5c):

$$\begin{aligned} ATT &= E[Y_{1i}|X, I = 1,] - E[Y_{2i}|X, I = 1,] \\ &= (\theta_1 - \theta_2) X_{1i} + (\sigma_{1v} - \sigma_{2v}) \lambda_{1i} \end{aligned} \quad (6)$$

Likewise, ATU of non-adopters is computed as the difference between (5b) and (5d):

$$\begin{aligned} ATU &= E[Y_{1i}|X, I = 0,] - E[Y_{2i}|X, I = 0,] \\ &= (\theta_1 - \theta_2) X_{2i} + (\sigma_{1v} - \sigma_{2v}) \lambda_{2i} \end{aligned} \quad (7)$$

According to Khonje et al. (2015), Shiferaw et al. (2014) and Ahmed et al. 2017, ESR models have a very strong exclusion restriction and the falsification test may not be adequate to confirm identification. Thus, results may be sensitive to selection of instrumental variables. Therefore, we also used binary PSM to further check the robustness of the results obtains from ESR. PSM helps to adjust for the initial differences between treated and control groups by constructing a statistical comparison group that is based on a model of the probability of treatment participation, using observed farm

and socio-economic characteristics (Caliendo and Kopeinig 2008; Rosenbaum and Rubin 1983; Winters et al. 2011). Adopters are then matched on the basis of this probability (propensity score) to non-adopters (Rosenbaum and Rubin 1983). The ATT of the SWC can be obtained by comparing the mean outcomes between treatment and control groups (Imbens and Wooldridge 2008; Wooldridge 2002; World Bank 2010). This approach is widely applied in the literature (e.g., Amare et al. 2012; Dillon 2011; Kassie et al. 2010; Manda et al. 2018) and we do not present the detail methodology here. For a detailed specification and the steps of PSM, see Imbens and Wooldridge (2008), Wooldridge (2002), and World Bank (2010).

3.2 Vulnerability as expected poverty

We adopt an econometric model for analyzing household vulnerability to food insecurity proposed by Chaudhuri et al. (2002) and Christiaensen and Subbarao (2005). The model follows the VEP approach, using PCFCE as a measure of household welfare. Hence, this paper uses the VEP approach to the analysis of vulnerability of sample households in the context of food security.

The vulnerability of a household during time t is expressed as the probability of the household falling below the minimum food requirements at time $t + 1$:

$$V_{it} = P(c_{it+1} < z) \quad (8)$$

Where the vulnerability of a household (V_{it}) during time t , C_{it+1} , is the household's PCFCE (welfare indicator) at time $t + 1$ and z is the threshold level (food poverty line).

The VEP approach, using expected mean and variance of household PCFCE, estimates household vulnerability in the context of food insecurity. According to Bogale (2012) and Günther and Harttgen (2009), the expected mean of PCFCE is determined by the household socio-economic, institutional, and farm characteristics as well as community characteristics, whereas the variance (also known as volatility) in household consumption captures the household and community shocks that influence differences in PCFCE for households, which share the same characteristics (Günther and Harttgen 2009). As proposed by Christiaensen and Subbarao (2005), the stochastic process generating the PCFCE of a farming household i can be expressed as follow:

$$\ln c_i = x_i \beta + \varepsilon_i \quad (9)$$

Where C_i is log of PCFCE level, X_i is represents observable farm and household socio-economic characteristics, β is a vector of parameters, and ε_i is a disturbance term with mean

zero and variance of $\sigma^2 \varepsilon_i$ (heteroscedastic). This implies that variances of the error term vary across households depending on farm and household socio-economic characteristics. Then, the variance of the unexplained part of PCFCE, ε_i regressed on household characteristics (X_i) to generate estimates for the expected variances is specified as:

$$\sigma^2 \varepsilon_i = x_i \theta + \tau_i \quad (10)$$

Where θ represents the vector of parameters to be estimated and τ is the error term of Eq. 10.

However, due to heteroscedasticity, the estimated β and θ are inefficient but not biased. Hence, as Christiaensen and Subbarao (2005); Chaudhuri (2000), and Chaudhuri et al. (2002) suggest, we used Three Step Feasible Generalized Least Squares (FGLS) to obtain that to obtain efficient parameters ($\hat{\beta}$ and $\hat{\theta}$).

The steps involved include, first, an estimation procedure applying the Ordinary Least Squares (OLS) method to Eq. (9) and estimates the residual. Then Eq. (10) is estimated by OLS using the squared residuals from the estimation of Eq. (9) as dependent variables. The predictions from this regression were used to re-estimate Eq. (10) by OLS after having weighted each residual by $X_i \theta$. The new estimates of θ are asymptotically efficient and are used to weight Eq. (9), which is re-estimated using weighted least squares to obtain asymptotically efficient estimates of β (Bogale 2012). Finally, we used the FGLS asymptotically efficient of β and θ to estimate the expected and variance of log of PCFCE for each household using the following equation as detailed in Bogale 2012 and Mutabazi et al. 2015).

$$\begin{aligned} E [\ln c_i / x_i] &= x_i \hat{\beta} \\ V [\ln c_i / x_i] &= x_i \hat{\theta} \end{aligned} \quad (11)$$

Assuming that household PCFCE is log-normally distributed, each household's probability of food insecurity at time $t + 1$ is expressed as:

$$\hat{V} = \hat{P}(\ln c_i < \ln z / x_i) = \Phi \left(\frac{\ln z - \ln \hat{c}_i}{\sqrt{\hat{\sigma}_i^2}} \right) \quad (12)$$

Where Φ is the cumulative density of the standard normal distribution; $\hat{\sigma}_i^2$ is a variance of standard error of the regression; \hat{c}_i and Z are the expected household PCFCE and threshold level (food poverty line), respectively; and \hat{v} is the probability of each household falling below the threshold level, with values ranging between zero and one. Chaudhuri et al. (2002), justify a threshold measure that is used to define vulnerable households as those with an estimated vulnerability

coefficient of above or equal to 0.5. Thus, we classify households as vulnerable if \hat{V} is above or equal to 0.5 and, otherwise, non-vulnerable.

To determine current household food insecurity status, we used the amount of money required to achieve the daily minimum dietary requirement. The government of Ethiopia set the minimum acceptable level of per capita calorie intake per day as 2200 (MoFED 2002). Thus, a household is considered to be food insecure if the amount of money it spends on food is not adequate to purchase a basic diet that is nutritionally adequate. Accordingly, the amount of money required to achieve the daily minimum dietary requirement (food poverty line) was Birr 2637.86 per annum. The CSA (2017) country and regional level consumer price indices show that the Consumer Price Index (CPI) of the study area (Oromia regional state) was 171.4% (December 2011 = 100). Thus, the food poverty line was deflated in order to take into account the effect of inflation. Therefore, the adjusted food poverty line was estimated at Birr 1539 per adult equivalent, per year, at the end of 2011 constant price. Thus, a household was considered food insecure if PCFCE was less than the food poverty line; otherwise the household was food secure.

By combining vulnerability status with the current food insecurity status of a household, we extended the analysis into several food insecurity and vulnerability categories among the adopters and non-adopters of SWC practices. Accordingly, currently food secure and less vulnerable households were considered to have a stable food secure status. The currently food insecure and highly vulnerable households were considered as chronically food insecure; households that were currently food secure but highly vulnerable and vice versa were considered to be transiently food insecure.

4 Result and discussion

4.1 Descriptive analysis

Before embarking on the impact assessment, it is important to describe the socio-economic, institutional, and farm characteristics of the sample households (Table 2). About 91 and 83% of adopter and non-adopter households, were respectively male headed. The average ages of household heads were 39.94 and 40.43 years for adopters and non-adopters, respectively. However, the majority of family members had ages of less than 15 or greater than 64 years, which means that the dependency ratio was high (averaging 1.33 for adopters and 1.25 for non-adopters). The average family sizes for adopters and non-adopters were 6.24 and 6.18, respectively. As far as the household head educational status is concerned, 40.69% of household heads never attended formal education. Overall farmers who adopted SWC practices were relatively more educated (with an

Table 2 Description of explanatory variables among adopter and non-adopter

Characteristics	Description	Adopters		Non-Adopters		Total Sample	
		<i>N</i> = 200		<i>N</i> = 208		<i>N</i> = 408	
		Mean	SD	Mean	SD	Mean	SD
Age of hh	Age of household head (years)	39.940	12.545	40.428	12.940	40.189	12.735
Education of hh	Level of education (number of years in formal education)	4.460***	3.631	2.875	3.547	3.652	3.671
Family size	Household size (number)	6.240	1.998	6.178	2.074	6.208	2.035
Sex of hh	Dummy of sex of household head (1 = male)	0.910***	0.287	0.827	0.379	0.868	0.339
Dependence ratio	Dependence ratio	133.445	96.725	125.194	96.275	129.239	96.466
Cultivated land	Total cultivated land holding	0.317***	0.188	0.263	0.155	0.289	0.174
Numbers of plot	Total numbers of plots owned	1.995	0.848	1.889	0.806	1.941	0.827
Off-farm	Dummy for engagement in off-farm activities (Yes = 1)	0.440	0.498	0.476	0.501	0.458	0.499
Use of fertilizer	Dummy for using fertilizer (Yes = 1)	0.595**	0.492	0.490	0.501	0.542	0.499
Livestock TLU	Livestock owned (Tropical Livestock Units)	1.939*	1.825	1.627	1.957	1.780	1.898
Information EA	Dummy for access to information from extension agents (Yes = 1)	0.850***	0.357	0.659	0.475	0.752	0.432
Information FC	Dummy for access to information from farmers' cooperative (Yes = 1)	0.215*	0.412	0.149	0.356	0.181	0.385
Dis. FTC	Average walking distance to FTC (minutes)	29.425	27.962	27.197	22.995	28.289	25.544
Use of irrigation	Dummy for using irrigation (Yes = 1)	0.375	0.485	0.322	0.468	0.348	0.477
Erosion problem	Dummy for erosion problem (Yes = 1)	0.650*	0.478	0.558	0.499	0.603	0.490
Received credit	Dummy for receiving credits (Yes = 1)	0.155	0.363	0.115	0.320	0.135	0.342

***, **, and * significant at the 1, 5, and 10% probability levels, respectively

average of 4.46 years in formal education) than their counterpart non-adopter farmers (average of 2.88 years in formal education).

Generally, adopters had larger cultivated land area and livestock holdings than the non-adopters. Moreover, nearly 65% of adopters and 56% of non-adopters indicated that their cultivated land was degraded. Both the adopters and non-adopters relied mainly on rain-fed agriculture, with only 35% practicing irrigation and 54% using chemical fertilizers. Concerning institutional variables, about 14% of the respondents received credits from formal financial institutions. Furthermore, out of the total sample households, 75.20 and 18.10% of households accessed information from government extension agents and farmers' cooperatives, respectively, with those adopting SWC having greater access to information than non-adopters from both sources.

4.2 Food insecurity and vulnerability to food insecurity

Table 9 in the appendix presents the three-step FGLS regression results showing explanatory variables that were used to estimate the expected PCFCE and its variance, as well as to show the relationship between explanatory variables with expected PCFCE and its variance. The model outcome reveals that the age of household head and family size, as expressed by adult equivalence, influenced expected food consumption expenditure negatively. Use of improved seeds, size of cultivated land, adoption of SWC practices, and access to credit influenced expected food consumption expenditures

positively. The results of vulnerability assessment indicated that about 43% of the sample households were vulnerable, with fewer farmers who adopted SWC practices being vulnerable (31%) than those who did not (54%). Overall, the PCFCE and expected PCFCE of adopters were greater than that of non-adopters.

The results of net crop value and current food insecurity status for adopters and non-adopters are presented in Table 3. The average net crop value was significantly higher (by Birr 4176.66 per ha per year) for SWC adopters than that of non-adopters. Again, the results of analysis of current food insecurity status show that farmers who adopted SWC were relatively less food insecure than their counterpart non-adopters.

By combining vulnerability status with the current food insecurity status of households, we classified food security status of adopters and non-adopters into stable food secure, chronic food insecure, and transient food insecurity. The results of analysis are summarized in Table 4.

The results reveal that 57.50% of adopters were categorized under the stable food security status, compared with only 34.14% for non-adopters. In general, adopters were food secure and had a low probability of falling into food insecurity in the near future (they were less vulnerable to food insecurity). In contrast, about 18.00% of adopters and 30.29% of non-adopters were food insecure for an extended period of time and were considered to be chronic food insecure. Furthermore, 24.50% of adopters and 35.58% of non-adopters frequently moved into and out of the state of food insecurity (transient). The Chi-test result indicates

Table 3 Descriptive statistics of outcome variables among adopters and non-adopters

Outcome variables	Adopters		Non- Adopters		Total	
	N = 200		N = 208		N = 408	
	Mean	SD	Mean	SD	Mean	SD
PCFCE/annum	3453.32***	1405.13	3067.04	1552.51	3256.39	1492.86
Expected PCFCE /annum	3280.82***	684.85	2842.64	537.95	3057.43	651.62
VFI	0.31***	0.46	0.54	.49	0.43	0.49
Food insecurity	0.305***	0.4	0.42	0.49	0.36	0.48
Net crop value (Birr)	10,791.02***	6723.25	6614.36	5356.15	8661.74	6407.99

***, **, and * significant at the 1, 5, and 10% probability levels, respectively

that there is a systematic relationship between the household's food insecurity status and the adoption of SWC at the 1% level of significant.

These descriptive statistics indicate that households who adopted SWC practices were less prone to food insecurity and vulnerability than their counterpart non-adopter farmers. However, at this level, it is difficult to conclude that adopting SWC practices reduces current and future food insecurity. Thus, an impact assessment is needed to determine if this decrease in food insecurity and VFI is due to SWC adoption, by controlling for the observed and unobserved heterogeneity that affect the adoption decision and outcome variables.

4.3 Endogenous switching regression estimation results

The first stage ESR binary probit estimation results are presented in Table 5. Our probit model fits the data reasonably well [Wald Chi-squared = 78.2, $P = 0.000$]. The model results reveal that household, socio-economic, and institution factors influenced the SWC adoption decisions significantly. Use of fertilizers was positively and significantly associated with adopting SWC. Thus, farmers with access to fertilizer had a higher probability of adopting SWC practices. The adoption of soil and water conservation increased with the level of education of household heads. Household heads who attended formal education have better understanding of the advantages and challenges of adopting SWC practices (Fentiel et al. 2013; Asfaw and Neka 2017). Similarly, male headed households were also more likely to

adopt SWC practices than female headed households. A possible explanation is that male headed households have better access to information and the labor required to implement new technology than the female headed households (Mekuriaw et al. 2018; Bekele and Drake 2003).

Farmers with access to information from government extension agents and farmers' cooperatives are more likely to adopt conservation technology. This is because the provision of information helps farmers to become aware of the problem of land degradation and its consequences, while also acquiring new knowledge regarding the new technological measures to address it (Chilot 2007; Bogale et al. 2007; Shimeles et al. 2011). Another factor that significantly and positively influenced the adoption of SWC was the size of cultivated land. Farmers who owned and/or operated larger sizes of cultivated land were more likely to allocate a proportion of land for SWC than those with small holdings of cultivated land. Moreover, ownership operation of large cultivated or land holdings are often linked to rich farmers with relatively large capital, which directly influences the adoption of SWC practices (Paulos 2001).

The results of ESR model-based ATT and ATU for the key outcome variables related to the adoption of SWC practices are presented in Table 6. As discussed earlier, the main outcome variables considered in this analysis are PCFCE and net crop value in Birr, as well as the binary outcomes like food insecurity, VFI, chronic food insecurity, and transient food insecurity.

The ESR impact results reveal that the adoption of SWC practices reduces the probability of current food insecurity, VFI, transient food insecurity, and chronically food insecurity.

Table 4 Food security status among adopters and non-adopters

Categories of food insecurity	Adopters		Non- Adopters		χ^2 -value	Total	
	N = 200		N = 208			N = 408	
	No.	Percent	No.	Percent		No.	Percent
Stable food secure	115	57.500	71	34.135	24.762***	186	45.588
Chronic food insecure	36	18.000	63	30.288		99	24.265
Transient food insecurity	49	24.500	74	35.577		123	30.147

***, **, and * significant at the 1, 5, and 10% probability levels, respectively

Table 5 Decision of adopting SWC: Probit model

Number of observations	408.000		
Wald chi2(15)	56.58		
Prob > chi2	0.000		
Pseudo R2	0.108		
Log pseudo likelihood	-252.139		
Variables	Coef.	Robust Std. Err.	Marginal Effects
Sex of hh	0.335*	0.203	0.131
Age of hh	0.007	0.006	0.003
Education of hh	0.067***	0.023	0.027
Family size	-0.043	0.036	-0.017
DPR	0.001	0.001	0.000
Use of fertilizers	0.252*	0.146	0.100
Distance FTC	0.002	0.003	0.001
Number of plots	-0.010	0.089	-0.004
Use of irrigation	0.149	0.150	0.060
Size of cultivated land	0.938**	0.462	0.374
TLUs	-0.029	0.042	-0.011
Received credit	0.112	0.204	0.045
Information EA	0.685***	0.163	0.262
Information FC	0.437**	0.222	0.172
Off-farm	0.034	0.142	0.013
Erosion problem	0.209	0.143	0.083
_cons	-1.902***	0.438	

***, **, and * significant at the 1, 5, and 10% probability levels, respectively

On the other hand, the adoption increases PCFCE and net crop value. For farmers who adopted SWC practices but theoretically would have not adopted, then their PCFCE decreased by Birr 205.97 (\$8.83). This means, for an average family size expressed as adult equivalent of 4.89 per household, the ATT

of food consumption expenditure at household level would decrease by Birr 1007.19 (\$42.19) as a result of not adopting SWC practices. Similarly, if non-adopters would have adopted SWC practices, then their average PCFCE would have significantly increased by Birr 297.084 (\$12.74). Considering the

Table 6 Endogenous switching regression model result (average treatment effects)

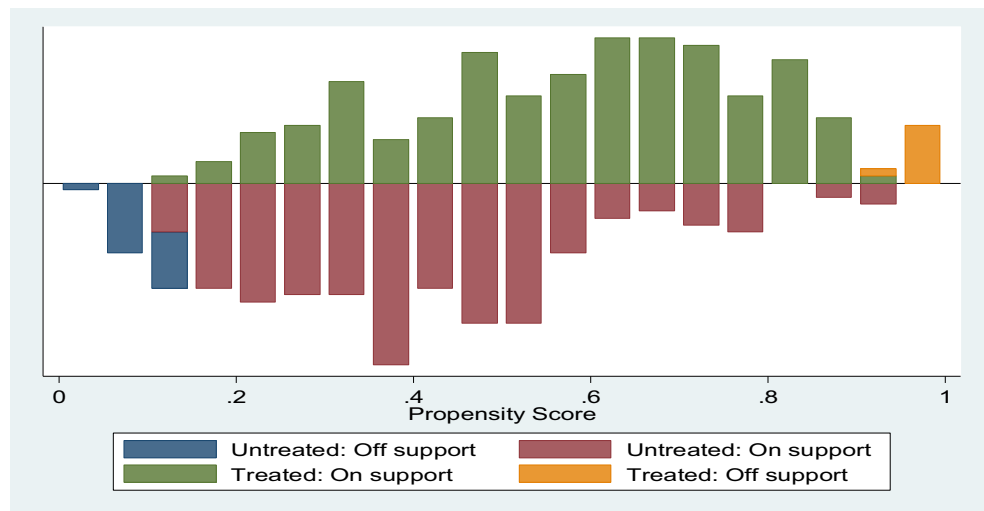
Outcome variables	Farm household type and treatment effect	Decision stage		Treatment effect
		To adopt	Not to adopt	
PCFCE	ATT	3451.763	3245.793	205.970**
	ATU	3365.626	3068.542	297.084***
Food security	ATT	0.295	0.400	-0.105***
	ATU	0.299	0.420	-0.121***
VFI	ATT	0.312	0.452	-0.141***
	ATU	0.306	0.539	-0.233***
Transient food insecurity	ATT	0.244	0.422	0.178***
	ATU	0.281	0.356	0.075***
Chronic food insecure	ATT	0.175	0.243	-0.068**
	ATU	0.137	0.293	-0.156***
Net crop value	ATT	10,791.02	7506.935	3284.088***
	ATU	9594.495	6614.361	2980.135***

***, **, and * significant at the 1, 5, and 10% probability levels, respectively

ATT average treatment effect on the treated

ATU average treatment effect on the untreated

Fig. 1 Distribution of estimated propensity distribution for treatment and control groups and common support area



average family size (in adult equivalent) of 4.89, this would translate to Birr 1477.02 (\$62.30) per household. If SWC adopters had they not adopted, the average probability that they will be food insecure would increase by 10.50%. Likewise, if SWC non-adopters had adopted, the average probability of food insecurity would decrease by 12.10%. On the other hand, households who actually adopted switching to non-adopted, then the probability of VFI status would have increased by 14.10% but decreased by 23.30% for non-adopters had they adopted SWC. Moreover, the adoption of SWC practices reduced the probability of chronic food insecurity by 6.80% for adopters and 15.60% for non-adopters. Likewise, the average probability of transient food insecurity status (shift from food secure to food insecure and vice-versa) for adopters would increase by 17.80%, if they had not adopted SWC practices, while if non-adopters had adopted SWC, then transient food insecurity would decrease by 7.50%.

In addition to food insecurity and vulnerability outcome variables, we also checked the impact of SWC practices on

net crop value. The results indicate that the average net crop value for adopters would drop by 3284.088 (\$140.83) per ha if the adopters would not have adopted. In the same way, if the non-adopters had adopted, their average net crop value would have increased by Birr 2980.135 (\$ 127.79) per ha. Therefore, ESR reveals that the adoption of SWC practices in Ethiopia would have not only reduced food insecurity and related vulnerability but also increased food consumption expenditure by increasing net crop value.

The results of second stage ESR, the estimated coefficients of PCFCE, and binary food insecurity and VFI are presented in Table 10 of the appendix.

4.4 Binary propensity score matching results

In addition to the ESR model, this study uses the PSM technique to check the robustness of the results obtained from the ESR model. Propensity scores (the probability of adoption in SWC) are estimated using a probit model. Fig. 1 shows the distribution

Table 7 Covariates balancing tests before and after matching

Matching algorithm	Pseudo-R ²		LR χ^2 (p value)		Mean standardized bias		Total % bias reduction
	Before	After	Before	After	Before	After	
NNM ^a	0.1082	0.008	61.17 (0.000)	4.63 (0.997)	22.2	4.2	70.01
KBM ^b	0.1082	0.017	61.17 (0.000)	8.93 (0.916)	22.2	5.8	47.49
KBM ^c	0.1082	0.010	61.17 (0.000)	5.67 (0.991)	22.2	5.4	49.87
RCM ^e	0.1082	0.014	61.17 (0.000)	7.32 (0.967)	22.2	5.8	47.73
RCM ^f	0.1082	0.009	61.17 (0.000)	4.63 (0.997)	22.2	4.8	54.38

NNM^a = One nearest neighbor matching and common supports

KBM^b = Kernel with band width 0.01 and common support

KBM^c = Kernel with band width 0.025 and common support

RCM^e = Radius Caliper 0.01 matching

RCM^f = Radius Caliper 0.025 matching

Table 8 Average treatment effects: propensity score matching. Features

Outcome variables	Matching algorithm	Mean of outcome variables based on matched observations		ATT	SE
		Adopters	Non-adopters		
PCFCE	NNM ^a	3457.124	3224.441	232.683*	135.682
	KBM ^b	3412.933	3066.386	346.546*	206.996
	KBM ^c	3454.214	3115.266	338.948*	185.058
	RCM ^e	3412.933	3060.657	352.276*	200.755
	RCM ^f	3454.214	3135.852	318.362*	181.284
Food insecurity	NNMa	0.291	0.383	-0.091*	0.054
	KBMb	0.307	0.418	-0.111*	0.064
	KBMc	0.296	0.410	-0.115**	0.058
	RCMe	0.307	0.413	-0.106*	0.062
	RCMf	0.296	0.409	-0.113**	0.057
VFI	NNM ^a	0.307	0.463	-0.157***	0.055
	KBM ^b	0.312	0.441	-0.129**	0.065
	KBM ^c	0.311	0.448	-0.137**	0.059
	RCM ^e	0.307	0.472	-0.166***	0.054
	RCM ^f	0.311	0.444	-0.133**	0.058
Chronic food insecure	NNM ^a	0.176	0.218	-0.042	0.038
	KBM ^b	0.178	0.215	-0.037	0.042
	KBM ^d	0.179	0.250	-0.071*	0.041
	RCM ^e	0.178	0.221	-0.043	0.041
	RCM ^f	0.179	0.253	-0.075*	0.045
Transient food insecurity	NNM ^a	0.246	0.412	-0.166***	0.053
	KBM ^b	0.254	0.440	-0.186***	0.060
	KBM ^c	0.250	0.426	-0.176***	0.056
	RCM ^e	0.254	0.435	-0.181***	0.059
	RCM ^f	0.250	0.421	-0.171***	0.056
Net crop value	NNM ^a	10,776.351	7649.246	3127.105***	677.304
	KBM ^b	10,613.861	6706.606	3907.255***	732.947
	KBM ^c	10,628.070	7134.457	3493.613***	712.120
	RCM ^e	10,613.861	6838.140	3775.721***	724.140
	RCM ^f	10,628.070	7266.212	3361.858***	704.070

***, **, and * significant at the 1, 5, and 10% probability levels, respectively

of adopter and non-adopter households with respect to estimated propensity scores. The figure illustrates the estimated propensity distribution for treatment and control households. The upper half of the graph refers to the propensity score distribution of treatment groups, while the bottom half shows the control groups. The y-axis refers to the densities of estimated propensity scores.

A common support condition should be imposed on the propensity score distribution of SWC adopters and non-adopters. The estimated propensity scores vary between 0.1437482 and 0.9463331 (mean = 0.5600339) and 0.0344507 and 0.8960822 (mean = 0.4203612) for the treatment and control groups, respectively. The common support region would then lie between 0.1437482 and 0.8960822. Accordingly, off support sample were discarded from the analysis in estimating the ATT in both groups. Thus, about 90% of adopters and non-adopters were in

the common support area, showing substantial overlap between the two groups. Table 7 presents the balancing tests of each matching algorithm before and after matching. The mean standardized bias was reduced after matching (4.2 to 5.8%) compared to before matching (22.2%). Similarly, the Pseudo-R² declines substantially, from 10.82% to a range of 0.8 to 1.7%. The likelihood ratio tests (*p* values) indicated the joint significance of all covariates at less than 1% probability level before matching, but it was insignificant after matching. Furthermore, the total bias significantly declined in the range of 47.49 to 70.01 through matching. Thus, these tests clearly show that the matching process balances the observed characteristics between treated and control groups after matching.

Table 8 reports the ATT, based on PSM technique, using three different matching algorithm techniques (nearest neighbor

matching (NNM), Kernel based matching (KBM), and Radius matching methods). The result reveals that, as in the ESR analysis, the adoption of SWC practices resulted in increase in both PCFCE and net crop value, while reducing the probability of food insecurity, VFI, transient food insecurity, and chronic food insecurity. The PSM result reveals that, on average, the adoption of SWC practices increased the households' PCFCE in the range of Birr 232.683 to 352.276 (7.21 to 11.51%). Similarly, it reduced the probability of food insecurity and VFI in the range of 9.10 to 11.50% and 12.90 to 16.60%, respectively. The probability of chronic (transient) food insecurity declined in the range of 7.10 to 7.50% (16.6 to 18.60%), respectively. Moreover, the adoption of SWC would significantly increase the annual net crop value, from Birr 3127.105 to 3907.255 per ha. It can therefore be concluded that, apart from the slight differences in magnitude between the PSM and ESR estimates, the adoption of SWC had positive impacts on PCFCE and net crop value. It reduced food insecurity and VFI in the study area. In line with this finding, Bekele (2003); Benin (2006); Kassie and Holden (2006); Pender and Gebremedhin (2006); and Kassie et al. (2009), all concluded that investing in SWC measures has positive impacts in terms of mitigating land degradation, while also improving crop production and income, especially in moisture deficit areas.

5 Conclusions and policy implications

This article analyzes the impact of SWC on food insecurity and vulnerability to food insecurity using primary data collected in eastern Ethiopia. We employ both parametric (ESR) and non-parametric (PSM) methods to reduce the effect of self-selection bias due to both observable and unobservable farm household socio-economic characteristics as well as to test the consistence of the results, respectively.

The first stage ESR indicates that access to irrigation and fertilizers, education level and sex of household head, access to

information, and size of cultivated land were significantly associated with SWC adoption. The results obtained from both the ESR and PSM models were consistent, indicating that the adoption of SWC practices not only generated a significantly positive impact on PCFCE and net crop value, but it also reduced food insecurity and VFI. In fact, the probability of food insecurity and VFI decreases by 10.5 and 14.1%, respectively, compared to their counterfactuals. Further, PCFCE and net crop value increased by Birr 205.97 and 3284.088 per ha due to SWC adoption, respectively.

Therefore, it can be concluded that SWC practices significantly contributed to the economic and social development of small-holder farmers by improving average PCFCE and net crop values as well as by reducing food insecurity and VFI. In addition, in countries like Ethiopia, where 40% of people suffer from food insecurity and land degradation is severe, SWC practices should be considered as a principle strategy for improving the livelihoods of the rural farm households and preventing land and water degradation. The findings of the study stress that policymakers and development organizations should focus on strengthening human and institutional capacity through enhanced education and continuous training on the effects of land degradation, as well as the use of appropriate SWC technologies, the use of fertilizer and rainwater harvesting, in order to increase productivity while restoring the health of the soil and agro-ecosystem. Furthermore, governmental and developmental partners should give more attention to integrated SWC programs not just to improve environmental conditions and increase agricultural productivity but also improve the food security status of farming households and reduce vulnerability to external shocks.

Compliance with ethical standards

Conflict of interest There is no conflict of interest among the authors.

Appendix

Table 9 Three-step Feasible Generalized Least Squares result for determinant of vulnerability to food insecurity ($N = 408$)

Variables	Log food consumption expenditure			Variance of food consumption expenditure		
	Coef.	Robust Std. Err.	t	Coef.	Robust Std. Err.	t
Sex	-0.017	0.065	-0.26	-0.073	0.042	-1.75*
Age	-0.003	0.002	-1.75*	0.001	0.001	0.72
Education	-0.001	0.005	-0.16	-0.001	0.002	-0.25
Adult equivalent	-0.107	0.014	-7.65***	0.002	0.006	0.29
Dependence ratio	1.93E-04	1.82E-04	1.06	1.98E-05	8.57E-05	0.23
Annual income	1.94E-07	2.20E-06	0.09	1.06E-08	9.14E-07	0.01

Table 9 (continued)

Variables	Log food consumption expenditure			Variance of food consumption expenditure		
	Coef.	Robust Std. Err.	t	Coef.	Robust Std. Err.	t
Off-farm Activity	-0.003	0.039	-0.08	-0.002	0.019	-0.1
Use of fertilizer	0.005	0.045	0.1	-0.004	0.018	-0.23
Use of improved seed	0.129	0.045	2.89***	0.026	0.020	1.28
Use of irrigation	0.057	0.037	1.53	-0.025	0.018	-1.39
Cultivated land	0.243	0.134	1.81*	-0.012	0.071	-0.17
Adoption of SWC	0.100	0.038	2.62***	0.022	0.019	1.13
Total Asset	0.000	0.000	0.94	2.65E-07	1.81E-07	1.46
Livestock TLU	0.015	0.012	1.25	-0.006	0.006	-1.03
Crop diversification	0.008	0.024	0.33	-0.014	0.011	-1.23
Coping strategy index	-0.003	0.004	-0.68	0.001	0.002	0.40
Number of Sick	0.038	0.028	1.39	-0.006	0.014	-0.40
Received credit	0.094	0.057	1.66*	0.020	0.028	0.71
Contact with DA	2.90E-04	0.009	0.03	4.70E-04	0.004	0.12
_cons	8.384	0.122	68.68***	0.162	0.060	2.68***
F(19, 388) = 8.12				F(19, 388) = 1.51		
Prob > F = 0				Prob > F = 0.077		
R-squared = 0.304				R-squared = 0.044		
Root MSE = 0.335				Root MSE = 0.163		

***, ** and * significant at the 1, 5 and 10% probability levels, respectively

Table 10 Second stage ESR estimates result

Variables	PCFCE (Birr)				Food insecurity				VFI			
	Adopters		Non-adopters		Adopters		Non-adopters		Adopters		Non-adopters	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Sex	-426.321	260.946	-174.221	444.679	2.061	0.608***	-0.336	0.296	-0.486	0.461	0.434	0.495
Age	-33.564	7.546***	0.639	7.674	0.046	0.011***	0.010	0.008	0.058	0.012***	0.075	0.016***
Education	-30.069	36.222	8.492	35.361	0.082	0.044**	0.013	0.038	-0.126	0.076***	0.016	0.059
Family size	-254.154	47.564***	-356.325	86.037***	0.248	0.065***	0.249	0.060***	1.095	0.144***	1.260	0.161***
DPR	-0.623	1.216	2.584	1.139**	0.002	0.001*	-0.002	0.001	-0.005	0.002*	-0.004	0.002**
Use fertilizer	207.537	208.906	15.590	224.804	0.315	0.255	-0.145	0.237	-1.440	0.355***	-0.701	0.347***
Distance FTC	-2.492	3.252	-4.595	2.490*	0.009	0.004***	0.002	0.003	0.004	0.004	-0.006	0.003*
Numbers of plot	273.262	113.885**	-103.980	115.713	-0.487	0.161***	0.044	0.144	-0.201	0.211	-0.113	0.221
Use of irrigation	38.457	211.661	411.458	192.417**	0.405	0.262	-0.568	0.228**	-0.666	0.318**	-1.500	0.377***
Cultivated land	-584.153	564.800	2397.716	934.104**	1.295	0.671*	-1.345	0.764*	-1.443	0.980	-4.610	1.230***
TLU	34.674	45.871	84.649	46.484*	-0.084	0.072	-0.111	0.053**	-0.289	0.101***	-0.272	0.068***
Received credit	102.810	292.532	413.881	369.584	0.435	0.335	-0.525	0.322	-1.852	0.602***	-1.129	0.427***
Off-farm	330.742	196.487*	-442.868	176.937**	0.426	0.250*	0.152	0.200	-0.043	0.331	0.510	0.300*
Erosion problem	-219.123	237.879	124.210	179.242	0.925	0.286***	0.151	0.204	-0.091	0.407	0.371	0.318
IMR	-643.589	569.941	99.487	411.321	1.807	0.683***	-0.410	0.529	-1.207	0.869	0.646	0.678
_cons	6938.765	1058.708***	4627.157	617.019***	-8.760	1.711***	-1.447	0.552***	-5.360	1.621***	-7.439	1.135
Number of obs.	200		208		200		208		200		208	
F-Value/Wald Chi2	6.62		3.68		65.430		33.010		87.390		76.980	
Prob > F	0		0		0.000		0.005		0.000		0.000	
R-squared/Pseudo r2	0.3146		0.260		0.299		0.139		0.653		0.619	
Root MSE	1207.4		1388.9		-84.949		-121.968		-42.944		-54.653	
Log pseudo likelihood												

***, ** and * significant at the 1, 5 and 10% probability levels, respectively

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