Global Social Welfare (2023) 10:235–247
https://doi.org/10.1007/s40609-023-00279-6

Analyzing the Impact of Climate-Smart Agriculture on Household Welfare in Subsistence Mixed Farming System: Evidence from Geshy Watershed, Southwest Ethiopia

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Accepted: 7 March 2023 / Published online: 17 March 2023

Abstract
This study assesses the effect of climate-smart agriculture (CSA) technology adoption on the welfare status of households in a subsistence mixed farming system in the Geshy watershed, South West Ethiopia. Due to the changing climate, characterized by changes in patterns of rainfall and rising temperature, the livelihoods of smallholder rural farmers in the Geshy watershed are highly threatened. For these households that are highly dependent on rain-fed agriculture, coping mechanisms, proper adaptation, and mitigation measures are hence important steps to secure household incomes and livelihoods. CSA offers this opportunity. A survey data collected from 384 households cross-sectionally was used to analyze the impact of CSA on food security and household income. The research model used in this study was the endogenous switching regression model which controls unobserved heterogeneity and selection bias, a method used commonly in analyzing adoption impacts. The study comes up with various socioeconomic and agricultural factors influencing food security and CSA adoption. The econometric analysis result shows that the variables that had a significant impact on farmers' decisions for CSA adoption were field soil fertility status, distance to market, asset ownership, and livestock ownership. The average values of the treatment effects of the untreated (ATU) and treated (ATT) result in a positive and significant impact on farmers' welfare. Factors such as household head education, size of labor, livestock size, and asset index significantly affected household income. The level of education, the size of irrigable land, and livestock size influenced food security. This study concludes that households that adopted more CSA practices experience better welfare. Access to inputs, encouraging investments in assets, irrigation, and livestock production, providing incentives to input dealers for rural areas decentralization, and access to weather forecasts need to be improved to exploit the full potential of climate-smart agriculture technologies as policy recommendations.

Keywords Food security · Household income · Endogenous switching regression model · Geshy watershed

Introduction

The agriculture sector remains to play a fundamental role in the economic growth and development of Ethiopia. It contributes 35.8% of gross domestic product (GDP), 90% of exports, 72.7% of employment, and 70% of raw material industrial requirements (Ayele et al., 2021; Caravaggio et al., 2021; Yigezu Wendimu, 2021). The nation is gifted with abundant agricultural resources in the form of fertile soil, which is ideal for high-value crop production of field cash crops such as sesame, coffee, and cotton, as well as cereal food crops such as wheat, maize, barley, legumes, and vegetables. Ethiopia's smallholder farmers cultivate more than 90% of the total cropland and provide more than 90% of agricultural output (Zerssa et al., 2021). The productivity of crops is influenced by limited technology use such as improved varieties and livestock productivity is affected by unreliable availability and low-quality forage in dry seasons (Headey et al., 2014). Additionally, farmers experience under-developed markets that constrain their financial returns, because they are characterized by low output prices and high input costs, coupled with climate changes and recurrent drought event effects (Aliyi et al., 2021). Climate change and extremes such as erratic rainfall,

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frequent droughts, and temperature extremes create favorable conditions for pest outbreaks, disease, and insects (e.g., armyworms and locusts), which resulted in declined crop yield (Mihiretu et al., 2021). Studies confirmed the impact of climate change and extremes on food and forage production will become more severe (Escarcha et al., 2018; Rettie et al., 2022; Rojas-Downing et al., 2017). Models predict that the warming in sub-Saharan Africa is greater than the global average leading to extreme events such as floods and droughts, thereby adversely affecting smallholder farmers that are heavily relying on rain-fed agriculture for their livelihoods (Etana et al., 2020; Tofu et al., 2022). Livestock and crop productivity have also been highly affected by disease and pest incidence (Tadesse et al., 2021). Progressive yield reduction over succeeding agricultural seasons will negatively influence household food security usually relying on staple food production of their own (Agidew & Singh, 2018; van Dijk et al., 2020). The unpredictable one-time high-intensity rainfall pattern raises a serious threat to farmers, as water is the basic resource that is becoming a determinant factor under such circumstances. Accordingly, the government of Ethiopia promoted climate-smart agriculture (CSA) by developing a national road map in 2020 (Ethiopia climate-smart agriculture roadmap, *2020–2030*, 2020).

Significance of CSA in Mixed Smallholder Farming Systems

One of the important routes toward improving the welfare of smallholder farming communities in developing nations, experiencing adverse climate change impacts, is CSA adoption (Mujeyi et al., 2021; Ogada et al., 2020a). CSA can support farmers achieve the growing food demand. Generally, CSA contributed to food security, poverty reduction, and economic development (Habtewold, 2021; Wekesa et al., 2018). Literature suggests that improved agricultural productivity can enhance household welfare by increasing income and food security (Capatina et al., 2016; Cleves et al., 2022; IPCC, 2014). There is empirical evidence on grain productivity and welfare improvement on CSA-based technologies of crop and livestock from on-farm and on-station trials. For instance, drought-tolerant maize varieties adoption improved the yield of maize among adopters by 13.3% and the exposure to downside risk by 81% (Wekesa et al., 2018). Furthermore, diversified crop production increased the yield of spring wheat in no-tillage by up to 30% and by 13% under plowing relative to monoculture (Jalli et al., 2021).

Soil and water management CSA practices reduce water losses from runoff and improve water infiltration (mulching), protect the soil (minimum tillage), improve soil fertility (intercropping), manure use and rotation, and reduce evaporation (Du et al., 2022; Ebabu et al., 2022). These are supported by CSA crop agronomy, such as using improved varieties (improved legumes and drought-tolerant maize). The recent innovations in CSA are, therefore, built in addition to the best water and soil management and best agronomic practices. Several research findings examined the effect of CSA on household welfare and revealed both direct and indirect results. Some of the direct results include crop and livestock productivity improvement, and declined variable costs, while the indirect results include increased household income, improved food security through enhanced availability of staple crops in the market and at the level of household (Jalli et al., 2021; Mujeyi et al., 2021), and high demand for farm labor, that results in better wages for agricultural returns (Ogada et al., 2020b; Sain et al., 2017). Researchers use various ways of studying the CSA impact on food security and other livelihood outcomes. Some use the endogenous regression model (ESR) by employing household food security measurement tools such as Household Dietary Diversity (HDD) and Household Food Consumption Score (HFCS) as food security proxies. Others use composite indexes that employ weighting and normalization methods such as Food Insecurity Multidimensional Index which incorporates the four food security dimensions, i.e., availability, access, utilization, and stability (Mujeyi et al., 2021; Sisha, 2020a). The study by Wekesa et al. (2018) came up with evidence that farmers using multiple CSA packages containing crop management, risk reduction practices, field management practices, and specific soil management practices showed 56.83% more food secure in terms of HFCS compared to their counterpart non-adopters (Wekesa et al., 2018). A study by Ogada et al. (2020b) indicated that CSA adoption such as using improved varieties increased household income by 83%, which in turn enhanced household asset accumulation.

The CSA technologies are hence very important for countries like Ethiopia, which are regarded as climate change "hotspots" due to the increased chance of occurrences of extreme events such as flooding and drought (Teshome & Zhang, 2019).

The purpose of this study was to examine mixed farming practices (crop production, forestry, and livestock production) effect on the welfare of households in subsistence farming systems. It also recommended the important characteristics that must be incorporated into the agricultural policies of the country to improve the welfare of smallholder households through CSA technologies adoption.

Methodology

Study Area Description

The study was undertaken in the *Geshy* watershed, South West Ethiopia. The research site was selected based on the representativeness of smallholder farmers that have experienced rainfall pattern anomalies characterized by delayed onset and early cessation with poor spring rainfall performance but abundant summer rainfall (Gezie, 2019; Habte et al., 2021). *Geshi* watershed (in South West Ethiopia) covers an estimated area of 13,935 ha and is situated approximately between 19°29′ to 20°56′N and 81°57′ to 82° to 1′E (Fig. 1). The altitude of the watershed ranges between 1200 and 2670 m above sea level (masl). The topography is characterized by undulating terrain with slopes ranging from 0 to 50% and is surrounded by intermittent rivers. Agroecologically, the area falls under sub moist mid-highlands (*Woin-adega*) to warm moist highlands (*Kolla*) climatic zones. This diverse zone enables the sub-watersheds to produce different crops, fruits, vegetables, and rearing livestock (Gangadhara Bhat & Moges, 2021). The annual rainfall ranges between 1200 and 2200 mm, while the annual maximum and minimum temperature ranges between 12 and 26 °C respectively (Ofgeha & Abshire, 2021). The distribution of rainfall is bimodal in nature and occurs mostly from June to mid-November (main rainy season), locally called *Kiremt*, and February to May is another season with light rain, which is locally regarded as *Belg* leading to two harvesting seasons (Gemeda et al., 2021). Early cessation, a delayed onset, abundant rainfall, and poor *belg* performance make the watershed food insecure and forced farmers to shift to livestock production, and grow short maturing and lower yielding varieties.

It has a total rural population of 14,518 of which 7261 are males. With an estimated area of 13,935 ha, the basic economic activity relies on agroforestry practices such as coffee planting, tea, cereals, and vegetables accounting for 41.9% of the total landmass. The remaining areas of the watershed are covered by natural forests (8.98%), degraded hillside land (2.6%), woodlot (8.48%), and the remaining other small fragments of land based on the 2017 survey data collected (Alemu et al., 2019).

Sampling Design

The selection of smallholder farmers followed a three-level multistage sampling technique. The first stage involved the identification of the district where the Geshy watershed is found. In the second stage, 9 *Kebeles* (the smallest governmental administration unit), which are beneficiaries of the watershed, were identified. The third stage follows randomly selecting three villages and finally, 384 households, that were traditionally practicing various packages of CSA, were selected using a simple random sampling technique. Endogenous cluster-level errors appearing due to cluster-level covariates can be correlated with regressors using a Multinomial Endogenous Switching Regression Model for clustering sampling method. For a binary outcome that follows a logistic mixed-effects model and a normally distributed endogenous variable but not linear in the random effect,

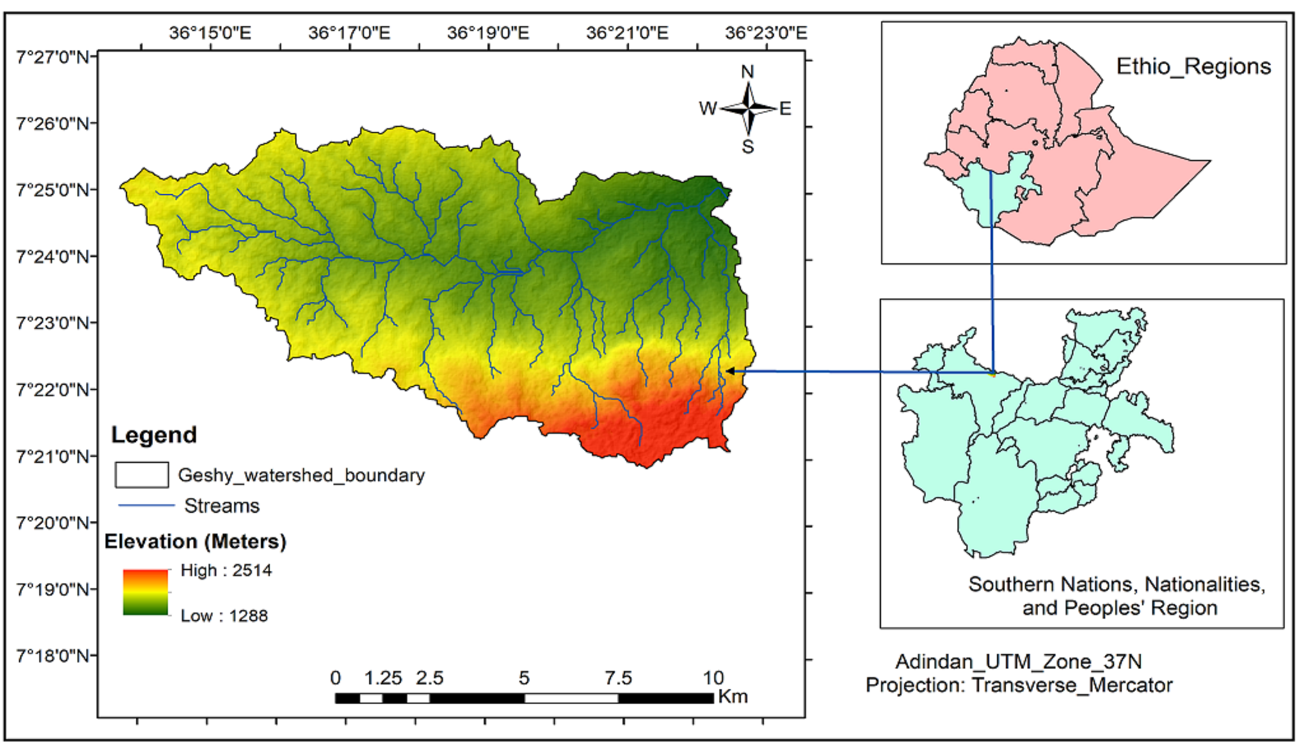

Fig. 1 Geographical location of Geshy watershed (source: own development)

the within-cluster variations of endogeneous variable work under the restriction that whether the endogenous or outcome variable has a linear relationship with the cluster-level random effect (Ruzzante et al., 202). A survey of structured household questionnaires was administered by the researcher to the smallholder farmers on demographic, socioeconomic conditions, and biophysical conditions. The interview was conducted in October 2021.

Model Specification

Earlier adoption studies and the empirical evidence on agricultural technologies suggested the choice of variables adopted in the Endogenous Switching Regression Model, which is a model of two-stage regression analysis usually used in adoption studies. The first stage entails the determination of CSA technology adoption using multinomial logit model. The next stage determines the drivers of CSA adoption. The model also shows the marginal effects which measures the expected change of a particular CSA strategy choice with respect to a unit change in an independent variable (Awotide et al., 2016; Jones-Garcia & Krishna, 2021; Ruzzante et al., 2021). These technology adoption drivers of CSA include household characteristics (gender, age, level of education, family labor, and household size), ownership of assets, technical and institutional factors (groups/farmers organization membership, access to extension services, credit access, training on CSA, ownership of assets such as television, radio, and mobile phones), perceived benefits (increased income, enhanced productivity, reduced cash inputs, reduced risk of livestock and crop loss, and food security), and farm characteristics (land tenure, soil fertility, and slope) (Branca & Perelli, 2020; Pagliacci et al., 2020a).

To enhance farmers' desire toward adopting CSA and make the required contribution in the effort to improve household welfare, it is imperative to be aware of the obstacles and drivers that affect farmers' choices and decisions and understand variables that influence variables of welfare, i.e., household food security and income (Mujeyi et al., 2021). Smallholder farmers are considered to be heterogeneous agents, and the tendency to decide to adopt new CSA technologies is influenced by the availability of technology, resources, and information (Kangogo et al., 2021a). Households find investments in new technologies attractive if they found the benefits significantly offset the cost (Mujeyi et al., 2021). Thus, the decision of adopting a certain CSA technology can be viewed through the lens of constrained optimization, where the choice of households choose the technology depends on its availability, affordability, and its beneficial use (Khatri-Chhetri et al., 2019). The expected benefits are determined by observable and non-observable factors. An adopter of a CSA is therefore a certain household that adopts a minimum of one CSA from a list of available eighteen practices (small-scale irrigation, alley cropping, use of organic fertilizer, use of improved varieties of crops, use of efficient inorganic fertilizer, planting trees for windbreak and shelter for crops, use of mulching, changing planting dates, cover crop practices, crop rotation using legumes, improved animal husbandry, poultry farming, use of terraces, apiculture, feed improvement, sheep fattening, use of grasses, and use of briquettes). It is so because farmers are considered to be rational, and as long, they adopt technologies that satisfy their objectives and address limitations they encounter during production.

To examine the effect of CSA technologies on selected household welfare, two indices were used, i.e., food security and average household income (Mujeyi et al., 2021; Wossen et al., 2019). Welfare is defined as the total utility derived from all the goods and services consumed (Wossen et al., 2019). Various outcome indicators are used by researchers to measure welfare that includes consumption, income, expenditure, poverty (poverty headcount and poverty gap), asset-based wealth indices, and food security (Mayfour & Hruschka, 2022; van Wijk et al., 2020). The Food and Agricultural Organization (FAO) of the United Nations defined food security as a condition when all people at all times have economic and physical access to adequate, safe, and nutritional foods to satisfy their dietary needs for an active and healthy life (FAO, 2008). Various proxies of indicators of food security have been used to capture the four dimensions (availability, access, utilization, and stability), including food insecurity scores, Dietary Diversity Scores, hunger scale, and food utilization (anthropometry as a proxy, i.e., weight for height, body mass index (BMI) for age, height for age, and weight for age (El Bilbeisi et al., 2022; Nicholson et al., 2021; Sisha, 2020). For this study, one of the indicators of food security used was the Household Food Consumption Score (HFCS). The HFCS is a score computed using the consumption frequency of various groups of foods consumed during the 7 days by a household before the survey. Standard weights are attached for each food group that comprises the score of food consumption and by summing up these weights, the food security level will fall into either of the three categories (poor, borderline, acceptable) (Fite et al., 2022).

Climate-smart technologies adoption of CSA can improve livestock and crop production, and thus the household can generate income by marketing the surplus in addition to the availability of food. Some CSA practices are labor-saving and help provide labor for other off-farm practices that can generate additional income for the household (Autio et al., 2021). The income of the household was the combination of incomes from on-farm (crop and livestock) and off-farm, as well as other income sources (gifts, in-kind transfers, and remittances).

Adoption has been measured, in various studies, as a continuous treatment (the Propensity score and Tobit methods) or as a binary treatment (the Logit and Probit models) (Awotide et al., 2016; Jones-Garcia & Krishna, 2021; Ruzzante et al., 2021; Yigezu et al., 2018). For the purpose of this study, the relationship between the outcome variables (food security and household income) and the exogenous variables was examined using the Endogenous Switching Regression (ESR) model. The study employed the switching of selection bias, which results from those that are not treated, due to the fact other than treatment status. The Switching Regression Model is a modified classical Heckman Selection model. The ESR has two simultaneously estimated equations in STATA using the outcome and selection equations.

Equation Selection

Two choices are available to farmers, either to adopt or not to adopt CSA. The relationship between these two alternatives is determined by the Probit model in the following equation:

$$A_i^* = \beta Z_i + u_i \tag{1}$$

$A = 1$ if $A_i^* > 0$; $A = 0$ if otherwise, i.e., $A_i^* \leq 0$.
A_i^* is the dependent latent binary (dichotomous) variable for CSA adoption
β is the vector of unknown parameters
Z_i is the vector of observable characteristics (farm, farmer, etc.) influencing the CSA adoption decision.
U_i is the error term that captures the unobservable characteristics

Outcome Equation

Using ESR, the outcome variables (income and food security status) are computed as follows:

Regime 1 (adoption of CSA):

$$Y_{1i} = X_{1i}B_1 + \varepsilon_{1i} \quad \text{if } A_1 = 1 \tag{2}$$

Regime 2 (non-adoption of CSA):

$$Y_{2i} = X_{2i}B_2 + \varepsilon_{2i} \quad \text{if } A_1 = 0 \tag{3}$$

where Y_1 and Y_2 levels of outcomes (food security (HFCS) or gross household income) for adopters and non-adopters, respectively, and X_1 and X_2 are vectors of factors that influence food security.

Equations 1, 2, and 3 are assumed to have a triumvirate normal distribution, with a covariance matrix and a zero mean:

$$Cov(eli, e2i, ui = \begin{pmatrix} \sigma^2{}_{e^2} & . & \sigma_{e2u} \\ . & \sigma^1{}_{e^1} & \sigma_{e1u} \\ . & . & \sigma_u^2 \end{pmatrix},$$

where

σ_u^2 = variance of errors term in the selection equation
$\sigma^2{}_{e^1}$ and $\sigma^2{}_{e^2}$= error term variances in the outcome equation
σ_{e1u} and σ_{e2u}= covariance of ui, e1i, e2i.

The expected outcome (food security and income) of the household that adopted the CSA technology (Eq. 4) and that did not (Eq. 5) is compared by the ESR model. It is also used to investigate the expected income and food security in the cases of counterfactual analysis (Eq. 6) that the CSA non-adopters did adopt and the CSA adopters did not adopt (Eq. 7). It is also more likely that some unobserved factors that influence CSA adoption may also affect the income or food security (outcome variables). Thus, in the outcome and selection equations, the error terms can be correlated (Eqs. 1, 2, and 3). The estimation of these three equations was done simultaneously to solve these problems. This analytical framework is hence used to estimate the treated and untreated mean treatment effects, i.e., the ATT and ATU, respectively using the following equations:

For adopters of CSA with adoption:

$$E(Y_{i1}|A = X_{i1}\beta_1 + \sigma_{1\varepsilon}\lambda_{i1} \tag{4}$$

For non-adopters without adoption:

$$E(Y_{i2}|A = X_{i2}\beta_2 + \sigma_{2\varepsilon}\lambda_{i2} \tag{5}$$

For counterfactuals:

1. CSA adopters, had they not adopted:

$$E(Y_{i2}|A = 1, x = X_{i1}B_2 + \sigma_{2\varepsilon}\lambda_{i1} \tag{6}$$

2. CSA non-adopters, had they decided to adopt:

$$E(y_{i1}|A = 0, x = X_{i2}B_1 + \sigma_{1\varepsilon}\lambda_{i2} \tag{7}$$

The actual expectations are given by Eqs. 4 and 5, from data observation, while Eqs. 6 and 7 provide the counterfactual expected outcomes. The measure of change in food security outcome (food security or income) is given by the mean treatment effect (ATT):

For average treatment effects on adopters:

$$\begin{aligned} ATT &= E\left(Y_{i1}|A = 1, x\right) - E(Y_{i2}|A = 1, x) \\ &= X_{i1}\left(\beta_1 - \beta_2\right) + \lambda_{i1}(\sigma_{i\varepsilon} - \sigma_{2\varepsilon}) \end{aligned} \tag{8}$$

For average treatment effects on non-adopters:

$$\begin{aligned} ATU &= E\left(Y_{i1}|A = 0, x\right) - E(Y_{i2}|A = 0, x) \\ &= X_{i2}\left(\beta_1 - \beta_2\right) + \lambda_{i2}(\sigma_{i\varepsilon} - \sigma_{2\varepsilon}) \end{aligned} \tag{9}$$

Table 1 Summary statistics and variables used in the ESR

Variable	Adopter		Non-adopter		Sum		*P* value
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	
HH food security (FCS)	82.11	69.35	45.25	39.4	77.45	65.75	0.021[b]
Annual HH income (ETB)	32500	29500	7900	5100	25500	18700	0.312
HH age (years)	37.45	13.25	41.25	17.55	40.5	27.25	0.128
HH size (number)	4.55	2.71	4.25	2.55	4.48	3.19	0.135
HH farm experience (years)	25.25	20.55	24.75	21.23	25.50	20.50	0.410
HH labor size (number)	3.45	1.97	3.25	2.01	3.15	2.73	0.512
Soil fertility (1 = fertile, 0 = otherwise)	0.65	0.33	0.25	0.31	0.44	0.34	0.172
Arable land size (acres)	1.75	1.5	0.5	0.5	1.5	1.25	0.111
TLU (number)	3.25	1.75	0.75	0.55	2.55	1.9	0.041[c]
Distance input market (Km)	30	27.1	21	18	25	20	0.999
Distance output market (Km)	120	401	25	13	77	120	0.711
Group membership (1 = yes, 0 = otherwise)	0.81	0.42	0.68	0.51	0.88	0.72	0.166
Contact with extension agents (number)	16.1	11.7	12.5	9.1	15.3	7.3	0.232
Access to weather forecast (1 = yes, 0 = no)	0.55	0.37	0.31	0.4	0.56	0.38	0.032[b]
CSA awareness (1 = yes, 0 = no)	0.41	0.12	0.39	0.11	0.40	0.22	0.888
Access to credit (1 = yes, 0 = no)	0.18	0.29	0.17	0.27	0.18	0.38	0.881
Income from crops (ETB)	11500	7200	2100	1500	9400	3400	0.716
Income from irrigation (ETB)	10000	2500	1800	950	7500	3800	0.000[a]
Income from livestock (ETB)	6000	3050	1500	390	4000	2500	0.126
Off-farm income (ETB)	5000	3023	2500	1900	4800	811	0.333
Safe water access (1 = yes, 0 = no)	0.79	0.29	0.63	0.57	0.81	0.42	0.000[a]
Sanitation access (1 = yes, 0 = no)	0.91	0.23	0.81	0.51	0.83	0.33	0.020[b]
Asset index	7.64	3.25	6.94	3.92	7.66	3.45	0.911

HH household, *ETB* Ethiopian Birr

[a, b, c]a significant level of 1%, 5%, and 10%, respectively

The unobserved factors are adjusted by λ_{i1} and λ_{i2} for ATT and ATU, respectively.

With observational data (as opposed to experimental data), the ESR model is used to address issues of self-selection and the estimation of treatment effects, when there is a non-random allocation of subjects to control and treatment groups (Aravindakshan et al., 2018).

In reviewing various literatures, the important food security determinants include the age of the household head, education level, availability of input, adoption of technology, farm size, land quality, input price, food expenditure, gender, size of household, credit access, level of household income, and access to sanitation and safe water (Habtewold, 2021; Mujeyi et al., 2021; Ogada et al., 2020b; Wekesa et al., 2018). The model formation for selection and outcome was based on the hypothesis that was justified by reviewing the literature. The decision of farmers to reject or adopt CSA is affected by the simultaneous effect of many factors associated with farmers' objectives, asset ownership, biophysical characteristics of locations, constraints, and characteristics, and the attributes of the technology (Amare & Simane, 2017; Musafiri et al., 2022; Waaswa et al., 2021). One of the factors hypothesized as a factor creating or minimizing confidence in new technology adoption was the farmers' age. Conservative and resistance to adopting new technologies may occur from more experienced farmers. Additionally, these farmers may be willing to try new technologies if they previously have tried and obtained a certain positive result. This variable can either positively or negatively affect decision of farmers' to adopt CSA technology.

Results and Discussion

Summary of the Descriptive Variables Used in the Estimation

The descriptive statistics of the data for the important variables included in the estimation of the ESR model are presented in Table 1. The *t*-test was used to see the variation between adopters and non-adopters of CSA technologies for relevant continuous variables (i.e., household FCS, log income, farming experience, education, labor size, household size, distance to input, TLU, frequency of contact with

Table 2 Results of food security ESR model

Variables	Selection equation (CSA adoption)		Outcome equation (Food security)			
			Adopter		Non-adopter	
	Coefficient	Robust Std. Err	Coefficient	Robust Std. Err	Coefficient	Robust Std. Err
Education	−0.06	0.06	0.07[b]	0.18	0.05	0.03
HH size			0.17	0.43	0.02	0.04
Cultivable land size	0.11	0.09	0.103[b]	0.088	−0.02	0.04
Extension agent contact	−0.03	0.04	−0.05	0.50	−0.002	0.03
Distance to output market	0.004[b]	0.003	0.22	0.22	−4.6	−0.003
Off-farm income			0.002	0.004	0.00	0.00
TLU	0.26[b]	0.20	0.30[b]	0.19	0.07	0.03
Access to safe water and sanitation			0.33[b]	0.18	−0.58	1.43
Distance to input market	−0.006[b]	0.002				
Small-scale irrigation	0.61	0.42	0.89[a]	0.73	0.01	1.41
HH age	−0.02	0.03				
HH farm experience	0.03	0.002				
Group membership	−0.34	0.64				
Weather forecast access	0.73	0.69				
Asset ownership	0.77	0.81				
Soil fertility	0.81[a]	0.51				
Access to credit	−0.18	0.47				

[a, b, c] a significant level of 1%, 5%, and 10%, respectively

extension agents, etc.), while the difference between the two groups for categorical binary variables (i.e., asset ownership, CSA awareness, credit access, safe water and sanitation access, access to the weather forecast, the status of soil fertility, and group membership, etc.) designated using chi-square test. Soil fertility was identified from the farm onsite, as the process of identification was supported by the enumerator to the household head during the survey. Black and red clay soils were categorized as fertile, whereas infertile soil is characterized by sand, sandy loam, and loam soils because these soils are N and P deficient inherently and have low retention of nutrients, low water holding capacity, and low organic matter content (Hailu et al., 2015; Laekemariam & Kibret, 2020; Laekemariam et al., 2017).

Table 1 shows the differences between CSA adopters and non-adopters, as provided by the summary statistics of the surveyed households. The result revealed a significant difference between non-adopters and adopters for variables such as household food security, livestock income share, income from irrigation, access to the weather forecast, access to water and sanitation, and total livestock unit. The status of food security of households, measured by FCS, of adopters of CSA, was about 45% higher than non-adopters. Farmers who are CSA adopters possess relatively significantly higher herd size, better access to weather information, earn significantly higher income from irrigation, and access to sanitation and safe water, as compared to non-adopters.

Switching Regression Analysis Results

The result of the selection equation of the first stage analysis (CSA adoption) revealed that the factors such as distance to inputs and output markets, soil fertility status, and ownership of assets significantly predicted CSA adoption in the mixed farming system (Tables 1 and 2). A unit increase in TLU and distance in the output market increase the likelihood of CSA adoption by 0.35 and 0.004, respectively. In smallholder farmers, livestock production is considered storage of wealth, and households that own them are financially less constrained. This livestock can be sold at any time and able to purchase any farm input necessary for new technologies. This is supported by multiple studies conducted by Kebebe (2019), Mathewos et al. (2021), and Ogada et al. (2020a). Kebebe (2019) described livestock production as a key area that plays a major role in rural livelihoods through providing income and employment. These studies used different models but the results were found pretty comparable. In addition, a decrease in odds of adoption of CSA by 0.006 was recorded for a unit increase in distance to the input market. This finding is substantiated by studies conducted by Kangogo et al. (2021b), Mujeyi et al. (2021), Pagliacci et al. (2020b), and Wekesa et al. (2018) that showed a significant relationship between distance to input market and CSA adoption. It is justified that longer distances incur high transaction costs due to corresponding high transportation costs. Tables 2 and 3 present the ESR model result.

The second set of outcome equations from the ESR (i.e., household income and food security) analyzed the relevant factors that affect these outcome variables with respect to CSA adoption. The result revealed that smallholder farmers and market factors, as well as farm characteristics, affected household welfare significantly. Tables 1 and 2 indicate that the level of education of the head of the household, size of cultivable land, labor size, the TLU, and asset index were the major factors that significantly predicted household income. Commonly, education was found out as having a significant impact on household income. This is supplemented by Mujeyi et al. (2021), as more educated households can engage in better yield-enhancing CSA technology adoption activities, which in turn creates better conditions for sending as many products as possible to the market. Education promotes the ability of farmers to make sound decisions on future investments through managing their profitability. A larger size in labor, which is the abundantly available resource, also contributes to income increase through operating the farm operations, which improves productivity and some household members can engage themselves in other non-farm economic activities thereby improving the income of households. TLU had a positive and significant effect on the income of households. Livestock is indeed one of the fundamental savings methods in rural households that can be liquidated easily to bridge income gaps that may arise from within the household (Chen et al., 2021). Ownership of assets also had a positive impact on household income. This calls the farmers' attention to invest in productive agricultural assets.

The food security level of households was affected by factors such as small-scale irrigation, the TLU, education of household heads, and access to safe water and sanitation. Small-scale irrigation practices had positively and significantly affected the food security status of smallholder farmers. This is substantiated by a study conducted in Ethiopia by Jambo et al. (2021), which revealed that participation in small-scale irrigation practices increased the daily intake of calories of users by 643.76 kcal as compared to non-user households. The finding further highlighted that irrigation had a positive impact on crop production, consumption, and revenue generation. Total livestock units and education have also a positive and significant impact on the status of food security of smallholder farmers. These findings concur with other studies in the literature. A study in Western Ethiopia by Kebebe (2019) revealed that the status of household food security of smallholder farmers was influenced by the household heads education and ownership of livestock. Another similar study in Northern Ethiopia also found a positive and significant relationship between education and food security and TLU and food security (Endale et al., 2014; Hadush, 2018). Households with higher education levels

Table 3 Results of income of household using ESR model

Variables	Selection equation (CSA adoption)		Outcome equation (Food security)			
			Adopter		Non-adopter	
	Coefficient	Robust Std. Err	Coefficient	Robust Std. Err	Coefficient	Robust Std. Err
Education	−0.06	0.05	0.03[c]	0.02	0.06[a]	0.40
Log crop income share			0.02	0.05	−0.13	0.30
Log livestock income share			0.09[b]	0.05	−0.09	0.18
Log irrigation income share			0.54[a]	0.43	0.08	0.09
Log non-agriculture income share			0.13[b]	0.05	0.16	0.25
TLU	0.35[b]	0.14	0.03	0.02	0.04	0.07
Cultivable land size	0.15	0.12	0.03	0.02	−0.07	0.08
Extension agent contact	−0.06[b]	0.03				
Distance to output market	0.005[b]	0.003				
Distance to input market	−0.02[b]	0.02				
Small-scale irrigation	0.99[a]	0.89				
HH age	0.02	0.03				
HH farm experience	0.22	0.02				
Group membership	−0.035	0.34				
Weather forecast access	0.45	0.41				
Asset ownership	0.87[b]	0.42				
Soil fertility	0.98[b]	0.45				
Access to credit	0.08	0.35				

[a, b, c]a significant level of 1%, 5%, and 10%, respectively

Table 4 Results of the average treatment effects on food security and household income

Index	Food security			Income		
	Estimate	Std Err	*P* value	Estimate	Std Err	*P* value
ATT	1.586	0.091	0.039[c]	0.814	0.024	0.044[c]
ATU	0.390	0.299	0.112[c]	-0.491	0.072	0.038[c]
ATE	1.439	0.092	0.041[c]	00.682	0.033	0.041[c]

[a, b, c]a significant level of 1%, 5%, and 10%, respectively

can transfer information on new innovations such as CSA, and they can adopt yield-improving packages quickly that ultimately improve food security. Studies from eastern African countries also showed food insecurity to be correlated with low levels of education (Gebre & Rahut, 2021). This finding also supports the results of Wekesa et al. (2018) who documented that higher education level at the household level could lead to a better understanding of new technologies. Education improves farmers' reasoning capability and enables them to have enhanced awareness of new technologies. It also enables smallholder farmers in reading and acquires knowledge on agricultural information, education, and communication (IEC).

There was positive relationship between access to safe water and sanitation with food security. A related study conducted by Young (2021) indicated that water and sanitation significantly contributed to food security by ensuring enhanced absorption capacity of the body and nutrient use in the food. Additionally, sanitation safeguards human fecal pollution thereby spread of disease can be reduced. The study revealed a positive and significant relationship between TLU and food security. Livestock provides households with food directly (meat and milk) and income generation through sales and the money can be used again for purchasing food during critical times.

The estimates of the treatment effects of the adoption of CSA on income and food security of households are presented in Table 4. The Treated Average Treatment effect (ATT) category measures the change between the adopters' welfare and what they could have if they had not adopted CSA. On the other hand, the Untreated Average Treatment effect (ATU) examines the change in the welfare of non-adopters and their counterfactual effects. Unlike the mean difference reported in Table 1, these estimates account for selection bias.

The ATT shows that household income and food security for the treated are positive and statistically significant with 1.58 and 0.81, respectively. This shows that adopters would have become food insecure and lost their income had they had not adopted CSA technology. However, the ATU was − 0.49 and statistically significant for the log household income of smallholder farmers, but it was found higher for food security (0.39), though it was not found to be statistically significant. Likewise, the outcomes of average treatment effects (ATE) from ESR show that, had the non-adopters CSA technologies, they would have attained crop income gains. These results show that, had adopters not adopted CSA technologies, they would have been worse off, in terms of welfare. In terms of food security, non-adopters would have benefited, had they adopted CSA technology. As shown in Table 3, both household income and food security of adopters were significantly affected by CSA adoption. This finding is in line with past studies, which supplement this study with evidence of the positive contribution of adoption of CSA technology on household welfare (Abegunde et al., 2022; Bongole et al., 2022; Musafiri et al., 2022; Sam et al., 2021). A study in the Nyando basin of Kenya by Ogada et al. (2020a) found that farmers who adopted CSA were more food secure as compared to non-adopters. The study demonstrated a robust relationship between CSA adoption and food security. Therefore, interventions of CSA aiming at food security improvement in smallholder farming communities may have significant welfare gains for smallholder farmers. In general, CSA technologies improve household welfare through enhanced agricultural productivity.

Implications for Policy and Practice

The agriculture and food system interface, defined by CSA where its objectives are sustainably increasing agricultural production, improving community resilience, and mitigating climate change impacts, is on the fast track to integrating into the global developmental agenda (Gebre & Rahut, 2021). Nevertheless, assembling the empirical evidence has complicated the transformation of the concept of CSA into concrete actions (Wekesa et al., 2018). Therefore, evaluating the present knowledge on CSA's effectiveness to achieve the intended benefits and at the same time informing the discourse on agriculture, food, and climate change is an urgent need (Young, 2021).

Evidence-based decisions through formulating workable policies and knowledge of technology transformation are, therefore, key. Considering development priorities is the first step as CSA should contribute to employment opportunity building, market, and education opportunities. The approach is termed smart because a range of key development issues is addressed by CSA (Kebebe, 2019). The next agenda must be connecting interdisciplinary research, policy, and practice. This enhances decision-making at all levels because a broader base of field experience and scientific evidence is crucial for decision-making (Chen et al., 2021). Integrating landscape systems with farms such as integrating crops, livestock, fish, and trees on the entire landscape or farms can improve productivity, and strengthen farming system resilience and income which thereby improve household welfare (Aravindakshan et al., 2018). In formulating CSA policies and practices, the inclusion of women and youth capacity building plays an important role in achieving the goals of CSA. Leadership skills as well as farming and facilitation skills can be established through the support of local people tailoring climate information, avail materials, and communicating needs (Fite et al., 2022). In conclusion, policies, practices, and regulations must be consistent for CSA to be effective.

Conclusion

This research assessed the impact of CSA on household welfare, using the ESR model. Variables associated with fertility status of the soil, TLU, access to input markets, and asset ownership emerged as showing a significant impact on farmers' decisions on CSA adoption. The ATT is positive and significant, which justifies the adoption of CSA resulting in a significantly positive impact on farmers' welfare. From these findings, several policy implications can be drawn. The government needs to consider incentive provisions for agro-dealers in agricultural business investments that sell inputs in rural areas. Government taxes should also be reduced for agro-dealers so that inputs will be accessible nearby to farmers. The government has to also provide incentives for financial service providers, to avail financial services affordable to agro-dealers and to enable them to store the necessary inputs in sufficient quantities. Alternatively, manufacturers of inputs or buyers of agricultural products can also be beneficial to these incentives, to encourage them to foster mutually beneficial and flexible arrangements of marketing with rural agro-dealers. The findings of this study show that reducing the distance of the input market will go a long way in maximizing the probability of adoption of CSA technology, which is related to enhanced productivity. Increased productivity will, in turn, improve household welfare by increasing household income and food security. Additionally, food availability alone does not guarantee household food security, as it needs to be implemented by access to safe water and good sanitation. Development practitioners have to target educated farmers due to their greater adoption ability. Information, Education, and Communication (IEC) need to be promoted CSA adoption to suit uneducated farmers. The findings of this study also indicated that there exists a robust association between CSA and food security (through a positive and significant ATT). As a result, climate-smart agricultural interventions in smallholder farmers may actually have positive and significant household food security and income benefits.

Acknowledgements The local agricultural offices are acknowledged for granting access to the study area and arranging all the necessary support during data collection. We also recognize the enumerators' contribution to getting the data collected as scheduled. Ginjo Gitima's expertise contribution in preparing a high standard study map is highly acknowledged. We also extend our thanks to smallholder farmers, community elders, and extension agents for providing useful data and information during the household survey, focus group discussion, and key informant interviews, without which this study could not have been accomplished.

Author Contribution The corresponding author collected, analyzed, and interpreted the data using SPSS and Stata, and drafted the manuscript. The second and third authors made substantial contributions to the design, content manipulation, and reviewing of the overall manuscript. All authors read, proofed, and approved the final manuscript.

Funding The candidate (Girma Tilahun Getnet) got little funds for data collection purpose only from the Ministry of Education and Bonga University.

Availability of Materials and Data During the study, the data analyzed and generated are not available publicly due to issues of confidentiality, but they can be available from the corresponding author with permission from Addis Ababa University and on reasonable requests.

Declarations

Ethics Approval The research follows all academic and researches procedures based on the journal requirements.

Consent for Publication Not applicable.

Conflict of Interest The authors declare no competing interests.

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