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Impact of adoption of climate-smart agriculture on food security in the tropical moist montane ecosystem: the case of Geshy watershed, South-West Ethiopia

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Abstract:

The traditional rain-fed agriculture system of Ethiopia is suffering from climate change impacts and extremes. It needs to be improved to feed the growing population and create a resilient society. Climate-smart agriculture (CSA) is an approach intended to sustainably increase productivity, enhance household resilience, and reduce greenhouse gas emissions. This study was, therefore, undertaken to examine the effect of climate-smart agriculture (CSA) practices adoption on the food security of smallholder farmer households in a moist tropical montane ecosystem of South Western Ethiopia. A semi-structured questionnaire was used to collect data from 384 purposively selected households in a cross-sectional study. Fifteen key informant interviews and eight focus group discussions were also conducted to triangulate the reliability of the survey data collected. A total of eighteen CSA practices, adopted by farmers, were identified in the study area. These practices were further grouped into five packages by using principal component analysis and linked to food security by the multinomial endogenous switching regression model. The findings revealed that the highest impact of CSA adoption on food security was by households that adopt all the five category practices. Adopters of this package were 41.2% more food secure in terms of per capita annual food expenditure, 39.8 percent in terms of Household Food Insecurity Access Scale (HFIAS), and 12.1 percent in terms of Household Food Consumption Score (HFCS) than the non-adopters. The adoption of this package was further positively influenced by farm size, gender, and productive farm asset values. Using CSA practices in combinations and to a relatively larger extent has the potential to alleviate food security problems. Farmers need to be motivated by providing income-generating activities and land fragmentation must be discouraged through public education. This in turn improves CSA adoption and initiates production assets investment that can absorb climate change risks.

Impact of adoption of climate-smart agriculture on food security in the tropical moist montane ecosystem: the case of Geshy watershed, South-West Ethiopia

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Abstract

The traditional rain-fed agriculture system of Ethiopia is suffering from climate change impacts and extremes. It needs to be improved to feed the growing population and create a resilient society. Climate-smart agriculture (CSA) is an approach intended to sustainably increase productivity, enhance household resilience, and reduce greenhouse gas emissions. This study was, therefore, undertaken to examine the effect of climate-smart agriculture (CSA) practices adoption on the food security of smallholder farmer households in a moist tropical montane ecosystem of South Western Ethiopia. A semi-structured questionnaire was used to collect data from 384 purposively selected households in a cross-sectional study. Fifteen key informant interviews and eight focus group discussions were also conducted to triangulate the reliability of the survey data collected. A total of eighteen CSA practices, adopted by farmers, were identified in the study area. These practices were further grouped into five packages by using principal component analysis and linked to food security by the multinomial endogenous switching regression model. The findings revealed that the highest impact of CSA adoption on food security was by households that adopt all the five category practices. Adopters of this package were 41.2% more food secure in terms of per capita annual food expenditure, 39.8 percent in terms of Household Food Insecurity Access Scale (HFIAS), and 12.1 percent in terms of Household Food Consumption Score (HFCS) than the non-adopters. The adoption of this package was further positively influenced by farm size, gender, and productive farm asset values. Using CSA practices in combinations and to a relatively larger extent has the potential to alleviate food security problems. Farmers need to be motivated by providing income-generating activities and land fragmentation must be discouraged through public education. This in turn improves CSA adoption and initiates production assets investment that can absorb climate change risks.

Keywords: Climate-smart agricultural practices · smallholder farmers · Food security · Multinomial endogenous switching regression model, Geshy watershed

1. Introduction

In the era of climate change, climate-smart agriculture was first launched in 2009 as an approach to guide the management of agriculture (Ramachandran et al., 2015). The impact on sustainable food production, resilience, and mitigation can best be addressed by this approach (Acevedo, 2011; Endale et al., 2014; Grote et al., 2021). The primary indicators of climate change are increasing temperature, rising sea levels, melting ice caps, changing rainfall patterns, and changing humidity (IPCC, 2021). Secondary consequences that are direct determinants of agriculture are tidal surges, cyclones, floods soil salinity, and droughts (Hasan et al., 2018). A crop model for sub-Saharan Africa forecasts that the adverse effect of crop damage on yields varies between 36 percent, 12 percent, and 13 percent for Ethiopia, Rwanda, and Uganda respectively (Thomas, 2020). Hence, climate change has noticeable negative impacts on food security (Atanga & Tankpa, 2021; Ilboudo Nébié et al., 2021; Mekonnen et al., 2021). Thus, the prioritization of food security in a changing climate has been subjected to discussions at all levels of government (Tefera et al., 2022). Climate-smart agriculture is recommended by development organizations and researchers in order to feed the growing population under scenarios of the declining yield of major crops.

Ethiopia is a victim of the global climate change phenomenon despite its negligible per capita CO2 emission, which is only 0.15 tons as compared to the global average of 4.79 in 2020 (Caporale et al., 2021). Ethiopia has experienced an increasing trend in average temperature (Belay et al., 2021; Gemeda et al., 2021a). It is also obvious that dry seasons will get drier and wet seasons wetter (Gemeda et al., 2021a). The study area is experiencing early cessation, a delayed onset, an abundant rainfall, and poor *belg* performance making the watershed food insecure and forcing farmers to shift to livestock production, and grow short maturing and lower-yielding varieties

The most cited definition of the concept of CSA as highlighted by Lipper et al. (2014) is ‘’an approach for transforming and reorienting agricultural systems to support food security under climate change realities’’. In a fluctuating climate, CSA can sustainably improve productivity and resilience (adaptation), remove/reduce greenhouse gas emissions (mitigation), and promote the efforts of national food security (Steenwerth et al., 2014; Thornton et al., 2018). For example, urea deep placement is a CSA practice that needs placing briquettes of urea (1 to 3 g/granule) deep in the soil from 7 to 10 cm depth after transplanting paddy rice. This practice, in Bangladesh, is found to minimize nitrogen loss by 40%, enhance 25% rice grain yield, reduce the cost of urea by 25%, and lower water pollution and greenhouse gas emissions (FAO, 2014; Hasan et al., 2018). Available literature documented that CSA practices can improve the productivity of crops and hence contribute to food security (Chemura et al., 2021; HABTEWOLD, 2021; Teklewold et al., 2019). More than a quarter of the population of Ethiopia is food insecure. Ethiopia is ranked 90th out of 116 countries and categorized as serious in the 2021 Global Hunger Index (WFP, 2022). Nevertheless, the establishment of the direct link between food security and CSA practices adoption has received little attention to date (Hasan et al., 2018).

The Ethiopian government, NGOs, and researchers are attempting to mitigate climate change's adverse effects by developing a national CSA roadmap, promotion, and dissemination (Eshete et al., 2020; HABTEWOLD, 2021). Important thematic areas of the Ethiopian climate change Action Plan Strategy (Hirpha et al., 2020) are food security and enhancing the resilience capacity of communities (Mekonnen et al., 2021).

The economy of Ethiopia is yet dependent on undeveloped rain-fed agriculture, which accounts for 80 percent of exports, 40 percent of GDP, and an estimated 75 percent workforce of the country (Eshete et al., 2020). Crop yields below the regional average, only 5 percent of irrigated land, weak market linkage, and limited use of improved seeds and fertilizers are common characteristics of Ethiopian agriculture (Alemu et al., 2019). Based on the Worldometer report of the United Nation, the population of Ethiopia has risen by 49 percent in the last 20 years alone and reaches approximately 122 million in 2022 while the agricultural system has not been improved since (CIAT, 2017). The agrarian population constitutes 85 percent of the total population and the food security and livelihood situations are worsening (Tesfaye et al., 2021). These problems are yet exacerbated by global climate change impacts and extremes in the form of rainfall pattern anomalies and temperature rise (Gangadhara Bhat & Moges, 2021). CSA is currently promoted as an approach that can sustainably increase agricultural productivity, improve resilience and thereby enhancing household adaptation to climate change impacts, and reducing potential greenhouse gas emissions in Sub-Saharan Africa. This is also an important intervention in Ethiopia to reduce the mentioned challenges.

Smallholder farmers, through their indigenous knowledge, have been undertaking farming practices such as agroforestry, soil fertility management using organic manure, crop rotation, etc. This experience though not in the name of CSA laid a foundation for current CSA technologies. However, CSA farming is acknowledged as an important segment in climate change adaptation of agriculture (Autio et al., 2021), CSA impact on food security of smallholder farmer studies is lacking, particularly in Ethiopia, where national development programs promoting the adoption of CSA are not currently implemented at full scale (CIAT, 2017; Tesfaye et al., 2021). The objective of this paper is to address this issue by identifying the adoption of CSA and food security status for smallholder farmers that are climatically vulnerable in the Geshy watershed, South-West Ethiopia Vulnerability in the context of this watershed is justified especially by the decreasing trend in the amount of rainfall, which was 56.6, 40.1, and 32.4 mm per day for 1986, 2005, and 2020 years respectively for the month of July. This month receives the maximum rainfall in Ethiopia. Due to the rugged mountainous landscape nature of the watershed, the high amount of rainfall sweeps the top fertile soil and sometimes creates gully erosion that makes agricultural practices difficult.

The first three CSA practices frequently used by farmers were selected. These practices are not capital or knowledge-intensive and are within the nearby of farmers to be adopted. If these technologies show food security improvement, planning food security programs with CSA will be easier. Taking into account the above perspective, this study examines the association of CSA adoption with household food security considering the socioeconomic characteristics of smallholder farmers.

2. Materials and methods

2.1 Study area description

The study 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 to 2670 meters above sea level (masl). The topography is characterized by undulating terrain with slopes ranging from 0-50% and is surrounded by intermittent rivers. Agroecologically, the area falls under sub moist mid-highlands to warm moist highlands climatic zones. This diverse zone enables the sub-watersheds to produce different crops, fruits, vegetables, and rearing livestock (Gangadhara Bhat & Moges, 2021). It has an annual rainfall ranging between 1,200 to 2,200mm; while the annual maximum and minimum temperature ranges between 12 to 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., 2021b). 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.

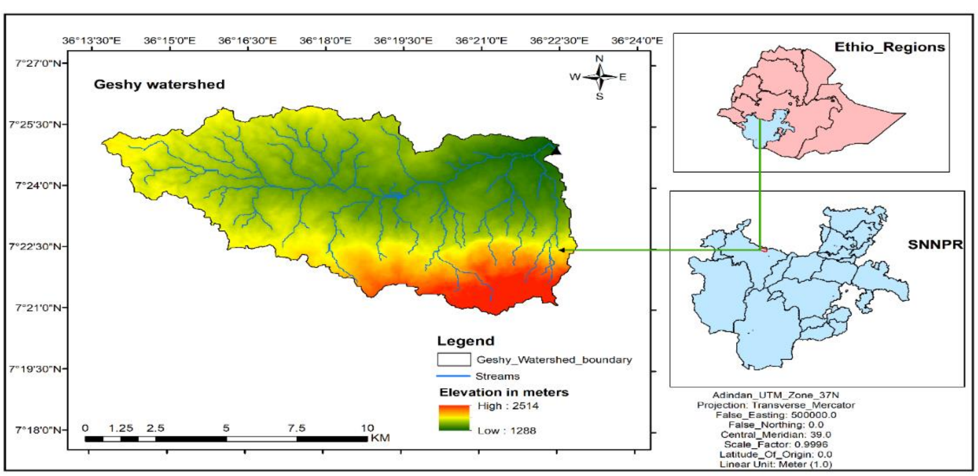

Fig. 1 Geographical location of Geshy Watershed (Source: own development)

Geshi watershed, which consists of seventeen micro watersheds benefiting nine Kebeles in Gimbo Woreda of Kaffa administrative Zone, has a total rural population of 14518 of which 7261 are males. With an estimated area of 13,935 ha, the major 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 lands are other small fragments of land (Alemu et al., 2019).

This study utilized data collected from farm household surveys carried out between October and December 2021 by well-trained enumerators. A multistage sampling technique was used for selecting 384 respondents. The sampling technique involved three stages. The first stage involved the identification of the *Woreda (Gimbo)* where the watershed is found. The second stage followed the evaluation of the number and names of 11 *Kebeles* that are beneficiaries of the watershed. The third stage involved identifying two villages from each *kebele* purposively, which are users and non-users of the watershed. Finally, using a simple random sampling technique, a total of 384 households were selected from the 22 villages using Yemane, 1967, the formula of sampling $(n=N/N(1-e)^2$ using a 95 percent confidence interval. The selected households were distributed proportionally among the three kebeles. Eventually, using a simple random sampling technique, individual households were selected for a face-to-face interview. Focus group discussions and key informant interviews were also conducted to collect qualitative information.

2.2 Analytical framework

Primarily, the currently available 18 CSA practices adopted by farmers: small-scale irrigation, alley cropping, use of organic fertilizer, use of improved crop varieties, use of efficient inorganic fertilizer, planting trees for windbreak and shelter for crops, use of mulching, changing planting dates, use of cover crops, crop rotation using legumes, improved animal husbandry, poultry farming, use of terraces, apiculture, feed improvement, sheep fattening, use of grasses, and use of briquettes, were identified. Then, using principal component analysis, these practices were further grouped into five packages of heterogeneous principal clusters: 1) crop management practices, 2) field management practices, 3) farm risk reduction practices, 4) supplementary income generation practices, and 5) soil and water conservation practices. This results in grouping a smaller number of highly correlated practices under one component for the ease of interpretation and generalization of the group (Jollife & Cadima, 2016; Wekesa et al., 2018). The rotation resulted in 5 principal components among a possible 19 extracted with eigenvalues >1 based on Kaiser's (1958) criterion. The principal component analysis is helpful in minimizing the dimensionality of data without losing much information. This is relevant in determining the relationships between practices with regard to usage and succeeding analysis through fitting the groups to the model and drawing conclusions. The method is superior to a conventional grouping of technologies that could make it hard to conclude about the group in conditions where the entire group is represented by few practices. Finally, a comparison between the impact of CSA adopters and non-adopters on food security status is computed using multinomial endogenous switching regression analysis.

Using principal component analysis with varimax rotation and iteration, the practices were grouped in the model shown in eq. 1

$$Y_1 = a_{11}x_{12} + a_{12}x_2 + \cdots + a_{1n}x_n$$
$$(1)$$
$$Y_j = a_{j1}x_{j1} + a_{j2}x_2 + \cdots + a_{jn}x_n$$

Where $Y_1, \ldots \ldots Y_j$ represents uncorrelated principal components, a_1–a_n indicates correlation coefficient and $X_1 \ldots\ldots X_j$ signifies factors affecting the choice of a particular strategy. The identified CSA practices are grouped using principal component analysis and presented in Table 1. Prior to the field study, the identification of these practices was guided by the Ethiopian CSA roadmap document ratified by the Ministry of Agriculture (Eshete et al., 2020).

The multinomial endogenous switching regression model (MNLESR) was then employed to model the determinants of choice and the impact of CSA practices on household food security after these practices are grouped.

Table 1 Climate-smart agricultural practices identified and widely used by farmers

S/No	CSA practices	Why are these practices climate-smart	Remark (Source)
1	Small-scale irrigation	Create carbon sink and improve yield frequency	FAO, 2022
2	Practicing alley cropping	Diversify income sources	CSA roadmap, 2020
3	Use of organic fertilizer	Reduce nitrous oxide and methane emission	FAO, 2022
4	Use of improved crop varieties	Improve productivity, reduce insect and disease attack	FAO, 2013
5	Use of efficient inorganic fertilizer	Improves soil productivity	GGGI, 2021
6	Planting trees for windbreak and shelter for crops	Providing shed to crops, trees store large amount of CO_2 and diversify income sources	CSA roadmap, 2020
7	Use of mulching	Reduces existing emissions	CSA roadmap, 2020
8	Changing planting dates	Reduce crop failure	FAO, 2013
9	Use of cover crops	Maintain soil moisture and reduce emission	FAO, 2022
10	Crop rotation using legumes	Improves soil fertility and increases crop productivity	GGGI, 2021
11	Improved animal husbandry	Improves household income	CSA roadmap, 2020
12	Poultry farming	Improve household income	GGGI, 2021
13	Use of terraces	Reduced erosion and soil detachment	CSA roadmap, 2020
14	Apiculture	Improve household income, pollination	FAO, 2013
15	Feed improvement	Improved livestock productivity	CSA roadmap, 2020
16	Sheep fattening	Improve household income	FAO, 2913
17	Use of grass strip	Feed for animals, soil and water conservation	FAO, 2013
18	Use of briquettes	Energy-saving, reducing deforestation, mitigation role	GGGI, 2021

Household food security status was computed using per capita annual food expenditure, Household Food Insecurity Access Scale (HFIAS), and Food Consumption Score (FCS) for measuring availability, access, and utilization dimensions respectively.

Smallholder farm households were assumed to face a choice of nine mutually exclusive packages/combinations for responses to changes in average rainfall and temperature (climate change) in the first stage. In the next stage, MNLESR econometric model was used to examine the effect of various CSA practices on the status of food security.

Step 1: Multinomial adoption selection model

At this point, the determinants of the choice of CSA packages were determined by using the multinomial logit model. Farm households were assumed to maximize the status of their food security Y_i by making revenue comparisons generated by 9(M) alternative CSA packages. The need for farmer *i* to make a choice over any strategy *j* over other alternatives *K* is that $Y_{ij} > Y_{ik}$, $K \neq J$, where *j* gives higher expected food security than any other technology. Y_{ij}^{*} is the latent variable representing the level of expected food security that can be affected by the observed household, plot features, climate shocks, and unobserved characteristics as follows:

$$Y_{ij}^{*} = X_i \beta_j + \varepsilon_{ij} \quad (2)$$

Where X_i denotes the observed exogenous variables (household and plot features), while the unobserved features are justified by the error term ε_{ij}. X_i is the covariate vector, which is assumed to be uncorrelated with the idiosyncratic unobserved stochastic component ε_{ij}, that is $E(\varepsilon_{ij}|X_i) = 0$, in that error terms ε_{ij} are considered to be identically independent and Gumbel distributed, which is, under the independent irrelevant alternatives (IIA) hypothesis (Fosgerau et al., 2020). The probability of choosing $j(P_{ij})$ is given by the multinomial logit model (Hoffman & Duncan, 1988) following the selection model as follows:

$$P_i = p\left(\varepsilon_{ij} < 0|x_i\right) = \frac{exp\ (X_i\beta_i)}{\sum_{K=0}^{J} exp\ (X_i\beta_k)} \quad (3)$$

Step 2: Multinomial endogenous switching regression model

The impact of each response package on food security was examined using endogenous switching regression (ESR) by applying Bourguignon et al. (2007) selection bias correction model. A total of 9 regimes have been faced by farm households with regime $j = 1$ being the reference non-responsive category. For each possible regime, the food security status equation is defined as:

$$
\begin{aligned}
&\text{Regime 1 } Q_{i1} = Z_i\alpha_1 + \mu_{i1} \;\; if\; i = 1 \\
&\vdots \qquad\qquad \vdots \\
&\text{Regime j } \; Q_{ij} = Z_i\alpha_j + \mu_{ij} \;\; if\; i = j
\end{aligned} \tag{4}
$$

Where Q_{ij}'s denote the status of food security, Z_i represents a list of exogenous variables (household, plot, location, climate shocks, and institutional variables), and the i^{th} farmer in regime j and the distribution of error terms μ_{ij}*'s* are with $E(\mu_{ij}|x, z) = 0$ and var $(\mu_{ij}|x, z) = \sigma_j^2$. The term Q_{ij} is observed if, and only if, CSA technology is used, which happens when $Y_{ij}^* > \max_{K\neq 1}(Y_{ik})$; if (3) and (4) error terms are not independent, OLS estimates were biased for eq. (4). A α_j consistent estimation needs inclusion of alternative choices selection correction terms in eq. (3). The following linearity assumption is considered in MNLSR: $E(\mu_{ij}|\varepsilon_{i1} \ldots. \varepsilon_{ij}) = \sigma_j \sum_{k\neq j}^{j} r_j(\varepsilon_{ik} - E(\varepsilon_{ik}))$. The correlation between error terms in (3) and (4) was zero by construction.

Eq. (3) can be expressed by using the above assumption as follows:

$$
\begin{aligned}
&\text{Regime 1 } Q_{i1} = Z_i\alpha_1 + \sigma_1\lambda_1 + \omega_{i1} \;\; if\; i = 1 \\
&\vdots \qquad\qquad \vdots \\
&\text{Regime j } \; Q_{ij} = Z_i\alpha_j + \sigma_j\lambda_j + \omega_{ij} \;\; if\; i = j
\end{aligned} \tag{5}
$$

Where σ_j is the covariance between μ*'s* and ε*'s*, while λ_j is the inverse Mills ratio calculated from the estimated probability in Eq. (5) as:

$$
\lambda_j = \sum_{m\neq j}^{j} \rho j \left[\frac{P_{ik} In(P_{ik})}{1-P_{ik}} + In(pij)\right] \tag{6}
$$

Where ρ signifies the correlation coefficient of μ*'s* and ε*'s*, whereas ω_{ij} are error terms with zero expected value. In the earlier expression of the multinomial choice setting, there were one j – 1 selection correction terms for each CSA alternative practice. To account for the heteroscedasticity arising from regressors generated given by λ_t, the standard errors in eq. (5) were bootstrapped.

Average treatment effects estimation

At this stage, a counterfactual analysis was conducted to examine average treatment effects (ATT) by making a comparison of the expected outcomes of adopters with and without the adoption of a certain CSA technology. In the counterfactual and actual scenarios, ATT was computed as follows (Liang et al., 2021):

Status of food security with adoption/usage

$$
E(Q_{i2}|i = 2) = z_i\alpha_2 + \sigma_2\lambda_2 \tag{7a}
$$

$$
E\left(Q_{ij}\middle|i = j\right) = z_i\alpha_j + \sigma_i\lambda_j \tag{7b}
$$

Status of food security without adoption (counterfactual)

$$E(Q_{i1}|i = 2) = z_i\alpha_1 + \sigma_1\lambda_2 \tag{8a}$$

$$E(Q_{i1}|i = j) = z_i\alpha_1 + \sigma_1\lambda_j \tag{8b}$$

The difference between 7a and 8a defines ATT, which is given by:

$$\begin{aligned} ATT &= E(Q_{i2}|i = 2) - E(Q_{i1}|i = 2) \\ &= z_i(\alpha_2\alpha_1) + \lambda_2(\rho_2 - \rho_1) \end{aligned} \tag{9}$$

It shows the expected change in mean food security status of adopters, if adopters and non-adopters have the same features of return, for example, while λ_j is the selection term that considers all the differences in potential effects of unobserved variables if adopters had the same features as non-adopters.

Table 2 presents variables employed in econometric analysis, which was derived from reviewing past studies (HABTEWOLD, 2021; Hasan et al., 2018; Lipper et al., 2014; Wekesa et al., 2018).

2.3 Food security measurement

The status of household food security was measured using per capita annual food expenditure, Household Food Insecurity Access Scale (HFIAS), and Household Food Consumption Score (HFCS), which were used as proxies for the food security of farmers. The per capita annual food expenditure is an indicator that approximates calorie consumption based on the total amount of food acquisition or consumption by the household. By attaching standard nutritional value weights in the index of the food groups, the indicator constructs the conversion of the food acquisition or consumption by the household into dietary energy (K/cals) by matching individual foods with the food consumption table. The amount of calories is calculated by measuring the portion consumed or purchased, divided by the total household members (Nicholson et al., 2021). If the data is collected over a number of days, the computation needs to be divided by the number of collection days in order to generate the number of calories per person per day. HFIAS was developed by the USAID-funded Food and Nutritional Technical Assistance II Project (FANTA) and measures the access dimension. It contains nine occurrence questions with severity based on four levels of questions on a recall period of the previous month. A range of questions (0 = not at all, 1 = rarely, 2 = sometimes, 3 = often) are represented by the four severity questions. The highest household score is 27, indicating severe food insecurity; the lowest score is 0, which shows that the household is food secure (Otekunrin et al., 2021). The HFCS was developed by World Food Programme (WFP) and measures the utilization dimension. It incorporates the frequency of consumption of diets over a seven-day period and weighs according to the relative nutritional value of the food group consumed. For instance, nutritionally dense foods such as animal products are given higher weights than foods such as tubers that contain lesser nutritionally dense foods.

According to this score, household food consumption can be further grouped into three classifications: poor, borderline, or acceptable (Douyon et al., 2022; Wiesmann et al., 2009).

Table 2 Variables employed in econometric analysis

Variable	Description	Measurement	Mean	SD
FOODSEC	Household food security status	Per capita annual food expenditure	0.98	0.21
		Food Insecurity Access Scale	16.21	7.13
		Food Consumption Score	65.71	12.64
AGE	Age in years of head of the household	Continuous	39.43	17.41
GENDER	Gender of the head of the household	Dummy = 1 if male, 0 = female	0.65	-
EDUC	Years of education of the head of the household	Discrete	6.00	2.13
H/SIZE	Number of household members	Discrete	5.34	3.14
OFF-FARM	Off-farm employment participation	Dummy = 1 if yes, 0 = otherwise	0.31	-
ASSETS	Productive farm assets values	Continuous	67,144.12	69,154.32
LAND	Farm size owned in acres	Continuous	1.51	2.34
TERRAIN	Terrain of the land	1= sloppy, 0 = otherwise	0.72	-
S/FERTILITY	Soil fertility status	1 = poor, 2 = medium, 3 = fertile	2.12	-
EROSION	Soil erosion severity	1 = severe, 2 = moderate, 3 = low	2.77	-
FLOOD	Experience of flooding in the past 5 years	Dummy = 1 if yes, 0 = otherwise	0.67	-
RAINS	Experience of insufficient rainfall in the past 5 years	Dummy = 1 if yes, 0 = otherwise	0.89	-
H/STRMS	Experience of hailstorms in the past 5 years	Dummy = 1 if yes, 0 = otherwise	0.43	-
DISTNCE	Walking time in minutes to input and output market	Continuous	57.31	25.43
EXTN	Number of contacts with extension agents annually	Discrete	16.51	4.52
GRPMSHIP	If the farm household is a member of a farm-related association	Dummy = 1 if yes, 0 = otherwise	0.54	-
CREDIT	Whether credit is received by the household	Dummy = 1 if yes, 0 = otherwise	0.72	-

3. Results and discussion

3.1 Principal component analysis

Table 3 comprises principal components (PCs) and linear combination coefficients known as loadings. Inspection of Table 3 visually reveals that the total variability of the data set is 85% explained by the five PCs. The PCA results explained the data highly and the results presented in table 3 are considered a good fit. The first component explained 37.2% variance and it is correlated with the use of efficient inorganic fertilizer, changing planting date, crop rotation using legumes, and use of organic fertilizer all with positive effects (factor loadings). Accordingly, this component was named crop management practices.

Table 3 Effects of the five components of CSA compositions

Strategies	Comp1	Comp2	Comp3	Comp4	Comp5	Communality
Irrigation	0.6347	0.5997	0.4992	0.6631	0.2741	0.7070
Planting crops on tree lands	0.5327	0.3217	0.2271	0.1173	-0.3325	0.6170
Use of organic fertilizer	0.2178	0.6184	0.6112	0.3312	0.1192	0.6915
Use of improved crop varieties	0.5718	-0.2998	0.5513	0.5538	-0.2174	0.6614
Use of efficient inorganic fertilizer	0.5561	0.2117	0.4828	0.2217	-0.3715	0.6618
Planting trees on croplands	0.3691	-0.2511	0.1735	0.3721	0.2721	0.6516

Use of mulching	0.1998	0.5771	0.5122	-0.3351	0.2193	0.6113
Changing planting dates	0.3978	0.4112	0.2172	-0.2935	-0.4271	0.6925
Use of cover crops	0.2975	0.5523	-0.2314	-0.4152	0.2221	0.6115
Crop rotation using legumes	0.4173	0.1192	-0.3142	-0.1184	-0.4416	0.7110
Cattle fattening	0.2756	-0.5532	0.3352	0.6824	-0.4618	0.6001
Poultry farming	0.3291	-0.4992	0.2741	0.5962	-0.6144	0.6591
Making terraces	0.2531	0.1184	-0.4472	-0.4997	0.7142	0.6481
Apiculture	0.4438	-0.3351	0.3624	0.4478	-0.5921	0.6284
Feed improvement	0.1962	-0.4463	-0.1178	-0.3182	-0.3726	0.6002
Sheep fattening	0.2749	-0.5172	0.2913	0.3824	-0.4426	0.6131
Planting grasses	0.2111	-0.1172	-0.6812	-0.6172	0.3927	0.6005
Use of briquettes	0.1175	-0.3247	-0.4711	-0.3153	-0.2226	0.6317
Eigenvalues	4.8153	3.116	1.9925	2.2241	1.1420	
Eigenvalues (%) contribution	37.2113	25.1711	10.6327	6.4118	5.2461	
Cumulative (%)	37.2113	62.3824	73.0151	79.4269	84.673	

Principal component 1, 2, 3, 4, and 5 accounted for 37.2, 25.17, 10.63, 6.4, and 5.2% variances respectively. This signifies the first five components have great importance in explaining variance in the data set. The second PC was related to the use of cover crops, planting crops on tree lands, planting trees on croplands, use of mulching, and use of briquettes where they all have positive loadings too. Component 2 was termed as field management and climate change mitigation practices. The third PC comprised feed improvement, use of improved crop varieties, and use of cover crops, irrigation with corresponding positive effects, which are collectively called farm risk reduction activities. The fourth PC consists of the use of fattening, apiculture, and poultry farming which had similar positive effects. These practices were together known as supplementary income generation practices. Finally, the last PC was related to planting grasses and making terraces where they have negative loadings. PC 5 was collectively called soil and water conservation practices.

The communality column indicates the total size of variance of each variable retained in the five components (Alavi et al., 2020) described that all items in PCs need to have communalities of over 0.60 or 0.7 average communality for small samples precisely below 50 to justifiably say a PCA is performed. With a 384-sample size, Table 3 presented a variance greater than 60% in the PCs and can be considered as meeting the minimum criteria. For PCs interpretation, variables with high communalities and high factor loadings were justified from varimax rotation (Bartholomew, 2010; Jollife & Cadima, 2016). [

The descriptive statistics of the composition of each component (climate-smart practices) are presented in Table 4. The most commonly used component used was crop management practices with 92.34% of smallholder farmers using a minimum of one unit of this component. The component consists of practices such as the use of efficient fertilizer, changing planting dates, crop rotation using legumes, and the use of organic fertilizer. The second component used greatly was field management and climate change mitigation.

Table 4 List of climate-smart agricultural strategies

Group	Users' percentage	Components
Crop management practices	92.34%	Use of efficient inorganic fertilizer
		Changing planting date
		Crop rotation using legumes
		Use of organic fertilizer
Field management and climate change mitigation practices	89.01%	Use of cover crops
		Alley cropping
		Tree planting for windbreak and shelter for crops
		Use of mulching
		Use of briquettes
Farm risk reduction practices	81.21%	Feed improvement
		Use of improved crop varieties
		Use of cover crops
		Small-scale irrigation
Supplementary income generation practices	42.24%	Improved animal husbandry
		Apiculture
		Poultry farming
Soil and water conservation practices	11.2%	Use of grass strip
		Use of terraces

practices used by 89.01%. This component comprised the use of cover crops, alley cropping, planting trees for windbreak and shelter for crops, use of mulching, and use of briquettes. The third component widely used by farmers was farm risk reduction activities which constituted 81.21% of responses from farmers that include practices such as feed improvement, use of improved crop varieties, use of cover crops, and small-scale irrigation.

Supplementary income generation practices were only used by 42.24% of farmers. The practices included under this component are improved animal husbandry, apiculture, and poultry farming. Finally, the least used component consisted of soil and water conservation practices, which include the use of grass strips and making terraces. This component was used by only 11.2% of farmers.

3.2 Econometric findings

The impact of CSA packages on food security is well understood following the computation of the determinants of the choice of CSA packages. The adoption of CSA practices in a wide range of combinations has implications on the status of food security smallholder households. With the set of available packages given, understanding the factors deriving an individual to choose a specific package is crucial for policy direction (Wekesa et al., 2018).

The various combinations of packages are presented in Table 5 whereby 8 out of 25 possible combinations were used by farmers. A relatively small proportion of farmers (9.37%) were non-adopters/non-users of any CSA package. About 3.92% of farmers used the $C_0F_0R_1I_1S_1$ package. This package is composed of risk reduction practices, income-generating practices, and soil and water conservation practices. Another 6.26% used the $C_1F_1R_1I_0S_1$ package that comprised crop management practices, field management and climate change mitigation practices, risk reduction practices, and soil and water conservation practices. Further, 6.52% of farmers used $C_1F_0R_0I_0S_0$ packages that consisted of crop management practices only. Another 7.29% of farmers used $C_1F_0R_1I_0S_1$ packages that contained crop management practices, risk reduction practices, and soil and water conservation practices. About 8.34% of farmers used the $C_1F_0R_1I_1S_1$ package which contained crop management practices, risk reduction practices, income-generating practices, and soil and water conservation practices. Again, 9.13% used the $C_1F_1R_1I_0S_0$ package that comprised practices of crop management, field management, and risk reduction. Approximately 10.16% used all the five packages ($C_1F_1R_1I_1S_1$) together.

The largest proportion of farmers (39.01%) used the $C_1F_0R_1I_1S_0$ package that contained crop management activities, farm risk reduction practices, and income regeneration practices. This indicates the efforts of many subsistence farmers to achieve food security are based on irrigation-based crop management practices despite anomalies in rainfall patterns. The observation is similar to the findings of Hasan et al. (2018) that recommended that farmers in the region undertake such self-initiated responsive strategies for survival amidst adverse climate change impacts. A careful observation of Table 5 shows that all users of CSA practices (66.6% of all farmers) used a pack of practices with the inclusion of crop management practices. This observation indicates the need of the majority of farmers to meet their fundamental crop production for food production and this is in conformity with the study conducted by Wekesa et al. (2018).

3.3 Determinants of specific CSA packages choice

The factors that influence the choice of CSA packages are described in this section. It is then followed by quantification of the effect of package use on the status of farm household food security in the last stage. This was generated using the multinomial endogenous switching regression (MNLESR) model, which is a model of two-stage regression analysis. The first stage of MNLESR entails the determination of the choice of CSA strategy using the multinomial logit model. This is a crucial step as it guides the appropriate intervention to enhance the adoption of CSA packages. The next stage determines the impact of CSA packages use on household food security. The marginal effects from the MNL model that measured the probability of the expected change of a particular CSA strategy choice being made with respect to a unit change in an independent variable, which is presented in Table 6.

Non-adopters of all practices ($C_1F_1R_1I_1S_1$) were the base category compared to the other 9 packages (refer to table 5 for the packages) used by smallholder farmers. The result presented nine sets of parameter estimates, one for each are strategies mutually exclusive. The Wald test is rejected for all regression coefficients are jointly equal to zero [$X^2(500) = 552.41$; $p = 0.000$]. Thus, the results indicate that across the alternative packages, the estimated coefficients differ substantially.

Table 5 Combination of CSA strategy specifications to form the packages

Choice (j)	Binary quadruplicate	C = Crop management		F = Field management		R = Risk reduction		I = Income generation		S = Soil & water conservation		Frequency	Percentage
		C_0	C_1	F_0	F_1	R_0	R_1	I_0	I_1	S_0	S_1		
1	$C_0F_0R_0I_0S_0$	✓		✓		✓		✓		✓		36.00	9.37
2	$C_0F_0R_0I_0S_1$	✓		✓		✓		✓			✓	0.00	0.00
3	$C_0F_0R_0I_1S_1$	✓		✓		✓			✓		✓	0.00	0.00
4	$C_0F_0R_1I_1S_1$	✓		✓			✓		✓		✓	15.00	3.92
5	$C_0F_1R_1I_1S_1$	✓			✓		✓		✓		✓	0.00	0.00
6	$C_1F_1R_1I_1S_1$		✓		✓		✓		✓		✓	39.00	10.16
7	$C_1F_1R_1I_1S_0$		✓		✓		✓		✓	✓		0.00	0.00
8	$C_1F_1R_1I_0S_0$		✓		✓		✓	✓		✓		35.00	9.13
9	$C_1F_1R_0I_0S_0$		✓		✓	✓		✓		✓		0.00	0.00
10	$C_1F_0R_0I_0S_0$		✓	✓		✓		✓		✓		25.00	6.52
11	$C_0F_1R_0I_1S_0$	✓			✓	✓			✓	✓		0.00	0.00
12	$C_1F_0R_1I_0S_1$		✓	✓			✓	✓			✓	28.00	7.29
13	$C_1F_0R_0I_0S_1$		✓	✓		✓		✓			✓	0.00	0.00
14	$C_1F_0R_0I_1S_1$		✓	✓		✓			✓		✓	0.00	0.00
15	$C_0F_1R_0I_0S_0$	✓			✓	✓		✓		✓		0.00	0.00
16	$C_1F_1R_0I_0S_1$		✓		✓	✓		✓			✓	0.00	0.00
17	$C_1F_0R_1I_1S_1$		✓	✓			✓		✓		✓	32.00	8.34
18	$C_0F_1R_1I_1S_0$	✓			✓		✓		✓	✓		0.00	0.00
19	$C_0F_0R_1I_0S_0$	✓		✓			✓	✓		✓		0.00	0.00
20	$C_0F_1R_0I_0S_1$	✓		✓		✓		✓		✓		0.00	0.00
21	$C_1F_0R_1I_1S_0$		✓	✓			✓		✓	✓		150.00	39.01
22	$C_0F_1R_1I_0S_1$	✓			✓		✓	✓			✓	0.00	0.00
23	$C_0F_1R_0I_0S_0$	✓			✓	✓		✓		✓		0.00	0.00
24	$C_1F_1R_0I_1S_1$		✓		✓	✓			✓		✓	0.00	0.00
25	$C_1F_1R_1I_0S_1$		✓		✓		✓	✓			✓	24.00	6.26
Total												**384**	**100**

The possible CSA packages are represented by the binary quadruplicate. In the quadruplicate, each element is a binary variable for a CSA combination of crop management practices(C), field management and climate change mitigation practices(F), farm risk reduction practices (R), supplementary income generation practices (I), and soil and water conservation practices (S). Subscript 1 = adoption and 0 = otherwise

The age of the head of the household was negatively associated with the usage of the $C_1F_0R_0I_0S_0$ package and positively associated with $C_1F_0R_1I_0S_0$ at 5% and 10% significant levels, respectively. An increase in the age of the head of the household by one year minimizes the likelihood of using the $C_1F_0R_0I_0S_0$ package by 0.18% while enhancing the likelihood of using the $C_1F_0R_1I_0S_0$ package by 0.17%. This implies that as age mounts up, farmers shift from smaller packages of practices to larger ones and this is in conformity with the study conducted by (Wekesa et al., 2018). Older farmers may be afraid of risks associated with climate change and decide to diversify their income sources from their past experiences and thus accumulate many packages. Contrary, Ali & Erenstein (2017) documented that old age is negatively associated with the adoption of climate change adaptation strategies, justifying that agriculture is a labor-intensive task that demands a healthy, risk-bearing, and energetic farmer. Recent innovations may not reach older farmers as well

With respect to household gender, male-headed households were 3.1% more likely to use the $C_1F_1R_1I_1S_1$ package that contains all the CSA practices only at a 5% level of significance as relative to $C_0F_0R_0I_0S_0$ (non-adopters of all practices) as compared to females. Women are generally resources and time-constrained. This may justify the inverse relationship with CSA practices usage under this study. A study by Autio et al. (2021) reported that one of the major barriers to CSA adoption is gender (females) stemming from gender roles customarily. Additionally, they described that access to resources such as inputs, land extension service, education, and credit to women is less than men where all of which can have important contributions to CSA transition. For female-headed households, land ownership presents another difficulty in CSA adoption.

The educational level of the household head negatively affected $C_1F_1R_1I_0S_0$ which comprises of crop management practices, field management and climate change mitigation practices, and risk reduction practices. The more educational years reduced the probability of using this package by a 5% level of significance. It might be due to the reason that this package never guarantees their resilience from prevailing climate change risks and opt-out this package as it doesn't fill this gap. A study by Kangogo et al. (2021) argues that an increased level of education tends to establish the ability and innovativeness to monitor risks by farmers for proper farm adjustments.

There exists a positive and significant relationship between the value of productive assets of farms (a wealth proxy) and CSA usage. Farmers endowed with resources (farmers with high value of productive farm assets) were more likely to use more packages $C_1F_1R_1I_0S_0$ and $C_1F_1R_1I_0S_1$ as opposed to non-adopters of any package. For resource-endowed farmers, the probability of using these packages increased by 0.15% and 6.1%, respectively. It is likely that wealthier farmers have the capacity to buy water-pump generators, improved varieties, and inorganic fertilizers and adopt these CSA practices that are unaffordable to buy by ordinary smallholder farmers. Besides, these assets improve the ability to absorb the risks related to failure and the length of time in realizing CSAs. This is in line with the work of van Wijk et al. (2020) that justifies the bigger size of farms increases the benefits of economies of farmers' scales and also furnish a way of product diversification. Farmers of only one farm package practice ($C_1F_0R_0I_0S_0$) that only contains crop management practices were less likely to implement the packages as farm size increased. The probable explanation would be these farmers prefer to rent out their large-sized farms for other users rather than practicing agriculture since the small package may not provide reasonable production in the face of harsh weather conditions and this is an existing experience by smallholder farmers in South Western Ethiopia

Table 6 Estimates of marginal effects for determinants of CSA packages by MNL

Variables	$C_1F_0R_0I_0S_0$ Dy/dx	$C_1F_0R_1I_1S_0$ Dy/dx	$C_0F_0R_1I_1S_1$ Dy/dx	$C_1F_1R_1I_0S_0$ Dy/dx	$C_1F_0R_1I_0S_1$ Dy/dx	$C_1F_0R_1I_1S_1$ Dy/dx	$C_1F_1R_1I_0S_1$ Dy/dx	$C_1F_1R_1I_1S_1$ Dy/dx
Socioeconomic factors								
Age of HH	-0.0018*	0.0006	0.0014	-0.0017	0.0017**	0.0015	0.0018	0.0000
Gender of HH	-0.0343	0.0054	0.0430	-0.0293	-0.0039	0.0040	-0.0041	0.0312**
Education years of HH	0.0014	0.0016	0.0022	-0.0305**	0.0018	0.0031	0.0018	0.0000
Size of HH	0.0077	-0.0005	-0.0030	-0.0328	0.0049	0.0002	0.0047	0.0003
Off-farm employment participation	-0.0314	0.0011	0.0523	-0.0429	-0.0217	-0.0261	-0.0156	0.0013
Farm size	-0.0269***	-0.0103	-0.01768**	-0.0216	0.0220*	0.0315*	0.0210***	0.0015**
Farm assets	0.0042	0.0008	-0.0054	0.0015***	0.0015	0.0003	0.0611***	0.0411*
Characteristics of farm								
Perception of land terrain	-0.0003	0.0066	-0.0213	0.0885	-0.0187	0.0051	-0.0166	0.0022
Perception of the severity of erosion	-0.0206	-0.0431**	0.0179	-0.0362	-0.0252**	0.0189	-0.0523***	0.0006
Perception of soil fertility	-0.0072	-0.0003	0.0206	0.1064***	-0.0215	-0.0023	-0.0152***	0.0005
Incidences								
Frequent floods	0.0371	-0.0277	-0.0340	0.0301	0.0220*	-0.0193	0.0213	0.0004
Hailstorms	0.0269	0.0051*	-0.0047	-0.0171	0.0284	0.0003	0.0182	0.0005
Insufficient rains	-0.0032	0.0007	-0.0186	0.517	-0.0422	0.0062	-0.0411	0.0003
Institutional factors								
Distance from farm to market	0.0001	-0.0002	-0.0006*	0.0022	-0.0005**	-0.0198	-0.0006**	0.0001
Membership in farmer's associations	0.0316	0.0265	-0.0215	0.1779**	0.0332	0.0058	0.0332**	0.0000
Contacts with extension agents	-0.0052	0.0031	0.0081	-0.0317***	0.0051	0.0018	0.0047**	0.0003*
Access to credit	-0.0482*	-0.0033	-0.0074	-0.1493**	0.0019	0.0427	0.0031***	0.0002
Number of observations = 384; Wald X2 (120) = 553.51, *p* = 0.000								

$C_0F_0R_0I_0S_0$ is the reference category base in the MNL; HH is the household head
** Significant at 5% level
* Significant at 10% level
*** Significant at 1% level

Farmers' perception of soil erosion was negatively associated with the use of these packages: $C_1F_0R_1I_1S_0$, $C_1F_0R_1I_0S_1$, and $C_1F_1R_1I_0S_1$. The probability of using these packages declined by 4.3%, 2.5%, and 5.2%, respectively for farmers that considered their plots severely eroded. It looks like farmers are highly encouraged to undertake CSA practices on less eroded farms and vice versa. Practically, these farmers were not responsive to countering severe erosion impacts but were discouraged by severe erosion in implementing CSA technologies. A similar study conducted by Ali & Erenstein (2017) indicated a positive relationship with many soil conservation practices adoption with the consent that farmers were responsive to effects of soil degradation brought by soil erosion.

Farmers' perception of farmland soil fertility had a positive and significant influence on the usage of the $C_1F_1R_1I_0S_0$ package and a negative impact on the use of $C_1F_1R_1I_0S_1$. The use of $C_1F_1R_1I_0S_0$ and $C_1F_1R_1I_0S_1$ by farmers is likely to increase by 10.6% and get reduced by 1.5% respectively, for farmers that consider their farmland is relatively fertile. This leads to the understanding that farmers who believe their farms are fertile likely opt to implement small package $C_1F_1R_1I_0S_0$, which is against the non-use of any package. This is a lean package that has insignificant soil replenishing effect. But those farmers who believe their farmland is less fertile preferably implement a $C_1F_1R_1I_0S_1$ package with more CSA practices included that play a soil fertility improvement role. Hasan et al. (2018) reported that the propensity for sustainable agricultural practices adoption such as improved maize is expected to be higher on plots with fertile soils because most improved varieties of maize demand expensive inorganic fertilizer application.

The choice of CSA packages is influenced by factors related to past experiences with extreme weather conditions. For example, frequent flood experiences in the past were more likely to use the $C_1F_0R_1I_0S_1$ package. The probability of using this package was increased by 2.2% for farmers with frequent flood experiences in the past. It is more likely that farmers opt to implement flood-related shocks response strategy to reduce soil degradation and maintain the fertility of the soil. On the other hand, Aryal et al. (2020) argued that climate adaptation technologies adoption such as using drought-resistant varieties and crop rotation is negatively and significantly influenced by adverse conditions induced by flooding such as waterlogging and frost stress.

Previous experience with hailstorms was also positively related to the use of $C_1F_0R_1I_1S_0$ package. It was indicated that the likelihood of using this package improved by 0.51% for farmers who had past hailstorm experiences. Likewise, these farmers could be implementing a strategy responsive to this problem including farm risk reduction and supplementary income generating practices. A study conducted by Hussain et al. (2020) contrarily reported that frequent hailstorms were the major source of production risks associated with climate change that discouraged production technologies adoption posing a threat to stable yield.

The use of CSA practices was negatively influenced by distance (measured by walking time) to the input-output market. An increase in the time elapsed to reach the market by 1 min declined the probability of using $C_0F_0R_1I_1S_1$, $C_1F_0R_1I_0S_1$, and $C_1F_1R_1I_0S_1$ by 0.06, 0.05, and 0.06%, respectively. The transaction costs associated with input purchase and output sale are increased as the distance to the market gets longer. Chavas et al. (2019) presented that distance can affect the accessibility of new technologies, credit institutions, and information, apart from access to the market, and thus confirms the negative association.

Farmers' membership in various associations/groups had a positive and significant impact on $C_1F_1R_1I_0S_0$ and $C_1F_1R_1I_0S_1$. With respect to the non-adopters, the probability of using these packages, as a result of being a member of farmers' associations, has increased by 17.7% and 3.3%, respectively. Farmer's associations are crucial channels through which extension agents and other service providers use to get farmers. In addition, field management practices such as terrace construction could be possibly achieved in mass mobilization using these channels as one option. Further, members of the associations exchange ideas, get connections for research output dissemination and handle farm demonstrations through this avenue. Kumar et al. (2020) reported that learning from pear experiences enhances the probability of adoption of technologies due to the reason that farmers put trust in more practical experiences shown by their peers since they share much in common.

The frequent contact with extension agents positively influenced the use of $C_1F_1R_1I_0S_1$ and $C_1F_1R_1I_1S_1$ but negatively affected the use of $C_1F_1R_1I_0S_0$ packages. Additional contact with extension agents annually increased the probability of using $C_1F_1R_1I_0S_1$ and $C_1F_1R_1I_1S_1$ by 0.47 and 0.03%, respectively but reduced the probability of using $C_1F_1R_1I_0S_0$ by 3.1%. This suggests that the adoption of larger packages by farmers is largely influenced by extension agents' contacts with farmers. It also highlights that the issue of climate change was included in information dissemination that promoted the use of many packages. Nevertheless, on the other hand, a reduced probability of using $C_1F_1R_1I_0S_0$ implies that extension agents' services had mixed roles. It looks evident that farmers using $C_1F_1R_1I_0S_0$ package with only crop, field management practices, and risk reduction practices only was skeptical about the information provided by the extension agents that it truly improves production, and decide to opt-out using any other package. This is consistent with the findings of the study in Kenya by Emmanuel et al. (2016) that described the involvement of extension agents in many more activities such as administering credit and delivering inputs, which pose questions of their skills impacting trust and finally declining implementation.

Access to credit had a positive and significant impact on the use of $C_1F_1R_1I_0S_1$ but a negative impact on the use of $C_1F_0R_0I_0S_0$ and $C_1F_1R_1I_0S_0$. The result depicted that farmers that received credit in the previous farming season were 0.31% more likely to use $C_1F_1R_1I_0S_1$. Access to credit enables farmers to meet costs involved in CSA technology implementation, especially high-priced ones such as the use of irrigation and improved livestock breeds present in this package containing a large package. Likewise, (Acclassato Houensou et al., 2021) discussed credit constraints that affect investment in inorganic fertilizer and improve seed negatively, explaining that credit-constrained farmers are less likely to adopt CSA practices that require cash expenditures. Credit access reduced the probability of using $C_1F_0R_0I_0S_0$ and $C_1F_1R_1I_0S_0$ packages by 4.8% by 14.9%, respectively. A negative influence of access to credit to the use of $C_1F_0R_0I_0S_0$ and $C_1F_1R_1I_0S_0$ may suggest that these farmers prefer the credit access to be diverted to non-farm expenses such as medical and school fees, thus use of any package is unnecessary.

3.4 Average treatment effects for the adoption of CSA packages

Once the drivers of choice of CSA packages are determined in the first stage, the effect of treatments was determined in the second stage to evaluate the effect of these packages' use on household food security.

The ordinary least squares regression of per capita annual food expenditure, Household Food Insecurity Access Scale (HFIAS), and Household Food Consumption Score (HFCS) of households were estimated for every combination of CSA practices, considering the selection bias correction terms from the primary stage. Treatment effects, which are the most important part of this stage are discussed.

Appendices 1 and 2 present the summary of questions and food categories for HFIAS and HFCS. The per capita annual food expenditure measured the amount of dietary energy in (K/cals) through converting the food acquisition or consumption by matching individual foods with the food consumption table. Thus, a high per capita annual food expenditure results in higher dietary energy content, and correspondingly the level of food security is understood as food secure. HFIAS, with its nine occurrence questions, finally resulted in different severity levels (0-27) of food insecurity. The severity levels approaching zero is regarded as food secure, a value approaching 27 corresponds to severely food insecure and values ranging from 9 to 16 are regarded as moderately food insecure. Further, HFCS, with a frequency of consumption of diets over a seven-day period gives higher weights for nutritionally dense foods with a score classified as acceptable for nutritionally dense foods such as animal products, and other low dense foods such as tubers are regarded as poor and other meal types fall under moderate classification. Generally, a high calorific value, lower severity levels, and acceptable food consumption score are considered food secure and vice versa.

Table 7 presents the average adoption effects in terms of per capita annual food expenditure, HFIAS and HFCS under actual and counterfactual conditions. In Table 7, X_1 represents the treated category (adopters) and X_2 represents the untreated (non-adopters), β_1 denotes treated characteristics (adoption state) and β_2 representing untreated characteristics (non-adoption state). The difference in food security status as a result of a specified package is regarded as the level effect. The result of the difference between treated with treatment features and untreated with untreated features $(\beta_1 X_1) – (\beta_2 X_2)$ is termed the impact. Except for users of $C_1F_0R_1I_0S_1$, $C_1F_1R_1I_1S_0$, and $C_1F_1R_1I_1S_1$, all the rest employing other packages would be better off in the counterfactual scenarios (non-adopters) signifying the availability other better possibilities. Apart from $C_1F_0R_1I_1S_1$, all other packages that included farm risk reductions and supplementary income generation practices had a positive impact on household welfare. This implies that farmers need to manage their farm risks and diversify income-generating practices to improve the food security status in the face of uncertain climate change events.

Table 7 Impact of use and non-use of CSA packages on food security estimated under the three parameters by ESR

Package		Per capita annual food expenditure (PCFE)			HFIAS			HFCS		
		Treated (β_1)	Untreated (β_2)	Impact/ returns	Treated (β_1)	Untreated (β_2)	Impact/ returns	Treated (β_1)	Untreated (β_2)	Impact/ returns
$C_1F_0R_0I_0S_0$	Treated(X_1)	0.54(2.10)	0.59(0.74)	-0.04	21.0(0.13)	24.1(0.34)	-3.14	45.2(1.54)	46.4(0.98	-0.42
	Untreated(X_2)	0.59(1.92)	0.64(0.48)	-0.05	23.14(0.71)	24.51(0.49)	-1.37	53.1(2.14)	63.2(0.75)	-13.44
	Level effects	-0.05	-0.15*	-0.09	-0.01	-0.16	-5.16	-7.90	-16.8***	-16.85
$C_1F_0R_1I_1S_0$	Treated	0.98(1.96)	0.72(3.17)	0.26	16.1(0.22)	16.9(0.42)	-0.73	66.7(7,56)	57.9(2.62)	8.17
	Untreated	0.62(3.14)	0.81(0.17)	-0.19	18.2(0.09)	18.6(0.11)	3.12	64.4(3.94)	64.7(0.81)	-0.47
	Level effects	0.36	-0.09	-0.71	-2.10	-2.3	1.91	2.30	-6.8***	2.7
$C_0F_0R_1I_1S_1$	Treated	0.35(3.4)	0.31(1.8)	0.04	20.1(0.51)	21.4(0.66)	-0.25	62.1(3.45)	59.2(0.94)	-17.26
	Untreated	0.29(1.9)	0.27(0.8)	0.02	21.4(0.07)	22.3(0.07)	-0.19	58.1(2.42)	66.4(1.02)	-5.36
	Level effects	0.06	0.04	0.06	-1.3	-2.5	-0.12	4.00	-7.2	-2.81
$C_1F_1R_1I_0S_0$	Treated	1.10(0.87)	0.99(0.12)	0.11	13.2(0.06)	12.9(0.12)	0.46	56.8(1.08)	66.7(1.04)	-11.04
	Untreated	1.21(0.99)	1.13(0.04)	0.04	11.1(0.07)	10.7(0.07)	0.12	59.9(0.99)	69.17(0.97)	-8.12
	Level effects	-0.11	-0.14	0.15	2.1	2.2	0.58	-3.20**	-2.4	-14.61
$C_1F_0R_1I_0S_1$	Treated	1.11(0.14)	1.09(1.99)	0.02	10.8(0.05)	9.1(0.09)	0.32	56.2(1.04)	64.9(1.07)	-10.43
	Untreated	0.99(0.72)	0.87(2.14)	0.19	8.4(0.11)	7.8(0.13)	0.16	59.9(1.99)	69.0(0.97)	-8.32
	Level effects	0.12	0.22*	0.22	1.6*	2.7*	0.48	-3.70**	-4.10***	-11.51
$C_1F_0R_1I_1S_1$	Treated	1.35(1.9)	1.28(2.5)	0.07	5.16(0.26)	6.12(0.07)	1.12	64.0(2.55)	68.1(0.90)	2.12
	Untreated	1.22(2.1)	1.18(0.5)	0.04	7.93(0.43)	8.08(0.19)	1.56	63.8(2.01)	64.2(0.87)	1.94
	Level effects	0.13**	0.1	0.14	2.17*	2.71	2.68	0.20	3.90***	4.06
$C_1F_1R_1I_0S_1$	Treated	1.42(1.02)	1.19(0.17)	0.23	5.07(0.15)	4.17(0.13)	0.9	75.1(1.04)	63.6(0.84)	10.59
	Untreated	1.01(0.77)	0.98(1.31)	0.03	6.31(0.09)	5.12(0.17)	1.19	75.4(1.30)	61.4(0.92)	12.13
	Level effects	0.21*	0.21	0.26	1.24**	0.95	2.19	-0.30	2.20*	22.72
$C_1F_1R_1I_1S_1$	Treated	1.54(0.91)	1.21(2.7)	0.33	0.11(0.01)	0.01(0.07)	0.10	82.1(1.17)	69.0(0.91)	17.2
	Untreated	1.37(0.77)	1.08(1.5)	0.29	1.31(0.06)	1.22(0.02)	0.09	78.0(1.21)	65.1(0.87)	15.1
	Level effects	0.27***	0.13**	0.72	1.20**	1.33***	0.19	4.10***	3.90***	32.3

Pairwise correlation

	PCAE	HFIAS	HFCS
PCAE	1		
HFIAS	-0.67**	1	
HFCS	0.88**	-0.71**	1

Standard errors are in parenthesis. C crop management, F Field management, and climate change mitigation, R risk reduction, I supplementary income, S soil and water conservation. PCAE per capita annual expenditure, HFIAS household food insecurity access scale, HFCS household food consumption score

For bigger packages ($C_1F_0R_1I_0S_1$, $C_1F_1R_1I_1S_0$, and $C_1F_1R_1I_1S_1$), all adopters were food secure compared to their counterparts that did not adopt CSAs in real scenarios. Based on these findings, a complete package with crop management practices, field management, and climate change mitigation practices, farm risk reduction practices, supplementary income generating practices, and soil and water conservation practices ($C_1F_1R_1I_1S_1$) had the highest overall effect of 1.45 kcals, 0.19 level of severity, and 32.3 scores on the status of food security of farmers estimated using per capita annual food expenditure, HFIAS, and HFCS, respectively. This implies that farmers using this package were 41.2%, 39.8%, and 12.1% more food secure compared to their counterparts who were using none of the practices included under this package. This wide-ranging package addresses a bigger spectrum of both field, income, mitigation, and soil conditions while also climate change mitigation, soil degradation mitigation for stabilizing productivity, and income diversification. In a general context, the overall finding is that non-adopters of this ($C_1F_1R_1I_1S_1$) package would suffer from food insecurity. Farmers using this package, in addition to productivity improvement (food security), also play a major role in mitigation and farmers' resilience to adverse climate change impacts.

4. Conclusion and policy implications

This paper evaluated the impact of climate-smart agriculture on food security of smallholder farmers in the tropical moist montane ecosystem of South Western Ethiopia. Climate-smart agriculture is currently promoted as an effective approach to improving food security and livelihood situations globally, especially in resource-poor developing countries including Ethiopia. It does this by sustainably increasing agricultural productivity, improving household resilience, and reducing greenhouse gas emissions.

The findings show that smallholder farmers adopting more than one CSA practice experience better food security and livelihood situations as compared to non-adopters. The bigger package that consisted of crop management, field management, climate change mitigation, risk reduction, income generation, and soil and water conservation practices ($C_1F_1R_1I_1S_1$) had the highest impact on household food security as compared to the non-adopters ($C_0F_0R_0I_0S_0$). Adopters of this package were 41.2% more food secure in terms of per capita annual food expenditure, 39.8 percent in terms of Household Food Insecurity Access Scale (HFIAS), and 12.1 percent in terms of Household Food Consumption Score (HFCS) than the non-adopters. The adoption of this package was further positively influenced by farm size, gender, and productive farm asset values. This package is covering a wide spectrum and comprehensive field, soil, income, climate change mitigation conditions for reducing soil degradation, diversifying income sources, climate change mitigation, and production stability. Accordingly, for farmers to get the maximum benefit from CSAs, they have to incorporate all CSAs as much as possible. The results depicted that the likelihood of using this package was influenced positively by farm size, gender, and farm assets. This package was more likely on larger self-owned pieces of plots, and male-headed households with greater farm assets. Thus, if CSAs are used in combination and to a larger extent, they have the potential to alleviate food insecurity.

Farmers have to then be encouraged to incorporate a larger number of CSA packages that consist of at least a member of each of the five categories. Crop management, field management, risk reduction, income generation, and soil and water conservation practices, have a higher effect on the status of food security. This would be primarily to enable them to absorb climate change-associated risks through sensitization on the need to invest in productive farm assets, which at the same time improves their ability to uptake important CSAs. Extension service providers play a great role in sensitization. Additionally, land fragmentation needs to be discouraged through public formal or informal education and engagement in alternative income-generating activities by farmers to benefit more from CSAs when practiced on a relatively bigger portion of land.

Significance statement

The findings of this study can help understand the severe impacts of climate change and smallholders' vulnerability to food security and thereby contribute its share in implementable policy responses. The study gives an on ground real information and provides a clear insight into supporting current efforts of addressing persistent food security problems of smallholder farmers.

Authors' contributions

This study is articulated and developed by the three authors listed. All authors read and approved the final version of the manuscript and consistently agreed to publish it in the journal Helion.

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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.

Ethics approval and participants' consent

Ethics approval was granted by Addis Ababa University research ethics guideline. Consent forms were signed by respondents before conducting interviews during data collection.

Consent for publication

Not applicable

Competing interests

No competing interests

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