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Impact of climate-smart agriculture adoption on food security and multidimensional poverty of rural farm households in the Central Rift Valley of Ethiopia

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Abstract

Background: Climate change has perverse effects on the natural resource base and agricultural productivity, negatively affecting the well-being of households and communities. There are various attempts by the government and NGOs to promote climate-smart agricultural (CSA) practices to help farmers adapt to and mitigate these negative impacts. This study aimed to identify CSA practices widely adopted in the study area and examined their impacts on rural farm households' food security and multidimensional poverty. A three-stage proportional to size sampling procedure was followed to select four districts out of nine districts, and 278 households were randomly selected from two kebeles from each district. A cross-sectional data of the 2020–2021 cropping season were collected using a structured and pretested survey questionnaire. The food consumption score, dietary diversity score, food insecurity experience scale, and multidimensional poverty index, constructed out of 9 indicators, were used to assess households' food security and poverty status, respectively. A multinomial endogenous switching regression model was used to assess average treatment effects on these outcome indicators.

Results: Widely adopted CSA practices are conservation agriculture, soil fertility management, crop diversification, and small-scale irrigation. The results illustrated that adopter households on average showed more food consumption score, dietary diversity score, and less food insecurity experience scale than non-adopters. The results also showed that CSA adopter households, on average, have a low deprivation score in multidimensional poverty than non-adopter households. Accelerating wider adoption of CSA through up-scaling incentives is quite important.

Conclusion: This study showed that CSA adoption improves households' food security and reduces multidimensional poverty. We conclude that up-scaling of CSA practices is important for contributing to the achievement of SDG1, SDG2 and SDG13 targets.

Keywords: Climate-smart agriculture, Poverty, Food security, Soil fertility management, Conservation agriculture, Ethiopia

Introduction

Various published documents [12, 13, 46, 74] report that climate change has perverse effects on water resources, natural resource base (environment) and agricultural productivity so that it is adversely affecting the livelihood of the human population [63]. It is becoming more alarming than ever before that the year 2019 is recorded

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as the second warmest since 1850, and greenhouse gas mole fractions also reached a new high in the same period [73]. It can exacerbate land degradation through increasing rainfall variability, flooding, and drought frequency [64]. It can affect food security and poverty due to warming, changing precipitation patterns and frequency of extreme events [38, 39].

In Africa, climate change is causing tremendous and unbalanced risk to safer, more resilient, and sustainable livelihoods [65]. Exposure to climate change risks coupled with its community's low adaptive capacity makes the continent highly vulnerable to the impacts of climate change [56]. In this regard, [60–62] suggest that the continent's agriculture-dominated livelihoods and heavy reliance on rain-fed crop production, combined with persistent poverty, demonstrate that the impacts of climate change could be more severe.

Frequent drought and floods are the most common climate-related hazards in Ethiopia [71]. It has a long-lasting history of drought exposure, and the frequency of extreme weather events is increasing over time [11]. The most recent El Nino incident in 2015 was one of the strongest that led to crop failure and severe food shortages, which doubled the number of food insecure people in the country [23]. Ethiopia scored 26.2 on the Global Hunger Index (GHI), in which it ranks 92nd out of 107 countries, indicating hunger is a serious issue [31]. Moreover, Ethiopia ranks 174th out of 189 countries with the Human Development Index (HDI) value of 0.485 and a purchasing power parity (PPP) adjusted GNP per capita of 2207 (US dollars), which puts the country in a low HDI category. This is very low, even compared to the average of sub-Saharan African countries [63].

Agriculture remains by far the most important economic sector in Ethiopia [28]. However, it is the most vulnerable sector to the impacts of climate change, as it is primarily rain-fed and, according to [33] only 5% of the farmers have irrigated plots. It is also the major source of greenhouse gas emissions through fertilizer and nitrous oxide (N_2O) since crop and livestock production are major economic activities of the sector [25]. Even though the agricultural sector remains the main source of livelihood for rural communities in Ethiopia, it is highly encountered in changing climates [11, 23, 24, 33]. The existence of severe rural poverty combined with food insecurity problems makes the situation very complicated, and all this debilitates the resilience of households to climate change by exhausting their coping capacity [71].

Climate-smart agricultural (CSA) concepts and practices are gaining considerable traction at international and national levels to address the challenges agricultural production faces under climate change [7]. CSA is an agricultural approach for transforming and reorienting agricultural systems to support food security in the face of new climate change realities [47]. The key question, however, is to understand how these climate-smart agriculture related interventions support efforts to respond to food security gaps and by what magnitude it helps to combat poverty.

Very few empirical studies have been conducted in Ethiopia and East Africa regarding the impact of CSA on households' poverty and food security. For example, a study by [60] examined the impact of CSA on rural households' poverty using panel data and an endogenous switching regression model. It also showed the effect of CSA practices on the incidence and depth of rural poverty using monetary poverty (income and expenditure), using Foster–Greer–Thorbecke (FGT) poverty indices, while the concept of poverty goes beyond a simple monetary measure [58]. Thus, it failed to measure households' poverty using multidimensional techniques. In Ethiopia, 83.5% of the country's population is under multidimensional poverty, while 8.9% of the population is vulnerable to multidimensional poverty [55]. More recently, [32] assessed the impact of CSA technology on multidimensional poverty in rural Ethiopia using PSM and endogenous switching regression methods and showed that CSA technology adoption can reduce households' multidimensional poverty. But it was limited to two CSA technologies, namely, row planting and chemical fertilizer adoption. The study failed to account for the impact of other CSA technologies like small-scale irrigation and crop diversification on multidimensional poverty. In addition to this, the impact of CSA on rural households' food security is unavailable for the central rift valley, where this study focuses.

The current study contributes to addressing existing knowledge gaps by first identifying determinants of households' CSA adoption in the CRV of Ethiopia. Secondly, by analyzing the impact of CSA adoption, using four CSA packages, on rural households' poverty using multidimensional poverty Index (MPI) through a combination of health, education, and standard of living dimensions. Thirdly, this study examines the impact of CSA on rural household's food security using dietary diversity score (DDS), food consumption score (FCS), and household's food insecurity experience scale (FIES) measures. Finally, it tries to identify determinants of households' intensity of CSA adoption and synthesizes the policy implications of the study.

Materials and methods

Description of the study area

The CRV is located in Ethiopia and is part of the Great East African Rift Valley (Fig. 1). It covers an area of 1 million hectares, and the Ethiopian Central Rift Valley (CRV) is known for its interconnected terminal lakes (a water system) involving Lake Ziway, Abyata, Shalla, and Langano. Lake Abyata and Ziway are hydrologically interconnected, and when Ziway water is high through runoff it receives from two major streams (Meki and Katar), it flows to Abyata via the Bulbula River. Abyata Lake, normally saline, gets its salinity level regulated through freshwater input from upstream of Lake Ziway through the Bulbula River. It is located between 38°00'–39°30' E and 7°00'–8°30' N. Annual rainfall in the area varies from about 600 mm near the lakes up to 1600 mm at a higher elevation at the border of the basin [50]. It has a tropical, dry climate, and the area is home to over 1.5 million people. The dominant farming system in the area is small-scale, rain-fed, and low-yielding mixed crop-livestock production [19].

Sampling techniques and sample size determination

We followed a three-stage random proportional to size sampling technique. In the first stage, among the nine districts in which the CRV basin of Ethiopia is encompassed, four districts were selected randomly, using the lottery method. These are the Arsi Negele, Dugda, Meskan, and Heban Arsi districts. They also have nearly similar agro-ecological characteristics [19]. In the second stage, two rural kebeles were selected from each district using a simple random sampling technique by lottery method. Finally, at the third stage, after receiving the sampling frame of farm households from kebele administration offices, based on each selected kebele's population size, sample households were selected following simple random sampling as it enhances representativeness [44].

To enhance the robustness of impact estimates, the sample size was determined using a power calculation. A power calculation was performed for each of the outcome variables [72], food security and poverty. According to [18], sample size (n) for a binary outcome variable is given by the formula:

$$n = \left[\frac{P}{T\delta^2} * \frac{-P+1}{-T+1}(-Z_1 - Z_2)^2\right], \quad (1)$$

where P is the proportion of the study population that has a value of 1 for the outcome, T is the proportion of individuals in the treatment group, δ is the minimum detectable effect which is a mean difference in the outcome variable of the controlled and treated groups and, Z_1 and Z_2 are the critical value for the desired level of significance and power of the study, respectively. In this study, by using literature, P is approximated at 0.918 [55] and 0.227 [71] for poverty and food security outcomes, respectively. These values indicate the percentage of multidimensional poor and food insecure population in Ethiopia. In addition to this, T is equals to 0.5 by the assumption that the control and treatment groups are equal. The minimum detectable effect (δ) is set at 15%. Moreover, the study uses a 5% level of significance (Type I error) and 80% power (20% type II error) that gives a critical value of 1.96 and 0.84 for Z_1 and Z_2, respectively [18]. Substituting these values in Eq. 1 gives a sample size of 105 and 245 for poverty and food security outcomes, respectively. We selected the higher sample size ($n = 245$) and it was adjusted by expecting an 80% response rate. Thus, the final sample size is 307.

Data description, collection and analysis

Both qualitative and quantitative data were collected through a household survey. It also used secondary data from both published and unpublished sources, including those collected from district and kebele administration offices. The primary data were collected through a structured and pretested questionnaire, administered by trained enumerators, from randomly selected sample households. Moreover, focus group discussions were held using selected stakeholders, community leaders, and households at both kebele and district levels.

The collected data were analyzed using both descriptive and econometric statistical techniques to address the research objectives. We estimated the average values of the groups of households, adopters and non-adopters, of CSA, and reported mean separation tests without controlling, at the same time, the effect of other covariates. The econometric analysis involves modeling food security and poverty and estimating the impact of CSA on poverty and food security. The whole methodology is discussed below.

Econometric approaches

Estimating food security and multidimensional poverty Commonly used methods to assess the food security status of households are the food consumption score (FCS), dietary diversity score (DDS), and food insecurity experience scale (FIES). FCS is a measure of food security based on diversity, food frequency, and relative nutritional significance of various food groups [70], while DDS is a qualitative measure of food consumption which indicates household/individual access to various food items as well as nutritional adequacy of diet of households [21]. FIES is a measure of access to food at individual or households' level, and it is based on perceptions or experiences reported by respondents [10, 14]. By adjusting food items to local circumstances, and as suggested by [70], a 7-day recall on consumed food items was used for FCS. Moreover, following [21] last 24 h consumption of food items was applied for DDS. Furthermore, as indicated on

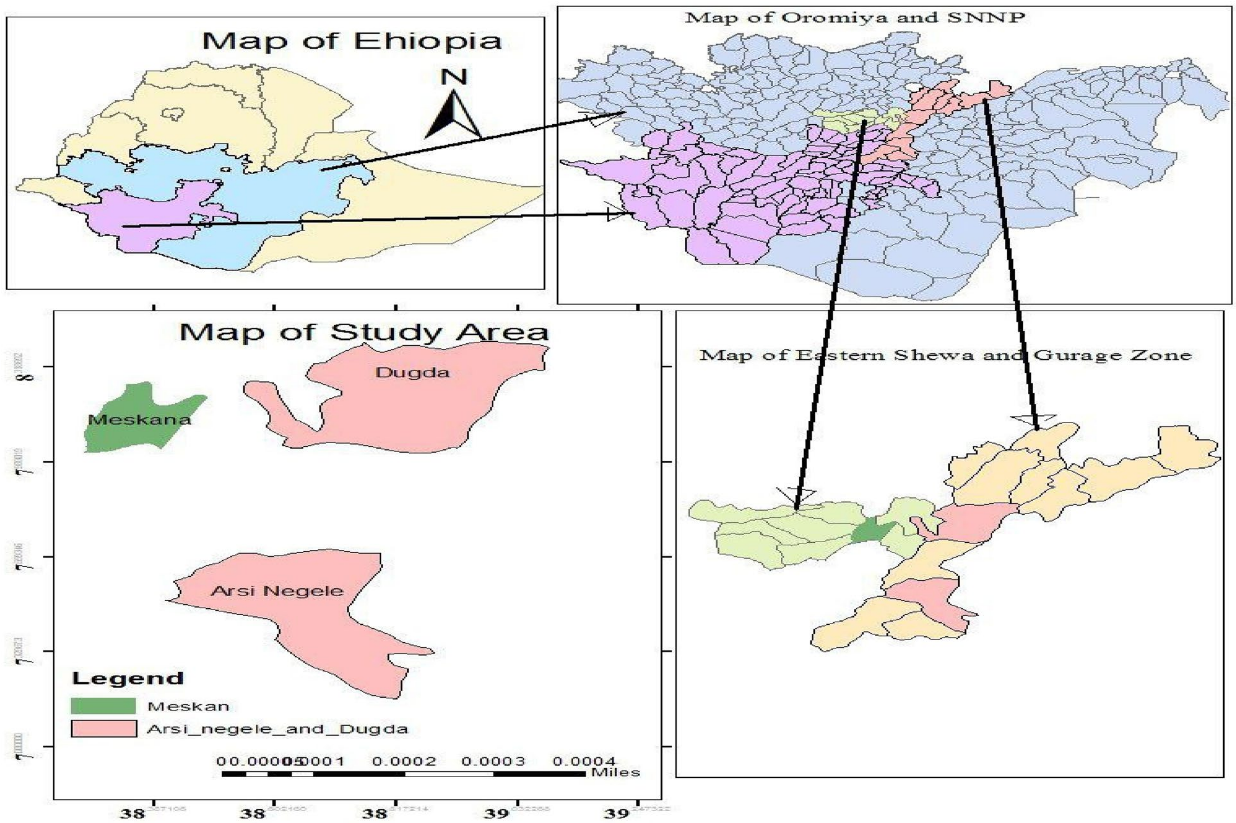

Fig. 1 Location of study site. Source: Authors (2022)

[14] last 30 days, household's experience of food security-related problems was also adopted for FIES, respectively.

Steps for estimating the multidimensional poverty index (MPI) are well documented (e.g., [4]). Following [4], this study used indicators such as: health, education, and standard of living (asset ownership, housing conditions, access to electricity and fuel wood use, drinking water and sanitation, and housing condition) dimensions to measure rural households' poverty. As suggested by [4] and [2] dimensions and their respective indicators that were used in this study are elaborated in Table 1. Following previous studies [26, 68], this study gives

Table 1 Summary of dimensions and indicators with respective weights used in the study area. Source: [3, 4]

Dimensions	Indicators	Household is deprived if	Weight
Education	Years of schooling	No household member aged 10 or older has completed 6 years of schooling	1/6
	School attendance	Any school-aged child is not attending school up to the age at which he/she would complete grade eight	1/6
Health	Child mortality	Any child has died in the family in the 5-year period preceding the survey	1/3
Standard of living	Electricity	The household has no access to electricity	1/18
	Drinking water	Does not have access to enough drinking water or clean water in more than 30 min' walk/ home round trip	1/18
	Housing conditions (roof, floor and wall)	At least one of the materials for roof, walls and floor is inadequate or natural materials	1/18
	Cooking fuel	Cooks food with wood, dung or charcoal	1/18
	Asset ownership	Does not own more than one of radio, TV, telephone, bicycle, motorcycle, and refrigerator or does not own car/truck	1/18
	Sanitation	Lacks adequate sanitation	1/18

equal weights for each dimension so that each indicator and dimension has equal importance for MPI. It shows the level of poverty of households by each indicator and households were identified as poor and non-poor based on their deprivation score from all possible indicators. The deprivation cut-off for each indicator to identify whether a given household is deprived or not is also elaborated in Table 1. Then deprivation score for each household is calculated as the sum of weight of indicators in which households are deprived based on the given deprivation cut-off. The proportion of a multi-dimensionally poor population (H) and their average deprivation score (A) indicate the poverty headcount and the intensity of poverty of rural households in the study area, respectively.

References [2] and [4] suggest that the multidimensional poverty index (MPI) is the product of the proportion of the multi-dimensionally poor population (H) and their average deprivation score (A). MPI usually lies between 0 and 1 in which the value of 0 represents no household is multi-dimensionally poor in the population, whereas a value of 1 shows everyone is deprived in all indicators in the society.

Estimating impact of food security and poverty, factors affecting CSA adoption

According to [37], individuals' preference among a set of available alternatives follow a random utility model. Hence, farmers' adoption of a single or a combination of CSA practices is determined by the expected utility from adoption compared to non-adoption. A given household adopts a set of CSA practices if the expected utility from the adoption of CSA (U_1) is higher than the expected utility from non-adoption of CSA (U_0), i.e.,$U_1 - U_0 > 0$ [40]. Following [6], let z_i^* be the latent variable that indicates the i^{th} farmer behavior in adopting a combination of CSA practices $j = 1, 2 \ldots J$ and compared with adopting any other q combination of CSA practices is given as follows:

$$Z_{ji}^* = \alpha_j X_{ji} + \varepsilon_{ji} \text{ Where } Z = \begin{cases} 1 \, if \, Z_{ji}^* > \max\limits_{q \neq 1}\left(Z_{qi}^*\right) \\ . \\ . \\ . \\ J \, if \, Z_{ji}^* > \max\limits_{q \neq j}\left(Z_{qi}^*\right) \end{cases} \quad \text{for all } q \neq j, \tag{2}$$

where X_i = the vector of households' characteristics that affect adoption decision and ε_i= the random disturbance term. As indicated in Eq. (2), the i^{th} farmer adopts the j^{th} combination of CSA practice if ${}_{j \neq q}{}^{\max}(Z_{ji}^* - Z_{qi}^*)$ is greater than zero.

Four CSA practices, namely, small-scale irrigation (R), crop diversification (C), and integrated soil fertility management and conservation agriculture (S), were considered. A given farm household will have eight possible combinations of CSA practices, which are no-adoption, only adoption of a single or some combination of CSA practice, and joint adoption of all CSA practices. Provided that the independent irrelevant alternatives (IIA) assumption is valid, the multinomial logistic regression model (MLRM) provides consistent parameter estimates [35]. It states that the characteristics of one particular choice alternative are independent of the relative probabilities of choosing other alternatives [67]. It involves comparison of two sets of estimates, one of which is carried out by dropping one or more of the available options from the choice set, and the other is performed by estimating the multinomial model with all available alternatives [36]. If the IIA assumption holds, then there will be no significant changes in estimates and vice versa [36]. In other words the assumption tests the null hypothesis of no-systematic difference in relative coefficients against the alternative hypothesis of there is systematic difference in relative coefficients between the two estimates [67].

Assuming that ε_{ji} in Eq. (2) satisfies the IIA assumption and following [30], the probability of adoption of j^{th} CSA practice among the four CSA practices is specified in multinomial logit as follows:

$$P\left(Z_{ji} = j | X_{ji}\right) = \frac{\exp\left(\beta_j^{'} X_{ji}\right)}{\sum_{j=1}^{J} \exp\left(\beta_j^{'} X_{ji}\right)}, \tag{3}$$

where X_{ji} is the vector of different household characteristics, and $\beta_j^{'}$ is the vector of parameters.

Furthermore, we assessed the intensity of adoption as the level of adoption varies among farmers. The intensity/level of adoption of CSA practices is measured by the number of CSA practices adopted by farm households [51, 53]. Ordered probit regression is used to identify factors that affect the intensity of CSA adoption in the study area [5, 49, 51, 54]. According to [30], the ordered probit model is specified as:

$$Y^* = X'\beta + \varepsilon, \tag{4}$$

where, Y^* is a latent variable, $X^{'}$ is a vector of different household socio-economic characteristics, and ε is the random disturbance term. Thus, in this study Y^* is an ordered choice variable and is measured as the number of CSA packages that a given household adopts on its own farmland. Since four CSA packages are used in this study, Y^* takes a value of $0, 1, 2, 3$ *and* 4. The ordered probit model simultaneously estimates the probability of households' adoption of a given CSA package including, non-adoption. Mathematically, it is given as:

$$Prob(Y = J|X) = 1 - \Phi\left(\mu_J - x'\beta\right), \tag{5}$$

where J is the households' intensity of CSA adoption and $\mu_1, \mu_2 \ldots \mu_J$ are cut-off points, Φ is the standard normal cumulative distribution function, and β is a vector of parameter estimates.

The propensity score matching (PSM) technique and endogenous switching regression (MESR) are commonly used for estimating the impact of CSA practices on food security and poverty [27]. However, PSM has a serious limitation that leads to the existence of unmeasured confounding variables and biased results [52]. To control these confounding variables, this study only used MESR. The MESR model is recommended in the literature [1, 6, 15, 40, 41, 42, 48, 59 and 69] to deal with these problems. The approach corrects selection bias for both unobserved and observed heterogeneity [42].

Specification and estimation of the MESR model follow a two-step procedure. The first stage involves the estimation of households' probability to adopt CSA practices and using what is known as identification/selection equation. This was done using MESR estimation as specified earlier. Since there is a sample selection and endogeneity bias, it is necessary to account for this problem by incorporating a selectivity correction term, usually known as inverse mills ratio (lambdas), in the second stage of estimation [29]. Following the work of [69], inverse mills ratio after multinomial logistic regression is calculated as follows:

$$\lambda_{ji} = \sum_{q \neq j}^{J} \rho_j [\frac{p_{iq} \ln\left(p_{iq}\right)}{1 - p_{ji}} + \ln\left(p_{ji}\right)], \tag{6}$$

where ρ is the correlation coefficient of the error terms and p_{ji} is predicted probabilities of the j^{th} CSA adoption category.

Assuming that no adoption of a particular CSA practice ($Z = 1$) is a reference category, following [1, 6, 9, 34, 40, 59] the outcome equation adjusted for selectivity correction term is specified as follows:

$$\begin{cases} Regime 1 : Y_{1i} = \Gamma_1 X_{1i} + \Theta_1 \hat{\lambda}_{1i} + U_{1i} \;\; if\, Z = 1 \\ \qquad\qquad\qquad . \\ \qquad\qquad\qquad . \qquad\qquad\qquad\qquad\qquad j..J\,, \\ \qquad\qquad\qquad . \\ Regime j : Y_{ji} = \Gamma_j X_{ji} + \Theta_j \hat{\lambda}_{ji} + U_{ji} \quad if\, Z = j \end{cases} \tag{7}$$

where Y_{1i} is the expected outcome variable of the study (food security and poverty). $U_{1i}..U_{ji}$ are independently and identically distributed random disturbance term with mean zero and constant variance. X_{ji} is a vector of explanatory variables indicating socio-economic characteristics of households.$\Gamma_j$andΘ_j are parameters to be estimated, while $\widehat{\lambda}_{ji}$ is the inverse mills ratio, which is derived from the first stage estimation of MESR.

According to [17], for the outcome equation (Eq. 7) to be identified, it is important to use selection instruments and these instruments affect the adoption decision but not the outcome variables of non-adopter households. Accordingly, we run falsification test whether these instruments are valid instruments. Distance to district market and distance to drinking water source were used instruments.

The MESR model can be applied to derive the average treatment effect for the treated (ATT), which measures the actual impact of intervention on expected outcome of interest, considering only those who received these interventions. Average treatment effect for the untreated (ATU) measures, on the other hand, the counterfactual effect of adopting CSA, i.e., the projection of potential outcomes in a target (sub-) population [66]. In other words, ATT is the average impact on those who actually participate in the intervention, and ATU is the average potential impact on those who do not participate in the intervention [72]. In this study ATT measures the impact of CSA practices on poverty and food security of CSA adopters while ATU measures the impact of CSA practices on poverty and food security of CSA non-adopters.

The actual expected value of outcome variables for adopters of a particular CSA practice is given by:

$$E\left(Y_{ji}|Z = j; X_{ji}, \hat{\lambda}_{ji}\right) \text{ for j } 2, 3, 4 \ldots J. \tag{8}$$

The actual expected value of outcome variables for non-adopters of a particular CSA practice is given by:

$$E\left(Y_{1i}|Z = 1; X_{1i}, \hat{\lambda}_{1i}\right). \tag{9}$$

The counterfactual expected value of outcome variables for CSA adopters is given by:

$$E\left(Y_{1i}|Z = j; X_{ji}, \hat{\lambda}_{ji}\right) \text{ for } j = 2, 3, 4...J\,. \tag{10}$$

The counterfactual expected value of outcome variables for CSA non-adopters is given by:

$$E\left(Y_{ji}|Z = 1; X_{1i}, \hat{\lambda}_{1i}\right). \tag{11}$$

Now the average treatment effect for the treated (ATT) is determined as the difference between Eq. 10 and Eq. 8 as follows:

$$ATT = E\left(Y_{ji}|Z = j; X_{ji}, \hat{\lambda}_{ji}\right) - E\left(Y_{1i}|Z = j; X_{ji}, \hat{\lambda}_{ji}\right). \tag{12}$$

Table 2 Characteristics of sample households: continuous variables. Source: Own household survey (2022)

Variable	Mean	Adopters Mean	Non-adopters Mean	t-test
Age of household head	41.1 (10.48)	43.05	39.23	−3.08***
Years of schooling of household head	4.1 (3.34)	5.38	2.85	−6.81***
Family size	4.77 (1.96)	4.88	4.66	−0.91
Land size in hectare	1.48 (1.06)	1.89	1.08	6.86***
Tropical livestock unit	7.82 (5.94)	10.92	4.8	−9.98***
Farm experience	20.44 (10.01)	24.03	16.95	−6.3***
Dependency ratio	0.302 (0.229)	0.18	0.42	10.02***
Number of income sources	4.4 (2.64)	5.92	2.92	−11.51***
Average monthly income (USD)	96.01 (83.21)	131.66	61.37	7.75***

*** indicates statistical significance at less than 1%

Numbers in parenthesis are standard errors

Similarly, the average treatment effect for the untreated (ATU) is determined as the difference between Eq. 9 and Eq. 11 as follows:

$$\mathrm{ATU} = \mathrm{E}\left(\mathrm{Y}_{1i}|\mathrm{Z}=1;\mathrm{X}_{1i},\hat{\lambda}_{1i}\right) - \mathrm{E}\left(\mathrm{Y}_{ji}|\mathrm{Z}=1;\mathrm{X}_{1i},\hat{\lambda}_{1i}\right). \tag{13}$$

Results and discussion

Descriptive summary

Table 2 indicates the socio-economic characteristics of sample households in the study area, disaggregated into adopters and non-adopters of CSA. As shown, the average age of the household head of sample households is 41 years. The average mean difference between adopters and non-adopters of CSA is also presented using mean comparison test (t-test). Moreover, the average family size of sample households is 4.77 (approximately 5 persons), which is almost equal with the national average (4.6), while the average years of schooling is 4.1 years. In addition to this, as Table 2 indicates, the average land size and tropical livestock unit[1] of sample households in the study area is 1.48 hectares and 7.82, respectively.

Moreover, the average monthly income of households in the study area is 96.01 USD[2] which is lower than the country's income poverty line of 140.5 USD in 2016 [25]. The mean comparison test indicated that there is a significant mean difference in most of these continuous variables between adopters and non-adopters. This suggests that CSA adoption in the study area may be affected those households' characteristics.

Table 3 indicates the characteristics of sample households related to several categorical variables. As indicated, 91.9% of sample CSA adopters are male-headed while the rest, 8.1%, are female-headed households. 91.2% of CSA adopters are married while the rest (8.8%) are unmarried. Regarding credit access, 45.9% of CSA adopters have access to credit, while 89.4% of CSA non-adopters have no access to credit, indicating that credit access can raise CSA adoption. Besides this, 94.2% of CSA adopters have access to extension services while only 52.4% of non-adopters have access to extension services. In addition to this, 92.7% of CSA adopters have access to weather information, while only 39% of non-adopters have access to weather information. The result suggests that most CSA adopters have more access to extension services and access to weather information than non-adopters. Table 3 also presents the Chi-square test of dependence, which indicates whether these categorical variables are associated with adoption (or non-adoption) of CSA practices. The Chi-square test for most of the variables is highly significant, suggesting that these categorical variables can affect households' CSA adoption in the study area.

[1] A tropical livestock unit is a live weight of an animal equivalent to 250 kg.

[2] 1 USD is on average exchanged for 51.12 Ethiopian birr in 2022.

Table 3 Characteristics of sample households: categorical variables. Source: Own household survey (2022)

Variables		Adopters of CSA		Non-adopters of CSA		Chi-square test (χ^2)
		Number	%	Number	%	
Gender of household head	Male	126	91.9	94	66.7	26.94***
	Female	11	8.1	47	33.3	
Marital status	Married	125	91.2	105	74.4	13.68***
	Unmarried	12	8.8	36	25.5	
Credit access	Yes	63	45.9	15	10.6	43.01***
	No	74	54.1	126	89.4	
Social responsibility	Yes	50	36.4	46	32.6	0.46
	No	87	63.6	95	67.4	
Access to weather information	Yes	127	92.7	55	39	88.61***
	No	10	7.3	86	61	
Access to extension service	Yes	129	94.2	74	52.4	61.27***
	No	8	5.8	67	47.6	

*** indicates statistical significance at less than 1%

CSA practices in CRV Ethiopia

Households and communities apply several policy responses to the challenges of climate change in Ethiopia and beyond. The documented CSA practices are eight or more [20, 22], including the following (see Table 4).

The major CSA practices widely practiced in Ethiopia are described below:

i) Integrated soil fertility management approach, promoted by Ministry of Agriculture, includes promotion of application of relevant fertilizer, intercropping, crop rotation, and composing, etc. These activities contribute to CSA via increasing agricultural productivity, reducing food insecurity problems, and reducing emissions of gases like methane and nitrous oxide.

ii) Conservation agriculture has been promoted by different organizations like FAO and the Agricultural Transformation Agency (ATA), including reduced tillage, crop rotation, intercropping, mulching, crop residue management, reduced tillage, etc. These activities are important in increasing carbon sequestration, reducing emissions and increasing the resilience of crops to dry and hot spells. Crop diversification is also one of the CSA packages in the study area and it involves the application of high-yielding, drought-tolerant, and early-mature crops, etc.

iii) Access to small-scale irrigation (SSI) enables farmers to increase the number of cropping seasons and reduces the risk related to crop failure caused by inadequate rainfall. Irrigated agriculture can produce crop yields two to four times greater than rain-fed agriculture [57]. SSI and other forms of agricultural water management are critical in building resilience to increased climate variability [23].

iv) Agroforestry involves integrated production of trees and plants along with crop farming since it is very important in reducing soil erosion. Reduction of carbon dioxide emission, increasing climate resilience and crop yield are major benefits of these activities in attaining the aims of CSA.

We focused on the impact on poverty and food security of four CSA practices; namely, integrated soil fertility management, conservation agriculture, crop diversification, and small-scale irrigation.

CSA practices and determinants of adoption

The adoption of CSA by sample households, specifically, on conservation agriculture and soil fertility management (S), small-scale irrigation (R) and crop diversification(C) is assessed. As indicated in Fig. 2, 50.72% (141) of sample households don't adopt any CSA packages, while 19.06% [53] of sample households adopt only conservation agriculture and soil fertility management. Moreover, 18% [50] and 23.74% (66) of sample households adopt only small-scale irrigation and crop diversification, respectively. The figure also shows that 8.27% of sample households adopt all kinds of CSA practices, implying that only a few households adopt all CSA practices in the study area.

In general, these suggest that CSA adoption is still low among farm households in the central rift valley of Ethiopia. The result of this study is in line with the findings of

Table 4 CSA practices in Ethiopia. Source: [20, 22, 23]

CSA practices	Components	Why it is climate smart?
Conservation agriculture	- Reduced tillage - Crop residue management(mulching) - Crop rotation/intercropping with cereals and legumes	- Carbon sequestration - Reduces existing emissions - Resilience to dry and hot spells - Enhances soil fertility resulting in improvement in soil productivity
Integrated soil fertility management	- Compost and manure management - Efficient fertilizer application techniques	- Reduces emission of nitrous oxide and CH4 - Improved soil productivity
Small-scale irrigation	- Year round cropping - Efficient water utilization	- Creating carbon sink, Improved yields, Improved food security
Agroforestry	- Tree based conservation agriculture practices both traditionally and as improved practice - Farmers-managed natural regeneration	- Trees store large quantities of Co2 - Can support resilience and increase agricultural productivity
Crop diversification	- Popularization of new crops and crop verities - Pest resistance, high yielding, drought tolerant and short seasons	- Ensuring food security - Resilience to weather variability - Alternative livelihoods and improved incomes
Improved livestock feed and feeding practice	- Reduces open grazing/zero grazing - Forage development and rangeland management - Feed improvement - Livestock breed improvement and diversification	- Improved livestock productivity - GHG reduction - CH4 reduction
Improved animal husbandry	- Animal breed improvement, improved animal health system - Improved manure management practices	- Improved livestock productivity - GHG reduction - CH4 reduction
Others	- Early warning systems and weather information's - Support to alternative energy - Crop and livestock insurance - post harvest technologies, etc.	- Resilience of agriculture - Improved incomes - Reduced emissions - Reduced deforestation - Reduce climate risk

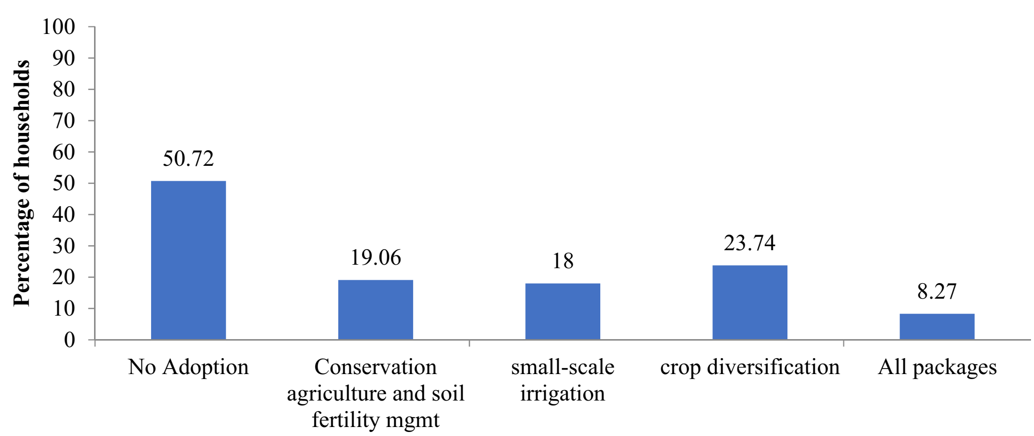

Fig. 2 Characteristics of sample households: adoption of CSA packages. Source: Survey (2022)

[43] and [11], which also showed low CSA adoption in their perspective study areas.

Adoption of CSA by sample households falls into five CSA categories. These are no-adoption of any CSA practices ($S_0R_0C_0$); only conservation agriculture and soil fertility management ($S_1R_0C_0$); conservation agriculture and soil fertility management and crop diversification ($S_1R_0C_1$); conservation agriculture and soil fertility management and small-scale irrigation ($S_1R_1C_0$); and adopting a combination of all CSA packages ($S_1R_1C_1$).

The test of the IIA assumption indicates that the model is correctly specified. The Hausman specification test is used, and the test accepts the null hypothesis of no-systematic difference between coefficients ($\chi^2 = 2.77, p > \chi^2 = 1.00$). It implies that the omission of one alternative from the estimation does not alter the coefficients of variables of the remaining alternatives significantly.

As shown in Table 5, average monthly income, dependency ratio, and access to extension statistically and significantly affect the adoption of conservation agriculture and soil fertility management ($S_1R_0C_0$) at 5% and 1% levels of significance, respectively. Moreover, the marginal effect of the model indicates that keeping other things constant, a rise in dependency ratio by 1 unit decreases the probability of adoption of $S_1R_0C_0$ by 46.83%, whereas access to extension service raises the probability of adoption by 24.17%. The education level of household head, distance from the drinking water source, livestock size (in TLU), and distance from the district market statistically and significantly affects the adoption of conservation agriculture and soil fertility management with irrigation ($S_1R_1C_0$) at 5%, 1% and 10% levels of significance, respectively.

Moreover, average monthly income, dependency ratio, and farm experience statistically and significantly affect the adoption of conservation agriculture and soil fertility management with crop diversification ($S_1R_0C_1$) at 1%, 5%, and 10%, respectively. In addition to this, Table 5 indicates access to credit, average monthly income, and livestock size (in TLU) affect the adoption of conservation agriculture and soil fertility management with crop diversification and small-scale irrigation ($S_1R_1C_1$) statistically and significantly at the 1% level of significance. Furthermore, family size, distance to the district market, and distance to the drinking water source also affect the adoption of $S_1R_1C_1$ statistically and significantly at 10% and 5%, respectively. The result implies that development actors should focus on family size, monthly income, education of households, and access to extension services to raise households' CSA adoption. The result is congruent with the findings of [11, 16, 69] and [45].

Table 6 presents the result of ordered probit regression with the associated marginal effects. The result indicates that access to credit, educational level of household head,

Table 5 Determinants of CSA adoption: result of multinomial logistic regression. Source: Own household survey (2022)

Variables	$S_1R_0C_0$		$S_1R_1C_0$		$S_1R_0C_1$		$S_1R_1C_1$	
	Coef	Marginal effects	Coef	Marginal effects	Coef	Marginal effects	Coef	Marginal effects
Age of HH head	0.0008 (0.0507)	0.004	−0.00006 (0.0843)	0.0003	−0.0903 (0.105)	−0.01	0.136 (0.113)	2.73e-06
Family size	0.0279 (0.138)	0.0013	0.0165 (0.229)	−0.0002	0.1039 (0.213)	0.0106	−0.559* (0. 306)	−0.000010
Gender of HH head	0.355 (0.510)	0.0706	0.927 (1.23)	0.0174	0.0212 (1.28)	−0.016	0.92 (1.18)	0.000011
Marital status	−0.112 (0.597)	0.0084	0.1208 (1.52)	0.0064	−0.629 (1.292)	−0.078	−0.36 (1.32)	−4.58e-06
Credit access	0.0804 (0.631)	-0.0459	0.924 (0.858)	0.022	0.978 (0.679)	0.121	4.8*** (2.13)	0.00051
Education level of HH head	0.1038 (0.0791)	0.0159	0.248** (0.138)	0.0052	0.113 (0.101)	0.0073	0.28 (0.196)	4.14e-06
Land size	0.0208 (0.066)	−0.0019	0.0517 (0.172)	0.00069	0.132 (0.088)	0.0141	0.10 (0.113)	1.37e-06
Average Monthly income	0.0003** (0.0001)	0.00004	0.0002 (0.0001)	2.14e-06	0.0005*** (0.0002)	0.00004	0.0004*** (0.0002)	5.47e-09
TLU	0.0869 (0.0708)	0.015	0.2442*** (0.087)	0.0054	0.05 (0.08)	0.0008	0.478*** (0.158)	8.00e-06
Dependency ratio	−2.85*** (1.013)	−0.46	−2.04 (1.69)	−0.014	−3.46** (1.38)	−0.259	−1.74 (4.059)	−4.13e-06
Distance from district market	0.0003 (0.025)	0.0033	−0.1381* (0.062)	−0.0035	−0.041 (0.036)	−0.004	−0.232** (0.061)	−4.12e-06
Distance from water source	−0.063 (0.066)	−0.0065	−0.349** (0.165)	−0.0083	−0.097 (0.112)	−0.007	−0.42** (0.182)	−6.92e-06
Access to extension	1.469*** (0.552)	0.241	2.063 (0.764)	0.0293	1.179 (0.78)	0.063	12.79 (1.044)	0.00046
Farm experience	0.0156 (0.055)	−0.0041	0.0143 (0.0997)	−0.0003	0.1608* (0.106)	0.017	−0.026 (0.124)	−9.91e-07

*, **, *** indicates significant variables at 10%, 5% and 1%, respectively. Numbers in brackets are robust standard errors

Table 6 Results of ordered probit regression and marginal effects. Source: Own household survey (2022)

CSA intensity	Coef	Marginal effects			
		Pr(Y = 0|X)	Pr(Y = 1|X)	Pr(Y = 2|X)	Pr(Y = 3|X)
Age of HH	−0.0011 (0.0207)	0.0004	−0.0001	−0.0002	−9.04e-06
Family size	0.0007 (0.0508)	−0.0002	0.0001	0.0001	6.01e-06
Gender of HH	0.323 (0.325)	−0.128	0.059	0.067	0.002
Marital status	−0.18 (0.333)	0.0714	−0.025	−0.044	−0.001
Credit access	0.65*** (0.203)	−0.24	0.068	0.16	0.008
Educational level of HH	0.08*** (0.028)	−0.034	0.013	0.02	0.0007
Land size	0.03 (0.026)	−0.014	0.0059	0.0085	0.0003
Average monthly income	0.00001 (0.00002)	−4.26e-06	1.71e-06	2.47e-06	8.82e-08
TLU	0.08*** (0.017)	−0.033	0.013	0.019	0.0006
Dependency ratio	−1.23*** (0.453)	0.48	−0.195	−0.282	−0.01
Distance from district market	−0.03*** (0.011)	0.013	−0.005	−0.0078	−0.0002
Distance from water source	-0.05* (0.029)	0.021	-0.008	-0.012	-0.0004
Farm experience	0.03 (0.022)	-0.012	0.005	0.007	0.0002
Access to extension	1.06*** (0.246)	-0.403	0.209	0.18	0.005

***,* represents statistical significance at 1% and 10%, respectively. Numbers in brackets are robust standard errors

livestock holding (in TLU), dependency ratio, access to extension service, and distance to the district market are major determinants of the intensity of CSA adoption in the study area. The result suggests that keeping all things constant, access to credit increases adoption of any CSA package by approximately 24%, while access to extension also increases the probability of adoption by 40%. Keeping other things constant, access to credit and extension services, raises the probability of households' adoption of two CSA packages by 16% and 18%, respectively. The result also indicates that other things remain unchanged; a unit rise in dependency ratio decreases the probability of adoption of one, two, and three CSA packages by 19%, 28%, and 1%, respectively. As shown in Table 6, the marginal effect of variables indicates a decreasing trend as households' intensity of CSA adoption rises. This may be attributed to the fact that households' resources are reduced as they adopt more diversified CSA packages. The result is consistent with the studies of [4, 49, 51].

Poverty characteristics of sample households

As reported in Table 7, 48% (133) of sample households are multi-dimensionally poor, with an average deprivation of 0.56 and MPI of 0.27. The highest headcount index (H), which shows the percentage of poor households in the sample, is recorded in the Dugda district (58%), and followed by the Arsi Negele (42%) district. Moreover, the highest poverty intensity (A) was recorded in Meskan district (0.58) followed by Heban

Table 7 Poverty headcount, intensity and MPI of the study districts. Source: Own household survey (2022)

Poverty indices	Study districts				All districts
	Meskan	Dugda	Arsi Negele	Heban Arsi	
H	0.42	0.58	0.5	0.42	0.48
A	0.58	0.57	0.55	0.57	0.56
MPI	0.24	0.33	0.27	0.24	0.27

Table 8 Mean value of households' food security measures by study districts. Source: Own household survey (2022)

Study districts	Food security measures FCS	DDS	FIES
Meskan	37.02	6.34	7.01
Dugda	30.6	5.5	10.1
Arsi Negele	26.1	5.3	8.7
Heban Arsi	35.7	7.1	10.1

Arsi district (0.57). The highest MPI is recorded in Dugda district (0.33), followed by Arsi Negele district (0.27).

From this, we can understand that the highest multidimensional poverty exists in the Dugda district while it is lower in Meskan and Heban Arsi districts. This could be due to the fact that most households in the Dugda district are CSA non-adopters and vice versa. The result also suggests that MPI, H and A in the study area are less than the national average of 0.49, 83.5, and 58.5, respectively.

Food security characteristics of sample households

As reported in Table 8, the maximum average FCS is recorded in the Meskan district followed by Heban Arsi and Dugda districts.

All four study districts have nearly the same average DDS, in which Heban Arsi has the highest (7.1), followed by Meskan, Dugda, and Arsi Negele districts, respectively. Moreover, the lowest average FIES is recorded in Meskan districts followed by Arsi Negele, Dugda and Heban Arsi, respectively. Thus, we can understand that, in terms of FCS and FIES, the Meskan district is found to be more food secure than the remaining districts. This variation could be attributed to CSA adoption in which Meskan district has the highest percentage of adopter households than other districts. Based on FCS, Arsi Negele is found to be less food secure than other study districts, and it may be due to the fact that most households in the Arsi Negele district didn't adopt CSA practices. The result also suggests that, on average, more food secure households have indicated low multidimensional poverty and vice versa in the study area indicating that food security and multidimensional poverty are inversely related in the study area.

Impact of CSA adoption on households' food security

Table 9 presents the average treatment effect on treated and untreated households to indicate the impact of CSA adoption on households' food security. It was found that, on average, adopters of conservation agriculture and soil fertility management ($S_1R_0C_0$) have 7.5% (2.34) higher values of FCS while their counterparts showed 24.7% (-7.58) lower values in the food consumption score and the difference was statistically significant. In addition to this, on average, adopters of conservation agriculture and soil fertility management with small-scale irrigation ($S_1R_1C_0$) have a 416% (34.39) increase in FCS while their counterparts showed a 32.67% decline, and the difference is also statistically significant. Moreover,

Table 9 Average treatment effect of CSA adoption on households' food security. Source: Own household survey (2022)

CSA packages	Adopters (actual)	If they would not adopt	ATT	Non-adopters (actual)	If they would adopt	ATU
Food Consumption Score (FCS)						
$S_1R_0C_0$	33.27	30.93	2.34***	23.02	30.6	−7.58***
$S_1R_1C_0$	42.65	8.25	34.39***	23.02	34.19	−11.17***
$S_1R_0C_1$	39.78	43.1	−3.32	23.02	39.05	−16.03***
$S_1R_1C_1$	62.17	5.68	56.48***	23.02	40.54	−17.52***
Dietary Diversity Score (DDS)						
$S_1R_0C_0$	6.73	6.51	0.22	3.95	5.94	−1.99***
$S_1R_1C_0$	8.33	5.76	2.57***	3.95	6.66	−2.71***
$S_1R_0C_1$	8.37	6.81	1.57***	3.95	8.61	−4.66***
$S_1R_1C_1$	11.17	8.1	3.07***	3.95	9.23	−5.28***
Food Insecurity Experience Scale (FIES)						
$S_1R_0C_0$	6.62	7.6	−0.98***	12.58	8.23	4.35***
$S_1R_1C_0$	7	19.03	−12.03***	12.58	8.11	4.47***
$S_1R_0C_1$	3.85	4.98	−1.23***	12.58	1.54	11.03***
$S_1R_1C_1$	2.39	1.42	0.96	12.58	6.79	5.79***

*** indicates significant variables at 1%

ATT average treatment effect on the treated, *ATU* average treatment effect on the untreated

Table 10 Average treatment effect of CSA on household's poverty. Source: Own household survey (2022)

CSA packages	Deprivation Score					
	adopters (actual)	If they would not adopt	ATT	Non-adopters (actual)	If they would adopt	ATU
$S_1R_0C_0$	0.31	0.39	−0.08***	0.50	0.34	0.16***
$S_1R_1C_0$	0.22	0.64	−0.42***	0.50	0.31	0.19***
$S_1R_0C_1$	0.17	0.25	−0.08***	0.50	0.15	0.35***
$S_1R_1C_1$	0.11	0.28	−0.17***	0.50	0.21	0.29***

*** indicates significant variables at 1%

ATT average treatment effect on the treated, ATU = average treatment effect on the untreated

on average, adopters of all CSA packages ($S_1R_1C_1$) have a 994% (56.48) increase in FCS whereas non-adopters recorded a 43.2% fall in FCS, and the difference is highly and statistically significant.

Besides this, on average, adopters of conservation agriculture and soil fertility management ($S_1R_0C_0$) have revealed a 3.3% (0.22) increase in DDS, but the difference is statistically insignificant. But non-adopters indicated a 33.5% (−1.99) fall in DDS, and the difference is statistically significant. It is also presented that, on average, adopters of conservation agriculture and soil fertility management with small-scale irrigation ($S_1R_1C_0$) have a 44.6% (2.57) rise in DDS, while their counterparts showed a 40.6% (−2.71) fall in DDS. In addition to these, adopters of conservation agriculture and soil fertility management with crop diversification ($S_1R_0C_1$) and adopters of all CSA packages ($S_1R_1C_1$) have a 23% (1.57) and 38% (3.07) rise in DDS, respectively. However, their counterparts recorded a 54% (−4.66) and 57% (−5.28) decrease in dietary diversity, and the difference is also statistically significant at less than a 1% level of significance.

Regarding FIES, adopters of conservation agriculture and soil fertility management ($S_1R_0C_0$) have been found to have a 12.8% (−0.98) decline, while their counterparts showed a 52.8% (4.35) rise, and the difference is statistically significant. In addition to these, adopters of conservation agriculture and soil fertility management with crop diversification ($S_1R_0C_1$), adopters of conservation agriculture and soil fertility management with small-scale irrigation ($S_1R_1C_0$) have recorded a 24.6% (−1.23) and 63.2% (−12.03) fall in FIES. Contrary to this, 716% (11.03) and 55% (4.47) rises are indicated in the FIES of their counterparts.

Furthermore, a 67% (0.96) rise in FIES is observed for households that adopt all available CSA packages ($S_1R_1C_1$), but the result is not found to be statistically significant. Their counterparts (non-adopters), on average, had a 85% (5.76) rise in FIES, and the result is statistically significant at less than a 1% level of significance.

Overall, we observed that households that adopt CSA packages have the highest FCS and DDS. But they have on average low FIES than non-adopters of CSA. On the contrary, non-adopters have on average low FCS and DDS. But they have high FIES. In addition to this, adopter households would have low FCS, DDS and high FIES if they did not adopt any CSA packages. Similarly non-adopters would have high FCS, DDS, and low FIES, if they did adopt CSA packages.

The results suggest that households should adopt more diversified combinations of CSA packages to increase their food security status. CSA can raise food security by raising crop productivity and reducing the risk of crop failure, as well as by reducing the adverse impacts of climate change. Thus, we can infer that the adoption of CSA has had a positive and statistically significant impact on farm households' food security in CRV. The results of this study indicate that CSA adoption plays an indispensable contribution to the achievement of the 2nd and 13th sustainable development goals (SDGs), which aim to end global hunger and mitigate adverse impacts of climate change through increasing adaptive capacity, respectively. The result of this study is in line with the findings of [17] and [69].

Impact of CSA adoption on households' poverty

As clearly shown in Table 10, on average, adopters of conservation agriculture and soil fertility management ($S_1R_0C_0$) have a 20.5% (−0.08) fall in deprivation score while it is a 47% (0.16) rise in deprivation score of their counterparts. Moreover, adopters of conservation agriculture and soil fertility management with small-scale irrigation ($S_1R_1C_0$), on average, have recorded a 65.6% (−0.42) decrease in deprivation score, while their counterparts showed a 61.2% (0.19) rise in deprivation score. Similarly, adopters of conservation agriculture and soil fertility management with crop diversification ($S_1R_0C_1$) as well as adopters of all available CSA packages ($S_1R_1C_1$) have indicated a 32% (−0.08) and a 60.7% (−0.17) fall in deprivation score. On the contrary, 233% (0.15) and 138%

(0.29) rise in deprivation scores is observed in their counterparts. The difference is also highly statistically significant at less than a 1% level of significance.

The estimation of the average treatment effect shows that CSA adopter households have a low deprivation score, and they would have a high deprivation score if they did not adopt any CSA packages. Moreover, non-adopters of CSA have a high deprivation score, and the counterfactual analysis showed they would have a low deprivation score if they did adopt CSA packages.

Hence, it can be concluded that adoption of CSA packages can improve rural farm households' multidimensional poverty by reducing their deprivation score in the CRV. In other words, through the up-scaling adoption of CSA practices, rural households' multidimensional poverty can be reduced. Last but not the least, the results of this study has an implication that CSA adoption is very important to achieve SDG1 which is aimed to end global poverty. The finding of this study is consistent with the findings of [1, 7, 8, 60].

Conclusion and policy implication

Climate change has perverse effects on the natural resource base and agricultural productivity, negatively affecting the well-being of households and communities. Too late, the government and NGOs have promoted various climate-smart agricultural (CSA) practices to help farmers adapt to and mitigate these negative impacts. This study aims to identify CSA practices practiced in the CRV of Ethiopia, factors that determine the adoption and examine the impact of climate-smart agriculture on rural households' food security and poverty. A three-stage random sampling procedure was followed to select sample households. Food consumption score, dietary diversity score, food insecurity access scale, and multidimensional poverty index were used to measure households' state of food security and poverty. Results indicate that households adopt different CSA practices such as conservation agriculture, soil fertility management, crop diversification, and small-scale irrigation. The major factors that affect CSA adoption in the study area are found to be households' wealth (monthly income), access to extension, access to credit, and dependency ratio. The findings also indicated that CSA has a positive and significant impact on households' food security, measured in terms of food consumption score and dietary diversity score, while it negatively affects households' food insecurity access scale and had a significant impact on reducing households' multidimensional poverty. Moreover, the study indicated that CSA can raise food security by raising crop productivity and reducing the risk of crop failure by mitigating the adverse impacts of climate change. The study revealed that CSA adoption is extremely important to attaining the SDG1, SDG2, and SDG13, which are directed to ending global poverty, hunger and mitigate the adverse impacts of climate change, respectively. It is very important to increase the intensity of CSA adoption by raising households' income, providing access to extension services, access to education, and increasing credit access. Moreover, improving implementation capacity (through better education and extension services) and innovative financing mechanisms could enhance household farmers' incentives to enable up-scaling of CSA practices.

Appendix

See Tables 11, 12

Table 11 A falsification test of instruments. Source: Authors (2022)

Outcome variable	*F*	*Prob > F*
MPI	0.71	0.49
FIES	0.03	0.85
DDS	0.53	0.46
FCS	0.04	0.96

Table 12 A IIA test result. Source: Authors (2022)

Hypothesis	$\chi^2(42)$	*Prob* $> \chi^2$
H0 = difference in coefficients not systematic	2.77 1.000	
H1 = difference in coefficients is systematic		

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Availability of data and materials
The data sets used/analyzed for this study are available from the corresponding author upon request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
All authors have given their consent so that this article is published.

Competing interests
The authors do not declare any conflict of interest.

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