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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, Southwest Ethiopia

Girma Tilahun[a,c,*], Amare Bantider[a,b], Desalegn Yayeh[a]

[a] Addis Ababa University, College of Development Studies, Center for Food Security Studies, Addis Ababa, Ethiopia
[b] Addis Ababa University, Resource Governance & Socioeconomic Research Division, Water and Land Resource Center, Addis Ababa, Ethiopia
[c] Bonga University, College of Agriculture and Natural Resources, Department of Natural Resources and Management, Bonga, Ethiopia

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ABSTRACT

The traditional rain-fed agriculture system of Ethiopia is suffering from climate change impacts and extremes. It must be improved to feed the growing population and create a resilient society. Climate-smart agriculture (CSA) is currently promoted as an approach intended to increase sustainable agricultural productivity, enhance household resilience, and reduce greenhouse gas emissions. This study was, therefore, undertaken to examine how food security can be improved by the adoption of multiple climate-smart agriculture (CSA) practices of smallholder farmers in a moist tropical montane ecosystem of Southwest Ethiopia. Data was collected from 384 purposively selected households through cross-sectional study design using a semi-structured questionnaire. Eight Focus group discussions and fifteen key informant interviews were also conducted to check the reliability of the survey data collected. In the study area, a total of eighteen CSA practices, adopted by farmers, were identified. Using principal component analysis, these practices were further grouped into five packages and a multinomial endogenous switching regression model was used to link these packages to the food security status. The findings revealed a great variation in the proportion of households using CSA practices where 92.3 % were using crop management practices whereas 11.2 % were using soil and water conservation practices. The study found that the maximum effect of CSA adoption on food security was by farmers who adopted all the five category CSA technologies. Households that adopted this package were more food secure by 41.2 % in terms of per capita annual food expenditure, 39.8% in terms of Household Food Insecurity Access Scale (HFIAS), and 12.1% in terms of Household Food Consumption Score (HFCS) than the non-adopters. The adoption of this group of practices was further influenced positively by farm size, gender, and productive farm asset values. Using CSA practices in combinations and to a relatively larger extent can potentially solve food security problems. Motivating farmers by providing income-generating activities and discouraging land fragmentation through public education is essential. This in turn improves CSA adoption and initiates production assets investment that can absorb climate change risks.

* Corresponding author. P.O.Box: 329, Bonga, Ethiopia.
*E-mail address:* girma2721@gmail.com (G. Tilahun).

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## 1. Introduction

In the climate change era, climate-smart agriculture was first introduced in 2009 as a means to guide the management of the agricultural sector [1]. The impact on sustainable food production, resilience, and mitigation can best be addressed by this approach [2–4]. The primary indicators of climate change are increasing temperature, sea level rise, rainfall patterns change, ice caps melting, and changing humidity [5]. Secondary consequences that are direct determinants of agriculture are tidal surges, cyclones, floods soil salinity, and droughts [6]. A crop model for sub-Saharan Africa forecasts that crop damage on yields varies between 36%, 12%, and 13% for Ethiopia, Rwanda, and Uganda respectively due to adverse effects [7]. Hence, the impact of climate change on food security is noticeably negative [8–10]. Thus, the prioritization of food security in a changing climate has been subjected to discussions at all governmental levels [11]. Climate-smart agriculture is recommended by development organizations and researchers under scenarios of the declining yield of major crops in order to feed the growing population.

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 4.79 tons of the global average in 2020 [12]. Ethiopia has experienced an increasing trend in average temperature [13,14]. It is also obvious that wet seasons will get wetter and dry seasons drier and [13]. The study area is experiencing a delayed start, early ending, 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 economy of Ethiopia is yet relying on undeveloped rain-fed agriculture, which accounts for 80% of exports, 40% of GDP, and an estimated 75% workforce of the country [15]. Crop yields below the regional average, only 5% of irrigated land, weak market linkage, and limited use of improved seeds and fertilizers are common characteristics of Ethiopian agriculture [16]. Based on the Worldometer report of the United Nations, the population of Ethiopia has risen by 49% in the last 20 years alone and reached approximately 122 million in 2022 while the agricultural system has not been improved since [17]. The agrarian population constitutes 85% of the total population and the food security and livelihood situations are worsening [18]. These problems are yet exacerbated by the global impacts of climate change and extremes in rainfall pattern anomalies and temperature rise forms [19].

Climate-smart agriculture (CSA) is currently promoted as an approach that reduces the impacts of climate change on agriculture and ensures a more resilient and food-secure community worldwide. The most cited definition of the concept of CSA as highlighted by Ref. [20] is "an approach of supporting food security by renovating and reorienting the agricultural system under climate change''. In a fluctuating climate, CSA can improve productivity and enhance household resilience (adaptation), remove/reduce greenhouse gas emissions (mitigation), and promote the food security efforts of nations [21,22]. For instance, deep placement of urea is a CSA practice that needs inserting briquettes of urea (1–3 g/granule) deep in the soil from 7 to 10 cm depth after transplanting paddy rice. This practice, in Bangladesh, is found to minimize loss of nitrogen by 40 %, enhance 25 % grain yield of rice, reduce the cost of urea by 25 %, and lower water pollution and greenhouse gas emissions [23,24]. Available literature documented that CSA practices can maximize crop productivity and hence contribute to food security [24–26]. More than a quarter of Ethiopian population is food insecure. Ethiopia is ranked 90th out of 116 countries and categorized as serious in the 2021 Global Hunger Index [27]. While CSA is an important approach for the resource resource-poor highly vulnerable agrarian societies such as Ethiopian smallholder farmers, the establishment of the direct link between food security and CSA practices adoption has received little attention to date [6].

Traditionally, smallholder farmers, through their indigenous knowledge, have been undertaking farming practices such as agroforestry, soil fertility management using organic manure, soil and water conservation, and crop rotation. This experience, though not in the name of CSA, laid a foundation for current CSA technology knowledge. These practices were then scaled up to fulfill the three goals of CSA; sustainably agricultural productivity increment, enhancing adaptation to the impacts of climate change and minimizing greenhouse gas emissions which is recently promoted as CSA practices by the government and other research organizations [21–23]. Thus, in Ethiopia, some of the CSA practices that have been implemented include integrated soil fertility management, integrated watershed management, sustainable land management, crop residue manipulation, agroforestry, conservation agriculture, livestock feed improvement, rangeland management and composting [17,18,28].

In Ethiopia, CSA practices adoption such as agroforestry and conservation agriculture remain low. Initial investment failures due to limitations in financial resources and the available land tenure insecurity are contributing to the low adoption. Theoretically, to adopt a single CSA practice or practices in combination, farmers need to maximize profits [8] and this is highly associated with the theory of utility that states: the choice being made to adopt a certain technology is whether an alternative has a greater utility than another [29].

To promote the uptake of CSA practices, a better understanding of factors determining farmers' adoption trends is crucial for developing working policy. Empirical evidence showed that CSA adoption by smallholder farmers is influenced by farm characteristics, socioeconomic, access to important infrastructure services, institutional, technology and information, climate-related and social capital factors [22,30–32].

Previous CSA adoption studies in Ethiopia focused mostly on factors influencing a specific CSA practice. Nevertheless, various technologies that can be combined and used, are frequently presented to farmers to address climate change impacts and ensure sustainable food security. Thus, one of the contributions of this study is CSA practices adoption modeling while considering the interrelatedness between them. In addition, farmers adopt various levels of CSA practices [25]. Evaluating the level/intensity of adoption of CSA practices using the Multinomial Endogenous Switching Regression model is the other contribution of this paper. The determinant factors influencing CSA adoption are also the other contribution of this paper.

This study aims to address three objectives. The first objective is to identify the level and adoption patterns of CSA practices adoption among different household typologies. Secondly, it examines the role of adoption of climate-smart agriculture on food security. Finally, the determinant factors for adopting climate-smart agriculture are evaluated.

Three research questions will then be addressed: 1) What do the levels and patterns of CSA adoption look like in the study area? 2)

How does the adoption of CSA affect the food security status of smallholder farmers in the study area? and 3) What are the influential factors that promote or hinder the adoption of climate-smart agriculture in the study area?

The remaining sections of this article are organized as follows: in section two, materials and methods have been briefly discussed. Descriptive and econometric estimation results are presented and discussed in section three. Finally, the conclusion and implications to policy are described.

## 2. Materials and methods

### 2.1. Description of the study area

The study area was selected based on the smallholder farmers' representativeness that has experienced rainfall pattern abnormalities justified by an early cessation and delayed onset with weak spring rainfall performance but abundant rainfall in the summer season [33,34]. In Southwest Ethiopia, Geshi watershed covers an estimated area of 13,935 ha and is located between 7°20′N to 7°25′N latitude and 36°15′E to 36°23′E longitude (Fig. 1). The watershed is found with an altitude ranging between 1200 and 2670 m above sea level (masl). An undulating terrain with slopes ranging from 0 to 50 % and surrounded by intermittent rivers characterizes the topography of the watershed. Agroecologically, the area falls under warm moist highlands to sub moist mid-highlands climatic zones. This diverse agroclimatic zone enables the watershed produce various crops, vegetables, fruits, and rearing livestock [19]. The annual rainfall ranges between 1200 and 2,200 mm; while the annual minimum and maximum temperature range between 12 and 26 °C respectively [35]. The rainfall distribution is bimodal in nature and occurs mostly from June to mid-November, locally called *Kiremt* (main rainy season), and February to May is another season which is locally regarded as *Belg* with light rain, leading to two harvesting seasons [36]. Late onset, early ending, abundant rainfall, and weak *belg* performance contribute to aggravating the food security problems of the watershed and force farm households to shift to livestock production and grow lower-yielding and short-maturing varieties.

Geshi watershed consists of seventeen micro watersheds. These micro watersheds benefit nine Kebeles with a total rural population of 14,518 of which 7261 are males. The landmass of the watershed is estimated to be 13,935 ha with the main economic activity relying on agroforestry practices such as cereals, coffee planting, vegetables and tea accounting for 41.9 % of the total area. The remaining watershed areas are covered by natural Afromontane forests (8.98 %), woodlots (8.48 %), degraded hillside land (2.6 %), and the remaining lands being other small land fragments [16].

### 2.2. Sampling design

This study utilized data collected from survey farm households by well-trained enumerators which was conducted between October and December 2021. Smallholder farmers' selection followed a three-level multistage sampling technique. The first stage encompassed the identification of the district where the Geshy watershed is found. Identification of beneficiaries of the watershed from 9 *Kebeles* (the smallest administrative governmental unit), was undertaken in the second stage. The third stage followed randomly selecting six villages out of the total twenty-two villages for administering the survey data collection. Finally, using sample size calculator, 384

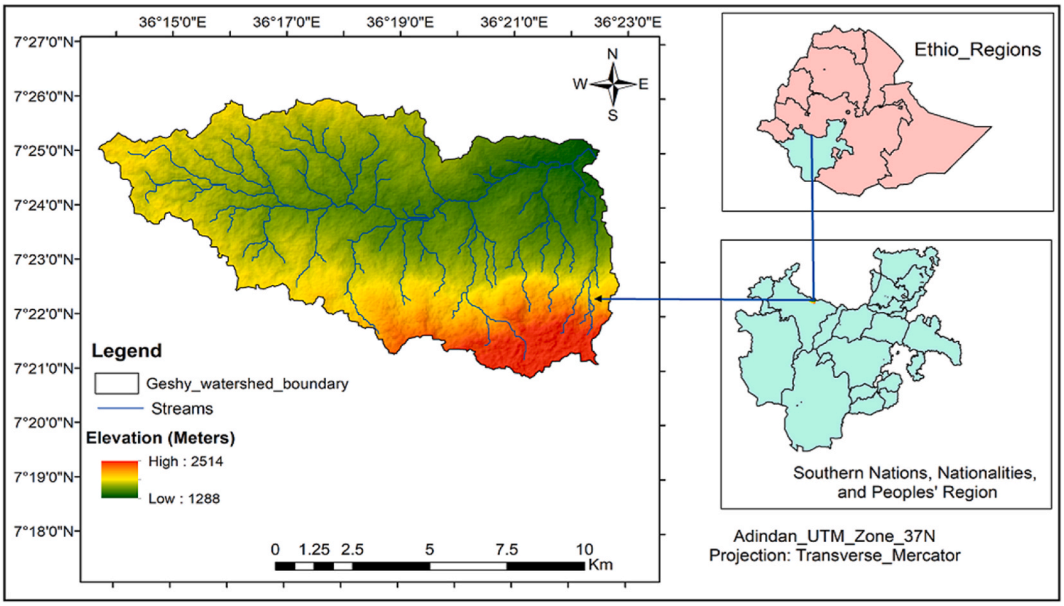


**Fig. 1.** Geographical location of the study area.

households that were conventionally practicing different packages of CSA, were identified from a sampling frame of 13,0000 households and distributed to the six villages using the probability proportional sampling method for survey data collection. Using the cluster sampling method, regressors can be correlated with endogenous cluster-level errors appearing due to level cluster-level covariates in a Multinomial Endogenous Switching Regression Model. For a binary outcome and normally distributed endogenous variable with a random effect model not linear and follows a logistic mixed-effects model, the cluster variations within the endogenous variable function under the limitation that whether the cluster-level random effect has a linear relationship with the outcome or endogenous variable (Ruzzante et al., 202).

The study used a mixed research design. The quantitative data analysis used the survey household data collected using a survey questionnaire. These include the demographic data, the socioeconomic data, the level and CSA adoption, status of food security and the effect of CSA adoption on food security. The qualitative data analysis on the other hand followed information generated and analyzed using key informant interviews and focus group discussions for validating the survey data collected. Community elders, women and local administrative bodies were among the participants during the focus group discussion whereas, development agents, Zone-level agricultural experts, and donor organizations focal persons were the key informant interview participants.

### 2.3. Theoretical underpinnings

This research adopted the theory of utility. As described by Ref. [29], the decision to adopt or not to adopt any CSA practice lies under the profit and utility maximization theory. The utility theory focuses on an individual's behavior on the basis that based on individuals' preferences they constantly rank their choices. The important aspect in the theory of utility concerning making choices is whether an alternative has a greater value than another and not the measure of the variability between the existing alternatives. The concern of making choices among farmers on selecting alternative agricultural practices for adoption lies in the idea of listing available alternatives based on the utility they provide.

The idea is that economic actors, including smallholder farmers, adopt CSA practices when the net benefit or expected utility is greatly higher than the non-adopters [37]. The economic agents' activities could be identified through farmers' choices, as the utility cannot be directly observed. Assume a farmer whose objective is to increase productivity over a certain period and has more than one CSA practices of *j* alternatives to select from. The *i* farmer make decision to adopt *j* CSA practice if the *j* utility is seeming to be higher than that from other alternatives (assume, *k*). This association is presented as Equation (1):

$$Uij = (\beta^{'}jXi + \varepsilon j) > Uik(\beta^{'}kXi + \varepsilon j), k \neq j \tag{1}$$

where U*ij* and U*ik* represent the perceived utility by *i* farmer from CSA practices options *j* and *k*, respectively; Xi is a vector regressor that affects the CSA alternative the farmer chooses; $\beta' j$ and $\beta' k$ are independent variable parameters; and εj and εk are terms of errors, which with regard to the economic assumption are identically and independently distributed [38].

Under the assumption of preference that the farmer's decision to adopt a CSA practice from available alternatives that generate net values and practice and does not adopt otherwise, the observable discrete practice chosen can be associated with the continuous net benefit latent variable as Equation (2):

$$Yij = 1 if\ Uij > 0 and\ Yij = 0 if\ Uij < 0 \tag{2}$$

In the generated formula, Y is a dependent binary variable designated as 1 when the farmer opts for a CSA practice and 0 if otherwise. The possibility that the *i* farmer will pick *j* CSA practice option from a number of available alternatives of CSA practices could be presented in Equation (3):

$$\left(X = \frac{1}{x}\right) = P\left(Uij > \frac{Uik}{x}\right) = P\left(\beta^{'}kXi - \varepsilon k > \frac{0}{x}\right) = P\left(\beta^{'}jXi + \varepsilon j - \beta^{'}kXi - \varepsilon k > \frac{0}{x}\right) = P\left(\beta * Xi + \varepsilon * > \frac{0}{x}\right) = F(\beta * Xi) \tag{3}$$

where P is a probability function; $\beta^* = (\beta' j - \beta' k)$ is an unknown vector parameter that can be justified as the net impact of the choice of CSA practice determinants; F($\beta^*$ *Xi*) is a cumulative $\varepsilon^*$ distribution estimated at $\beta^*$ X*i*; and $\varepsilon^* = \varepsilon j - \varepsilon k$ is a random error term [39].

### 2.4. Analytical framework

Primarily, the currently available 18 CSA practices adopted by farmers: small-scale irrigation, use of organic fertilizer, alley cropping, use of efficient inorganic fertilizer, use of improved crop varieties, 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, apiculture, terraces, feed improvement, sheep fattening, use of grass strips, and briquettes use, were identified during the household survey assessments and personal observation results. During the assessment, the Global Green Growth Institute (GGGI) compendium of CSA practices framework [40] and the Food and Agricultural Organizations of United Nations (FAO) database [23] were used to confirm whether the available practice is climate-smart or not. Seven of the available CSA practices have previously been traditionally practiced by smallholder farmers and the remaining 11 practices are being promoted by the government through its extension channels in the study area. Then, using principal component analysis (PCA), 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. A smaller number of highly correlated practices can be grouped under one component using principal component analysis for the ease of interpretation and generalization of the group [41,30]. The rotation resulted in 5 principal components among a possible 18 extracted with eigenvalues >1 based on [36 criteria. The principal component analysis is helpful in minimizing the dimensionality of data without losing much information. The purpose of CSA is to evaluate the underlying structures or patterns in a high-dimensional dataset (18 CSA practices) and represent them in a lower-dimensional space (5 components). This enables interpretation and visualization of the data and minimizes the computational burden for succeeding analysis [30]. This is relevant in determining the relationships between practices with regard to usage and succeeding analysis by 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.

With varimax rotation and iteration and using principal component analysis, the practices were grouped in the model shown in Eq. (4)

$$\begin{aligned} Y_1 &= a_{11}x_{12} + a_{12}x_2 + \ldots + a_{1n}x_n \\ Y_j &= a_{j1}x_{j1} + a_{j2}x_2 + \ldots + a_{jn}x_n \end{aligned} \tag{4}$$

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 specific strategy. The identified practices of CSA are clustered using principal component analysis and presented in Table 1. Before conducting the field study, the identification of these practices was aided by the Ethiopian CSA roadmap document ratified by the Ministry of Agriculture [15].

After these practices are grouped, the determinants of choice and the impact of CSA practices on household food security was modeled using multinomial endogenous switching regression model (MNLESR).

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

**Table 1**
Definition of climate-smart agriculture (CSA) practices used in this study.

| S/No | CSA practices | Definition | Why are these practices climate-smart |
|---|---|---|---|
| 1 | Small-scale irrigation | Irrigation on small plots, in which small farmers have the controlling influence of all activities [23,17,40] | Create carbon sink and improve yield frequency |
| 2 | Practicing alley cropping | Agroforestry practices that place trees within agricultural cropland system [17] | Diversify income sources |
| 3 | Organic Fertilizer use | Putting animal dung or manure on farmlands for soil fertility improvement [23] | Reduce nitrous oxide and methane emission |
| 4 | Improved crop varieties use | Any variety that has been bred using formal plant breeding methods for enhancing yield [40] | Improve productivity, reduce insect and disease attack |
| 5 | Efficient inorganic fertilizer use | Application of optimum amount of artificial fertilizer for increasing productivity and reducing greenhouse gas emissions [42] | Improves soil productivity |
| 6 | Planting trees for windbreak and shelter for crops | Planting trees around farmlands to reduce wind effects and provide protection [17] | Providing shed to crops, trees store large amounts of $CO_2$ and diversify income sources |
| 7 | Mulching use | Covering the soil between plants with material layer/s [23] | Reduces existing emissions |
| 8 | Planting Date change | Adjusting the time of crop sowing in accordance with the onset of the rainy season [17] | Reduce crop failure |
| 9 | Cover crops use | Planting cover crops [23] | Maintain soil moisture and reduce emission |
| 10 | Crop rotation using legumes | Planting various crops on the similar farmland in successive planting seasons [23] | Improves soil fertility and increases crop productivity |
| 11 | Animal Husbandry improvement | Transferring inherited superior traits from one animal to another of the same species with an improved good feed conversion, growth rate, meat quality, high milk yields etc. [17] | Improves household income |
| 12 | Poultry farming | Raising domesticated birds such as chickens and turkeys to produce meat or egg for food [40] | Improve household income |
| 13 | Terraces use | Physical or biological structures built to prevent soil loss from erosion by different agents [16] | Reduced erosion and soil detachment |
| 14 | Apiculture | The scientific method of rearing honeybee [43] | Improve household income, pollination |
| 15 | Feed improvement | Improving animal diet to gain more protein with small feed and minimum emission [40] | Improved livestock productivity |
| 16 | Sheep fattening | The feeding of nutrient-rich feed to stimulate rapid growth and fat deposition for targeted carcass growth and quality [40] | Improve household income |
| 17 | Grass strip use | Undisturbed areas of permanent vegetation around the edge or within fields [25] | Feed for animals, soil and water conservation |
| 18 | Bio-briquettes use | A renewable fuel (briquette) with a combustion property prepared from coffee residual waste [44] | Energy-saving, reducing deforestation, mitigation role |

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

Step 1 Multinomial selection model for adoption

Here, the determinants of the CSA package choice were determined by using the multinomial logit model. The multinomial logit model considers that the odds of preferring one class of CSA technology over another do not depend on the presence or absence of other irrelevant alternatives (IIA), which is not always desirable [45]. As a result, farm households were assumed to improve the food security status $Y_i$ by comparing the income generated by 9($M$) CSA package options. The need for the $i$ farmer to make a choice over any technology $j$ over other options $K$ is that $Y_{ij} > Y_{ik}$, $K \neq J$, where $j$ gives the maximum 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 household observed, climate shocks, plot features and unobserved features as follows:

$$Y_{ij}^* = X_i\beta_j + \varepsilon_{ij} \tag{5}$$

Where the observed exogenous variables (plot and household features) is denoted by $X_i$, while the unobserved features are justified by the error term $\varepsilon_{ij}$. $X_i$ is the covariate vector, which is considered to be uncorrelated with the idiosyncratic unobserved stochastic component $\varepsilon_{ij}$, that is $E(\varepsilon_{ij} \mid X_i) = 0$, in that error terms $\varepsilon_{ij}$ are considered to be identically Gumbel distributed and independent, which is, under the hypothesis of independent irrelevant alternatives (IIA) [46]. The probability of choosing $j(P_{ij})$ is given by the multinomial logit model [45] following the selection model as follows:

$$P_i = p\left(\varepsilon_{ij} < 0|x_i\right) = \frac{exp\ (X_i\beta_i)}{\sum_{K=0}^{J} exp\ (X_i\beta_k)} \tag{6}$$

Step 2: Endogenous switching regression model

The impact of each response package on food security was examined using the selection bias correction model of endogenous switching regression (ESR) [45]. A total of 9 regimes have been faced by farm households with regime $j = 1$ being the non-responsive reference category. For each possible regime, the status of food security equation is defined as:

$$\begin{array}{l} Regime\ 1 Q_{i1} = Z_i\alpha_1 + \mu_{i1} if\ i = 1 \\ \vdots \qquad\qquad \vdots \\ Regime\ j Q_{ij} = Z_i\alpha_j + \mu_{ij} if\ i = j \end{array} \tag{7}$$

Where $Q_{ij}$'s denote the status of food security, $Z_i$ denotes a list of exogenous variables (household, location, plot, institutional variables and climate shocks), and the $i$th farmer in regime $j$ and the distribution of error terms $\mu_{ij}$'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 $Y_{ij}^* > \underset{K \neq 1}{max} (Y_{ik})$; if (6) and (7) error terms are not independent, OLS estimates were biased for eq. (7). A $\alpha_j$ consistent estimation needs inclusion of alternative choices selection correction terms in eq. (6). 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 error terms correlation between (6) and (7) was zero by construction.

Eq. (6) can be expressed by using the above assumption as follows:

$$\begin{array}{l} Regime\ 1 Q_{i1} = Z_i\alpha_1 + \sigma_1\lambda_1 + \omega_{i1} if\ i = 1 \\ \vdots \qquad\qquad \vdots \\ Regime\ j Q_{ij} = Z_i\alpha_j + \sigma_j\lambda_j + \omega_{ij} if\ i = j \end{array} \tag{8}$$

Where the covariance between $\mu's$ and $\varepsilon's$ is represented by $\sigma_j$, while $\lambda_j$ is the inverse Mills ratio calculated from the probability estimation in Eq. (8) as

$$\lambda_j = \sum_{m \neq j}^{j} \rho j \left[\frac{P_{ik} In(P_{ik})}{1 - P_{ik}} + In(pij)\right] \tag{9}$$

where $\rho$ signifies the correlation coefficient of $\mu's$ and $\varepsilon's$, whereas $\omega_{ij}$ are error terms with zero expected value. In the earlier expression of the multinomial choice setting, there were one j – 1 correction selection terms for each CSA practice option. The standard errors in eq. (8) were bootstrapped to account for the heteroscedasticity arising from regressors generated given by $\lambda_b$.

### *2.5. Average treatment effects estimation*

The average treatment effects (ATT) were examine using a counterfactual analysis by making a comparison of the expected outcomes of adopters with and non-adopters of CSA technology. In the counterfactual and actual scenarios, ATT was computed as follows [47]:

Status of food security with adoption

**Table 2**
Econometric analysis and variables used.

| 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 (in Ethiopian Birr which is equivalent to $0.017. | 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 | – |

$$E(Q_{i2}|i=2) = z_i\alpha_2 + \sigma_2\lambda_2 \tag{10a}$$

$$E\left(Q_{ij}\middle|i=j\right) = z_i\alpha_j + \sigma_i\lambda_j \tag{10b}$$

Status of food security without adoption (counterfactual)

$$E(Q_{i1}|i=2) = z_i\alpha_1 + \sigma_1\lambda_2 \tag{11a}$$

$$E(Q_{i1}|i=j) = z_i\alpha_1 + \sigma_1\lambda_j \tag{12b}$$

ATT is defined by the difference between 7a and 8a, which is given by:

$$\begin{aligned} ATT &= E(Q_{i2}|i=2) - E(Q_{i1}|i=2) \\ &= z_i(\alpha_2\alpha_1) + \lambda_2(\rho_2 - \rho_1) \end{aligned} \tag{13}$$

It shows the change in the expected average food security status of adopters, if adopters and non-adopters have the same features of return, for example, while the selection term $\lambda_j$ considers all the differences in possible impacts of unobserved variables if adopters had the same features as non-adopters.

Table 2 presents variables derived from reviewing past studies and employed in econometric analysis [6,20,25,30].

### 2.6. Food security measurement

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 status of farmers. The per capita annual food expenditure is an indicator that approximates the consumption of calories based on the total amount of household food consumption or acquisition. By attaching standard weights of nutritional value in the index of the food classes, the indicator constructs the conversion of household food consumption or acquisition into dietary energy (K/cals) by referring to the individual foods with the food consumption table. The calorie amount is calculated by measuring the consumed or purchased portion, divided by the total number of household members [48]. The computation needs to be divided by the number of collection days in order to generate the number of calories per person per day if the data is collected over a number of days. HFIAS measures the access dimension which is developed by the Food and Nutritional Technical Assistance II Project (FANTA). 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, showing severe food insecurity; the lowest score is 0, which shows a food secure household category [49]. 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 example, animal products of nutritionally dense foods are given higher weights than foods such as tubers that contain lesser nutritionally dense foods. According to this score, three classifications of household food consumption (poor, borderline, or acceptable) can be resulted [50,51].

**Table 3**
Principal component analysis outcomes for the five components.

| Strategies | Component 1 | Compponent 2 | Component 3 | Component 4 | Component 5 | 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 |
| Organic fertilizer use | 0.2178 | 0.6184 | 0.6112 | 0.3312 | 0.1192 | 0.6915 |
| Improved crop varieties use | 0.5718 | −0.2998 | 0.5513 | 0.5538 | −0.2174 | 0.6614 |
| Efficient inorganic fertilizer use | 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 |
| Mulching use | 0.1998 | 0.5771 | 0.5122 | −0.3351 | 0.2193 | 0.6113 |
| Planting date change | 0.3978 | 0.4112 | 0.2172 | −0.2935 | −0.4271 | 0.6925 |
| Cover crop use | 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 |
| Terrace use | 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 |
| Grass strips | 0.2111 | −0.1172 | −0.6812 | −0.6172 | 0.3927 | 0.6005 |
| Bio-briquette use | 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 | |

### 2.7. Limitations of the study

The study has potential limitations. In the model, the effect estimations are made based on prospective observational and interventional studies. Our model estimates have therefore been affected by confounding and biases. The etiological effects of food security status however were estimated from confirmatory validity analysis with meta-analysis.

## 3. Results and discussion

### 3.1. Principal component analysis output

Table 3 comprises principal components (PCs) and coefficients of linear combination known as loadings. In using principal component analysis, the identified eighteen CSA practices are reduced into five components that contain all the CSA practices, which is based on [41,52]. These components are abbreviated as Comp1, Comp2, Comp3, Comp4, and Comp5 that represent crop management practices, field management and climate change mitigation practices, farm-risk reduction practices, supplementary income generation practices, and water conservation practices, respectively. Close observation of Table 3 visually reveals that the total variability of the data set is 85 % explained by the five PCs. The PCA results greatly explained the data 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, planting date changing, crop rotation using legumes, and use of organic fertilizer all with positive factor loadings. Accordingly, this component was named crop management practices.

Principal components (PC) 1, 2, 3, 4, and 5 accounted for variances of 37.2, 25.17, 10.63, 6.4, and 5.2 %, respectively. This signifies the first five components have great significance in justifying variance in the data set. The second PC was related to cover crop use, planting crops on tree lands, planting trees on croplands, mulching use, and bio-briquette use where they all have positive loadings too. Component 2 was termed field management and climate change mitigation practices. The third PC comprised feed improvement, improved crop variety use, and cover crop use, irrigation with corresponding positive effects, which are collectively called farm risk reduction activities. The fourth PC consists of cattle 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 grass strips and making terraces where they have negative loadings. PC 5 was collectively called soil and water conservation practices.

The total size of variance retained in the five components for every variable is presented by the communality column. To justifiably say that a PCA is performed [53], described that all items in PCs need to have 0.60 or 0.7 average communality for small samples below 50. 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 [41, 54].

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 efficient fertilizer use, planting date change, crop rotation using legumes, and organic fertilizer use. The second component used greatly was field management and climate change mitigation.

Practices used by 89.01 %. This component comprised the cover crops use, alley cropping, planting trees for windbreak and shelter for crops, mulching use, and bio-briquette use. 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, improved crop variety use, cover crop use, and small-scale irrigation.

Supplementary income generation practices were only used by 42.24 % of farmers. The practices included under this component

**Table 4**
Climate-smart agricultural strategies list.

| Group | Users' percentage | Components |
|---|---|---|
| Crop management practices | 92.34 % | Efficient inorganic fertilizer use<br>Planting date change<br>Crop rotation using legumes<br>Organic fertilizer use |
| Field management and climate change mitigation practices | 89.01 % | Cover crop use<br>Alley cropping<br>Tree planting for windbreak and shelter for crops<br>Mulching use<br>Bio-briquette use |
| Farm risk reduction practices | 81.21 % | Feed improvement<br>Improved crop variety use<br>Cover crop use<br>Small-scale irrigation |
| Supplementary income generation practices | 42.24 % | Animal husbandry improvement<br>Apiculture<br>Poultry farming |
| Soil and water conservation practices | 11.2 % | Grass strip use<br>Terrace use |

are improved animal husbandry, apiculture, and poultry farming. Finally, the least used component consisted of soil and water conservation practices, which include grass strip use and making terraces. This component was used by only 11.2 % of farmers.

### 3.2. Econometric findings

The food security impact of CSA packages is well understood following the computation of the choice of CSA packages determinants [55]. The adoption of CSA practices in a wide combination ranges has implications for the status of food security of smallholder households. With the available set of packages given, the factors deriving an individual to choose a specific package which is crucial for policy formulation must be well understood [30].

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 is composed of 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 [6] 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 for the majority of farmers to meet their major crop production for food production demands and this is in line with the study conducted by Ref. [30,56].

**Table 5**
Specifications of CSA strategy combinations.

| 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 likely 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.

### 3.3. Determinants of choice of climate-smart agricultural packages

Factors affecting the choice of CSA package are described in this section. Quantifying the use of CSA packages on the food security status of farming households is also included. For this purpose, a two-stage regression analysis multinomial endogenous switching regression (MNLESR) model. 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 CSA packages adoption. The next stage determines the impact of CSA packages use on food security status of farming households. The MNL model marginal effects 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 is presented in Table 6.

The base category was the non-adopters of all practices ($C_0F_0R_0I_0S_0$) as compared to the other 9 packages (refer to Table 5 for the packages) used by smallholder farmers. The result presented nine sets of parameter values, one for each strategy 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 coefficient estimates differ considerably and this result was similar to the study findings of [55, 47,51], and [43] that state the variabilities of estimated coefficients in the adoption of multiple CSA package choices of small-scale farmers differ significantly.

The age of the head of the household was negatively related with the use of the $C_1F_0R_0I_0S_0$ package and positively linked with $C_1F_0R_1I_0S_0$ at 5 % and 10 % levels of significance, respectively. An increase in the age of the head of the household by one year minimizes the possibility 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 Ref. [30]. 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 [43], documented that old age is negatively related 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

**Table 6**
Estimates of marginal effects for determinants of CSA packages.

| 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[b] | 0.0006 | 0.0014 | −0.0017 | 0.0017[a] | 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[a] |
| Education years of HH | 0.0014 | 0.0016 | 0.0022 | −0.0305[a] | 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[c] | −0.0103 | −0.01768[a] | −0.0216 | 0.0220[b] | 0.0315[b] | 0.0210[c] | 0.0015[a] |
| Farm assets | 0.0042 | 0.0008 | −0.0054 | 0.0015[c] | 0.0015 | 0.0003 | 0.0611[c] | 0.0411[b] |
| ***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[a] | 0.0179 | −0.0362 | −0.0252[a] | 0.0189 | −0.0523[c] | 0.0006 |
| Perception of soil fertility | −0.0072 | −0.0003 | 0.0206 | 0.1064[c] | −0.0215 | −0.0023 | −0.0152[c] | 0.0005 |
| ***Incidences*** | | | | | | | | |
| Frequent floods | 0.0371 | −0.0277 | −0.0340 | 0.0301 | 0.0220[b] | −0.0193 | 0.0213 | 0.0004 |
| Hailstorms | 0.0269 | 0.0051[b] | −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[b] | 0.0022 | −0.0005[a] | −0.0198 | −0.0006[a] | 0.0001 |
| Membership in farmer's associations | 0.0316 | 0.0265 | −0.0215 | 0.1779[a] | 0.0332 | 0.0058 | 0.0332[a] | 0.0000 |
| Contacts with extension agents | −0.0052 | 0.0031 | 0.0081 | −0.0317[c] | 0.0051 | 0.0018 | 0.0047[a] | 0.0003[b] |
| Access to credit | −0.0482[b] | −0.0033 | −0.0074 | −0.1493[a] | 0.0019 | 0.0427 | 0.0031[c] | 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.
[a] Significant at 1 % level.
[b] Significant at 5 % level.
[c] Significant at 10 % level.

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 Ref. [28] 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 services, 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 level of education of the household head affected $C_1F_1R_1I_0S_0$ negatively 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 Ref. [31] 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 significant and positive 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 possibility of using these packages was increased by 0.15 % and 6.1 %, respectively. It is likely that rich farmers have the ability 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 [57] that justifies the bigger size of farms increases the benefits of economies of farmers' scales and also furnish a way of product diversification. As farm size increased, farmers are less likely to implement one farm package practice ($C_1F_0R_0I_0S_0$) that only contains crop management. 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.

The use of $C_1F_0R_1I_1S_0$, $C_1F_0R_1I_0S_{1,}$ and $C_1F_1R_1I_0S_1$ packages were negatively associated with farmers' perception to soil erosion. The possibility of using these packages declined by 4.3 %, 2.5 %, and 5.2 %, respectively for farmers that considered their farmlands severely eroded. It looks like farmers are highly encouraged to undertake CSA practices on relatively less eroded farmlands. Practically, these farmers were discouraged by severe erosion in implementing CSA technologies but their initiative in countering severe erosion impacts was very low. A similar study conducted by Ref. [43] indicated a positive association with the adoption of many soil conservation practices with the consent that farmers were responsive to soil erosion leading to soil degradation.

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 artificial fertilizer application.

The choice of CSA packages is influenced by factors associated with past extreme weather condition experiences. For example, past experiences of frequent flood were more likely to use the $C_1F_0R_1I_0S_1$ package. The possibility 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 [58], argued that climate adaptation technologies adoption such as using drought-resistant varieties and crop rotation is significantly and negatively influenced by adverse conditions induced by flooding such as frost stress and water logging.

Previous hailstorms experience was also positively related to the use of $C_1F_0R_1I_1S_0$ package. It was indicated that the probability of using this package improved by 0.51 % for farmers who had past hailstorm experiences. Likewise, these farmers could be practicing a strategy responsive to this problem including farm risk reduction and supplementary income generating practices. A study conducted by Ref. [59] 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 [60]. presented that distance can cause new technologies accessibility, credit institutions, and information, apart from access to the market, and thus confirms the negative association.

Farmers' membership in various associations/groups had a significant and positive 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 communication 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 [42]. reported that learning from pear experiences enhances the probability of adoption of technologies due to the reason that farmers share many experiences in common and put trust in their peers.

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

**Table 7**
Estimation of the impact of use and non-use of CSA packages on food security under the three parameters by ESR.

| Package | | Per capita annual food expenditure (PCFE) | | | HFIAS | | | HFCS | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Treated ($\beta_1$) | Untreated ($\beta_2$) | Impact/ returns | Treated ($\beta_1$) | Untreated ($\beta_2$) | Impact/ returns | Treated ($\beta_1$) | Untreated ($\beta_2$) | 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, HFCS household food consumption score, HFIAS household food insecurity access scale.

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 Ref. [61] 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 significant and positive impact on $C_1F_1R_1I_0S_1$ use but impacted on the use of $C_1F_0R_0I_0S_0$ and $C_1F_1R_1I_0S_0$ use negatively. The result depicted that farmers that received credit in the past 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 [62,44], 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. Access to credit decreased the likelihood 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 impact 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 CSA adoption*

In the first stage, once the choice of drivers of CSA packages are determined, the effect of treatments was examined in the second stage to evaluate the effect of these packages' use on the food security status of farming households. 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 CSA combination of practices, considering the selection bias correction terms from the primary stage. Discussing treatment effects is vitally the crucial part of this stage.

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 animal products of nutritionally dense foods, 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 shows the average effects of adoption in terms of per capita annual food expenditure, HFIAS and HFCS under actual and counterfactual conditions. In Tables 7 and $X_1$ indicates the adopters (treated category) and $X_2$ denotes the non-adopters (untreated), $\beta_1$ denotes adoption state (treated characteristics) and $\beta_2$ representing non-adoption state (untreated characteristics). The level effect is the difference in food security status as a result of a specified package. The outcome of the difference between treated with treatment features and untreated with untreated features $(\beta_1X_1) - (\beta_2X_2)$ 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 influenced household welfare positively. The implication is that farmers must diversify income-generating practices and manage their farm risks to enhance the food security status in the face of uncertain climate change impacts.

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 non-adopters 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 suggests that farmers using this package were 41.2 %, 39.8 %, and 12.1 % more food secure compared to those farmers 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. Policy implications

The findings of this research have fundamental implications on policy for promoting the adoption of CSA among Geshy watershed beneficiary farmers. As demonstrated in the result section, the CSA practices are complimentary in terms of adoption. This informs that the implementation of CSA and the agricultural policy must recognize the complementarity among CSA practices so as to expand their adoption among Geshy smallholder farmers and expand CSA practices in other parts of the nation. Secondly, policy makers must consider institutional, household, socioeconomic, and resource related factors that influence CSA adoption positively. Frequent and regular extension and advisory service provision to smallholder farmers needs to be prioritized. This enables farmers adopt more CSA practices. In addition, disseminating information and creating awareness about the benefits of CSA practices adoption and the potential impacts of climate change using different media outlets helps farmers make informed decisions on CSA adoption and, thus, coping with climate change adverse effects. Few CSA practices, for instance soil and water conservation practices are unpopular among farmers in the Geshy watershed. Hence, high incentive payments re required for scaling-up of its adoption. In Ethiopia, one of the important capital that has an intergenerational impact on agricultural technology adoption, is land. The finding of this study reveals that farmers with relatively bigger land sizes are more likely to adopt CSA practices. And thus, agricultural policies should focus on controlling rental markets of agricultural lands, which helps smallholder farmers that engage in rental farming practices acquire more land.

## 5. Conclusion

This paper evaluated the impact of climate-smart agriculture adoption 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 adaptation to climate change, and minimizing 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 household food security impact as compared to the non-adopters ($C_0F_0R_0I_0S_0$). This package's adopters were 41.2 % more food secure in terms of per capita annual food expenditure, 39.8% in terms of Household Food Insecurity Access Scale (HFIAS), and 12.1% in terms of Household Food Consumption Score (HFCS) than the non-adopters. The adoption of this package was further influenced positively by gender, farm size, 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 should include all CSAs as much as possible. The results depicted that the probability of using this package was positively influenced by farm assets, farm size and gender. This package was possibly on larger self-owned plots of farmlands, and with greater farm assets of male-headed households. Thus, if CSAs are used in combination and to a larger extent, they have the potential to improve food security.

## 6. Areas of future research

There are many CSA related issues that needs attention for future research. The empirical results of this study are based cross-sectional data on farm-level. Future research could improve policy implications and conclusions from panel data collection and interpretation. Besides, future research should analyze horticultural CSA technologies as well as the profitability of certain crops. There is also a need to investigate various policies effects on the adoption of CSA. Further, given various resource availabilities and input and output price ranges for various households over time, it could be important to consider some variable resource programming and variable price (simulation analysis) to recommend wider farm plan options.

## Significance statement

The results of this research can help understand the severity of climate change impacts 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 smallholder farmers' food security problems.

## Data availability

Data will be made available on request.

## Ethics approval and participants' consent

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

## Consent for publication

Not applicable.

## CRediT authorship contribution statement

**Girma Tilahun:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Amare Bantider:** Conceptualization, Data curation, Methodology, Supervision, Writing – review & editing. **Desalegn Yayeh:** Conceptualization, Data curation, Methodology, Supervision, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.


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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e22620.

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