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Impact of climate-smart agricultural services on farmer resilience in Ethiopia

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Abstract

Climate change poses significant threats to agriculture and livelihoods, particularly in developing regions. This study investigates the impacts of climate-smart agricultural (CSA) services on farmers' resilience in the Gubalafto district of Ethiopia. The study employed a quasi-experimental research design; data were collected from 355 randomly surveyed households. Principal component analysis and multinomial endogenous switching regression were employed to analyse the data. The findings revealed that 44% of the households had a low resilience capacity index (RCI), whereas 37% and 19% had medium and high RCIs, respectively. About 21.13%, 23%, 15% and 10% of households were classified as single, partial, multiple and full adopters, respectively. Adopters of partial, multiple and full practices experienced increases in resilience capacity of 7.4%, 12% and 17%, respectively. Households that adopted more diverse combinations of CSA practices were more resilient than non-adopters. Thus, enhancing adoption levels and capability aspects should be the primary goal of any intervention.

Key words: climate-smart agriculture, adoption intensity, multinomial endogenous switching regression, resilience capacity

1. Introduction

Climate change and variability have emerged as critical global constraints to agricultural productivity and community resilience, driven by increasingly erratic rainfall patterns and extreme temperatures that threaten food security and rural livelihoods (Fadairo *et al*. 2020). Rising sea levels, altered precipitation regimes and the intensification of extreme weather events – such as floods, heat waves and prolonged droughts – further exacerbate risks to agricultural systems and global food stability (IPCC 2021). Although Africa has contributed minimally to global greenhouse gas emissions, the continent has experienced substantial loss and damage across key development sectors due to anthropogenic climate change (Ayugi *et al*. 2022). Rural livelihoods, which are predominantly dependent on agriculture, are particularly vulnerable to adverse climatic shifts, resulting in diminished productivity, heightened food insecurity and reduced adaptive capacity (Ibrahim *et al*. 2017; Luqman *et al*. 2017; Mekonen & Berlie 2021). This represents a pressing global challenge that requires urgent action by individuals and governments.

Ethiopia has historically experienced recurrent droughts and increasingly frequent extreme weather events, such as the 1970s meteorological droughts and the 2015/2016 El Niño, leading to major crop failures, acute food shortages, and weakened household resilience (Bahta & Myeki 2022; Kosmowski 2018). In fact, Ethiopia's economy is heavily dependent on agriculture, which accounts for more than 40% of GDP, provides approximately 70% of employment and serves as a key source of foreign exchange – primarily through exports of coffee, oilseeds and pulses (Tekle 2025). The sector is characterised by low-productivity, small-scale mixed crop–livestock systems, and it is constrained by traditional farming practices, climate extremes, deforestation, poor market access and inadequate infrastructure (Gezie 2019). Smallholder farmers, who produce approximately 95% of the country's major crops, represent the majority of the population and are particularly susceptible to climate change due to their limited adaptive capacity (Zerssa *et al*. 2021). Moreover, the country's high vulnerability stems from its dependence on rain-fed smallholder agriculture and widespread poverty (Kassaye *et al*. 2022). In brief, recurrent droughts, extreme weather events and structural challenges severely impact smallholder farmers and household resilience.

Gubalafto Woreda, located in northeastern Ethiopia, is characterised by semi-arid conditions with erratic rainfall and frequent dry spells. Climate variability in the area is marked by significant inter-annual fluctuations in rainfall, directly affecting crop production. Rainfall is concentrated during the main cropping season, from June to September, yet its onset and cessation remain highly unpredictable, frequently resulting in shortened growing periods and heightened risks for rain-fed agriculture (Abegaz *et al*. 2020). Climate change further exacerbates this variability, reducing the productivity of staple crops such as teff and sorghum, while undermining household resilience. Gubalafto District thus faces a convergence of weather extremes, climate variability and long-term climate change pressures, making agricultural livelihoods highly vulnerable (Tsegaye 2018). The area is further challenged by recurrent droughts and land degradation, which diminish agricultural productivity and intensify household vulnerability to hunger and poverty (OCHA 2024). These climatic stresses are compounded by soil erosion, declining soil fertility, and decreasing water availability, all of which reduce crop yields and livestock productivity. Consequently, households remain highly exposed to climate-induced shocks that threaten food security and rural livelihoods.

In the light of these challenges, climate adaptation is crucial for minimising the adverse effects of climate change on food systems and resilience (Thorn *et al*. 2015). One widely endorsed strategy is climate-smart agriculture (CSA), which was formally introduced in 2010 and has been actively promoted by governments and development partners across Africa and globally to increase agricultural resilience, productivity and sustainability (FAO 2010). Lipper *et al*. (2014) define CSA as a strategic approach to transform and reorient agricultural development in response to the challenges posed by climate change. According to Lipper *et al*. (2014) and Thornton *et al*. (2018), CSA aims to achieve three goals: (i) increase agricultural productivity and food security, (ii) adapt and increase the resilience of people to climate change and (iii) mitigate GHG emissions. This integrated approach seeks to increase the resilience of food systems, while promoting sustainable agricultural practices. Many farm-level CSA practices offer multiple benefits boosting productivity, enhancing adaptation and supporting mitigation, but often involve trade-offs (Girardello *et al*. 2019; Ogola & Ouko 2021). For example, irrigation can enhance productivity (synergy), while increasing greenhouse gas emissions (trade-off) if mismanaged (Antwi-Agyei *et al*. 2023). Similarly, inorganic fertiliser and agrochemical use can improve yields and food security, yet may increase emissions or harm ecosystems if used in an inappropriate manner. Previous studies have recognised inorganic fertilisers and agrochemicals as part of CSA practices, despite their potential risks when applied inappropriately (Teklewold *et al*. 2017; Kurgat *et al*. 2020; Ogola & Ouko 2021; Shiferaw 2021).

Ethiopia has increasingly prioritised climate change adaptation, integrating CSA into its agricultural policy to enhance food security and smallholder resilience (Federal Democratic Republic of Ethiopia [FDRE] 2019). The government's commitment is reflected in the Climate Resilient Green Economy (CRGE) strategy and the National Adaptation Plan (NAP), both aimed at fostering carbon-neutral, climate-resilient development (MOEFCC 2017; FDRE 2019; Bisare 2023). Smallholder farmers have adopted a range of climate change adaptation practices, including soil and water conservation, improved varieties, small-scale irrigation, crop residue management, crop rotation, composting, row planting and agroforestry, to strengthen resilience and sustain food production (International Institute for Environment and Development (IIED), 2022; Teklu et al., 2023). These efforts align with Ethiopia's broader climate-smart agriculture strategies aimed at enhancing adaptive capacity and resilience outcomes (Kanter *et al*. 2018).

Resilience was first introduced by physical scientists to describe the stability of a material and its resilience to external shocks (Funfgeld & McEvoy 2012). The concept of ecological resilience was subsequently introduced by Holling (1973) and originated in the field of ecology as a measure of the persistence of systems and their ability to absorb disturbances, while maintaining the same relationships with state variables. In practical terms, resilience often refers to the ability of socioecological systems to respond and adapt to new conditions, particularly in the context of climate change. Recent studies emphasise a socioecological perspective, which not only values the ability to withstand disturbance, but also encourages adaptation and transformation (Walker & Salt 2012). This approach, known as resilience thinking, focuses on three key aspects of social-ecological systems: resilience as persistence, adaptability and transformability.

Despite the fact that studies on CSA have evolved (IEDD 2022; Teklu et al., 2023), the intensity of CSA adoption and its impact on resilience have not yet been adequately explored in Ethiopia. A study by Ali *et al*. (2023) investigated the impacts of adoption intensity to a limited extent, i.e. single, partial, multiple and full adoption. Teklu *et al*. (2023) also predominantly examined single technologies in isolation. Single technologies may provide incomplete estimates of resilience outcomes. Although studies conducted in various contexts have linked the adoption of CSA practices to improvements in farmers' livelihoods, including enhanced food security, many of these investigations have predominantly examined individual technologies in isolation or in general (Kurgat *et al*. 2020; Tesfaye *et al*. 2021; Jamil *et al*. 2021; Zeleke & Demeke 2025).

In practice, however, smallholder farmers often adopt multiple CSA practices concurrently to address complex production challenges, particularly those related to climate change and variability (Asante *et al*. 2024), and further research is needed to generate relevant insights for policymakers and development practitioners. Aseres *et al*. (2019) argue that assessing the impact of a single technology may lead to incomplete estimates of resilience outcomes. Despite the growing promotion of CSA practices adoption, empirical evidence that quantifies the extent of CSA adoption and its impact on household resilience remains scarce, particularly within the Ethiopian context. Notably, knowledge gaps exist regarding how smallholder farmers enhance their resilience through different levels of CSA practice adoption. Moreover, resilience capacity is dynamic across time and location, underscoring the need for current and context-specific evidence where data on rural household resilience remains scarce.

This study aimed to address the abovementioned gaps and adaptation puzzles by examining the effects of CSA adoption intensity – categorised as single, partial, multiple or full adoption – on the resilience capacity of rural households in the Gubalafto district, Ethiopia. Specifically, the study (a) assessed the adoption intensity of CSA practices by rural households; (b) estimated the resilience capacity of rural households; and (c) evaluated the impact of CSA adoption intensity on household resilience outcomes. In doing so, it contributes to the scant empirical literature on the CSA adoption portfolio by offering a holistic analysis of adoption intensity and its impact on rural household resilience. This study provides valuable insights to guide the design of agricultural policies and interventions aligned with national development goals. Ultimately, this study aims to inform evidence-based decision-making to strengthen rural household resilience to climate change.

2. Materials and methods

2.1 Conceptual framework

The conceptualisation of this study addresses four interrelated components: (i) climate shocks; (ii) determinants of CSA adaptation, which serve as explanatory variables; (iii) climate-smart agricultural practices; and (iv) the resilience capacity of rural farmers in relation to climate-induced shocks (Figure 1). Climate-related risks such as recurrent droughts, floods and irregular rainfall, which affect agricultural production and household income, have been consistently observed in the study area. Climate change involves noticeable shifts in weather patterns that affect human activities (Legesse *et al*. 2013). It influences agricultural output through increased crop pests and diseases, and declining soil fertility, ultimately undermining food security by disrupting the food system and reducing availability. Moreover, climate shocks undermine household adaptive capacity by affecting key components, such as human capital, physical assets, social networks and access to essential services. In response to these hazards, rural farmers have adopted climate-smart agricultural practices designed to improve agricultural productivity and resilience. As indicated in Figure 1, the leading climate-smart agricultural practices include inorganic fertiliser, improved crop variety, small-scale irrigation, agrochemical inputs and compost. The adoption of these practices is shaped by a range of factors, including socioeconomic conditions, institutional support and biophysical characteristics.

The conceptual framework in Figure 1 illustrates that the adoption of climate-smart agricultural (CSA) practices can increase households' resilience by increasing their absorptive, adaptive and transformative capacities (IEDD 2022). Resilience and its associated dimensions are considered latent variables, meaning that they are not directly observable. According to TANGO International (2018), key indicators of a household's absorptive capacity include asset ownership, access to savings, and preparedness for shocks. Similarly, Bahadur *et al*. (2015) emphasise that access to safety nets and savings accounts, the ability to exchange assets, and access to support and advisory services significantly influence a household's ability to absorb climate-related shocks. Therefore, for this study, the selection of indicators for absorptive capacity was guided by these studies.

Adaptive capacity relates to the strategies households use to sustain their livelihoods under climate stress (Béné *et al*. 2012). It is shaped by factors such as literacy, income diversification, agricultural experience and demographic structure (RIMA-II, 2016). A study by Asmamaw *et al*. (2019) highlighted the importance of access to credit, disaster management experience, farming practices, and technological inputs such as improved seeds and fertilisers. Accordingly, our study selected adaptive capacity indicators on the basis of these findings. Institutional factors, such as access to essential public services, are considered part of transformative capacity (Asmamaw *et al*. 2019).

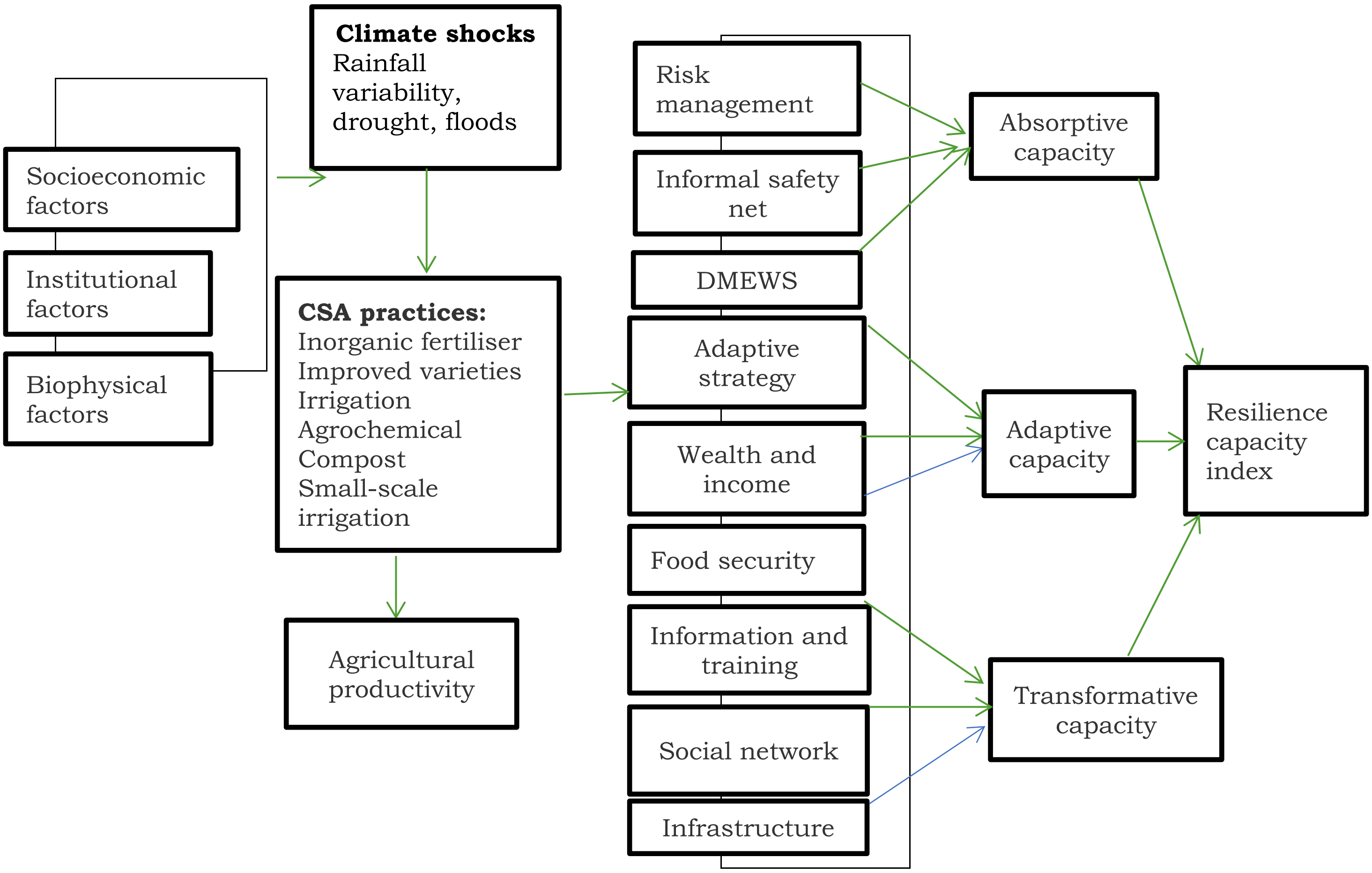

Figure 1: Climate-resilient agriculture framework
Source: Adopted from Béné *et al*. 2015

2.2 Description of study area

This study was conducted in the Gubalafto district, which is located in the southern part of the North Wollo Zone, Ethiopia (Figure 2). As reported by Asnake and Elias (2017), Gubalafto district is positioned between 39°6’9” and 39°45’58’’ east longitude and between 11°34’54’’ and 11°58’59’’ north latitude. The topography of the district is characterised mostly by a chain of mountains, hills and valleys, ranging from 1 379 m to 3 809 m above sea level (m.a.s.l.) and receives annual rainfall of between 800 mm and 1 200 mm, as well as experiencing average annual temperatures ranging from 21°C to 25°C. The area receives rain twice a year: in the short rainy months (the *belg* rain, from March to May), and in the longer rainy months (the *kiremt* rain, from June to September). In this context, rainfall during *the Belgian season* is highly erratic and unstable relative to that during the main growing season. The remaining months constitute the dry season and dry months.

The dominant soil type in the area is eutric leptosols, while eutric cambisols, lithic leptosols and vertic cambisols are also observed in the woreda (Mohammed 2010, as cited by Asnake & Elias 2017). The land use patterns of the woreda include arable land (34.1%), grazing land (17.9%), forest (27.1%), water bodies (6%), rocky land (5%) and others (9.9%) (Mengistie & Kidane, 2016). According to the

Ethiopian Statistical Service (2022) population projection, the study area has a total population of 172 818, of whom 87 027 are men and 85 791 are women. With an area of 900.49 square kilometres, Gubalafto has a population density of 191/km^2.

As reported by Andualem (2016), agricultural production systems are dominated by smallholder mixed crop–livestock production practices. The major crops cultivated include barley, wheat teff and sorghum. Livestock are also part of the household's economy, although their concentration varies from village to village and then benefits from stock raising, dairy farming, and fattening, such as of chicken, cattle, goats and sheep.

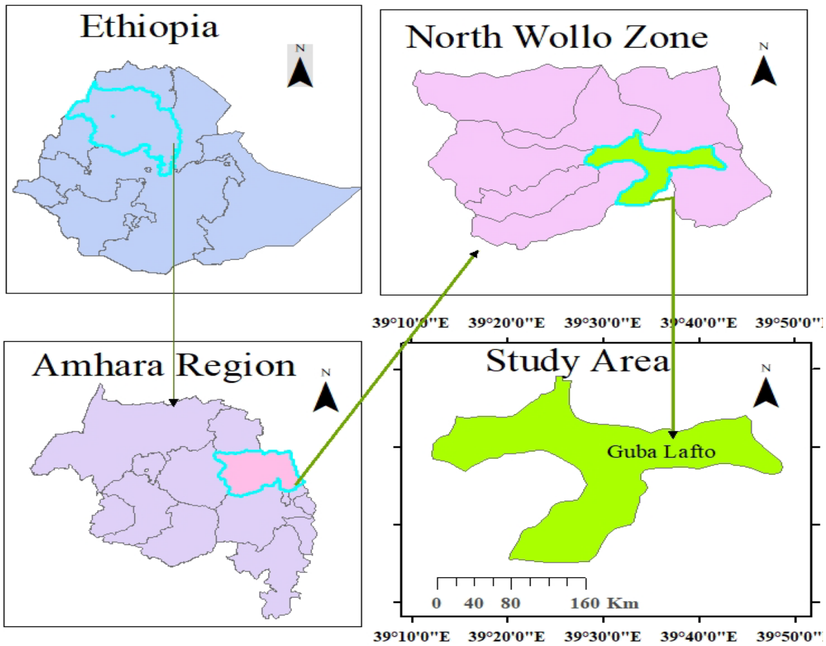

Figure 2: Location map of the study area
Source: Authors' conception 2024

2.3 Research design, sampling techniques and data collection

Globally, many studies have used cross-sectional data to analyse the impacts of interventions or treatments (Wekesa *et al*. 2018; Kurgat *et al*. 2020; Abegunde *et al*. 2022; Ali *et al*. 2023; Teklu *et al*. 2023). In line with this, our study employed a cross-sectional research design along with a mixed-methods approach that primarily emphasises quantitative methods, supported by qualitative insights to enhance the interpretation of the data.

Sampling aims to examine a representative subset of a clearly defined population to draw inferences about the whole population (Gilbert & Stoneman 2015). In doing so, purposive and multistage random sampling techniques were jointly employed to select representative households and study sites. Multistage cluster sampling was used to ensure the inclusion of specific groups of interest across meaningful clusters. As a probability-based method, this involves dividing the population into smaller units (the woreda's kebeles cluster into lowlands, midlands and highlands), allowing a proportional selection of respondents.

First, Gubalafto Woreda was purposively selected as the study area. This woreda represents areas in which CSA practices are being implemented practically. The woreda experiences significant climate variability, and irregular hydro meteorological patterns make it highly vulnerable to food insecurity and low adaptive capacity, highlighting the need for further research.

In the second stage, Gubalafto Woreda was classified into three agroecological zones on the basis of altitude and crop-growing period: lowlands (500 m.a.s.l. to 1 500 m.a.s.l.), with more than 210 days suitable for drought-tolerant crops; midland) (1 500 m.a.s.l. to 2 300 m.a.s.l.), with 150 to 210 days of diverse cereal and legume growth; and highland (2 300 m.a.s.l. to 3 200 m.a.s.l.), with less than 150 days of growth favouring cool-climate crops such as barley and highland pulses. This classification aligns with that of the Ethiopian Ministry of Agriculture ([MoA] 2022). Furthermore, the existing agroecological zones in Gubalafto Woreda are clustered into kebeles, with relatively even distributions across the highland, midland and lowland zones. Hence, via lottery-based sampling, one kebele was randomly selected from each agroecological cluster, ensuring representation of the respective zones. The selected kebeles were Masso-Dengolla (highland), Gedo-Ber (midland) and Doro-Gibr (lowland). Finally, sample households were drawn from the sample kebeles through systematic sampling using the lists available at the kebele administration offices as a sample frame.

Various methods are available in the literature for determining sample size, each suited to specific research contexts: Cochran's (1963) formula is used when the population is large or infinite and the estimated proportion is known. It is widely used in surveys involving categorical data. Kothari’s (2004) formula applies to finite populations with a known proportion. The Yamane (1967) formula is applied when the population size is finite and known, but the estimated proportion is unknown. It is particularly useful in development studies, where detailed population parameters may not be available.

In this study area, the estimated proportion of the population was unknown, and the population was assumed to be relatively uniform in characteristics relevant to the study. Therefore, the Yamane (1967) sample size formula was employed, as shown in Equation (1).

$$\mathrm{n} = \frac{N}{1+N*e^2}. \quad (1)$$

$$\mathrm{n} = \frac{3163}{1+3163*0.05^2}. = 355,$$

where n = the sample size, N = the total number of households in all kebeles, and e is the acceptance error (5%) at the 95% confidence level.

After the total sample size was determined, sample households were selected from each kebele via proportional allocation on the basis of their respective population sizes, as in Equation (2) (Table 1).

$$\mathrm{ni} = \frac{\mathrm{n}*N}{\sum Ni}, \quad (2)$$

where n is the sample size, n_i is the required sample size in the i[th] kebele, N is the total number of households across all kebeles, and N_i is the total number of households in the i[th] kebele.

Table 1: Number of sampled households

Woreda	Agroecological zone	Kebele	Total households	Sampled households
Gubalafto	Highland	Masso-dengolla	1 093	123
	Midland	Gedo-ber	908	102
	Lowland	Doro-gibr	1 162	130
Total			**3 163**	**355**

Source: Gubalafto Woreda Agricultural Office, 2024

The household survey was conducted by six well-trained enumerators who were fluent in the local language and had prior experience in administering interviews. Throughout the data collection process, the researchers provided continuous support and guidance to the enumerators, addressing any challenges that arose from start to finish. A combination of focus group discussions, key informant interviews and semi-structured questionnaires was employed to gather both quantitative and qualitative data. Prior to the main survey, the questionnaire and checklist were pretested with 35 non-sample households to assess their clarity and validity. On the basis of the feedback from this pretest, the instruments were revised and refined to improve their effectiveness. Data collection was carried out primarily via the Kobo Collect mobile application, with submissions uploaded daily to a centralised open networked analysis (ONA) server. The fieldwork took place between September 2024 and January 2025.

2.4 Data analysis techniques

We considered matching criteria for the treatment and control groups and model assumptions in a multinomial switching regression. Here, we (i) developed more than two discrete treatment groups, which are identified as single adopter, partial adopter, multiple adopter and full adoption of CSA practices; (ii) used observed covariates that influence both treatment assignment and outcomes; (iii) tested normality, often assumed to be normally distributed data, which was checked by means of a histogram and the Shapiro–Wilk test; (iv) found no perfect multicollinearity**,** i.e., covariates should not be perfectly correlated with each other to ensure reliable estimation, which was checked by pwcorr and vif.

2.4.1 Rates and indices of CSA practices

The extent of adaptation or adoption intensity was assessed via two complementary measures: (i) a binary indicator distinguishing adopters from non-adopters for each climate-smart agriculture (CSA) practice, and (ii) an adoption intensity score, calculated as the total number of CSA practices adopted by each household (count of top CSA practices adopted). To analyse the second measure, all 18 listed CSA practices were included in a scoring exercise to identify the top five practices currently implemented by farmers. The total overall score for each practice was computed in the process of scoring as the total score divided by the number of respondents. Eventually, we rated the practice with the maximum average score as the first, and the practice with the lowest score as the last, according to the study of Ogola and Ouko (2021). Hence, a practice was selected in rank 1, which received 5 points, and for rank 5 it received 1 point. The total score of each practice was then calculated by multiplying the number of responses in the selection. The practices were then ranked, with number one receiving the highest total score and the last one garnering the lowest score. Similar procedures were applied by Tilahun *et al*. (2023).

The top five CSA practices were identified and subsequently indexed on the basis of the extent of the adopted top practices. On the basis of the adoption intensity score, households were categorised into distinct groups according to the number of CSA practices implemented on their farmland.

The indexed variable was measured as follows:

Y1 = 0 (non-adopter), if a farmer adopts zero climate-smart practices
Y1 = 1 (single adopter), if a farmer adopts one practice
Y1 = 2 (partial adopter), if a farmer adopts a combination of two climate-smart practices
Y1 = 3 (multiple adopters): if a farmer adopts a combination of three to four CSA practices
Y1 = 4 (full adopter): if a farmer adopts a combination of five climate-smart agricultural practices.

2.4.2 Estimating resilience capacity

Measuring resilience is not a straightforward activity, as it is not directly observable. In this study, we treated resilience as a latent variable to be estimated via indicators, which were estimated via observable household-level variables. Béné *et al*. (2014) propose that resilience emerges as a result of three capacities: absorptive, adaptive and transformative capacities. In our study, three major dimensions of resilience were identified: (i) absorptive capacity (ABPC), (ii) adaptive capacity (ADPC), and (iii) transformative capacity (TRNC). These three major dimensions were subdivided into subcomponents/indicators (Figure 3). Each of the indicators has a specific set of observable variables. The resilience capacity index (RCI) was created using these indicators, which can be combined to determine the absorptive, adaptive and transformative capacities of households. The same procedures were used by the IEDD (2022) and Teklu *et al*. (2023).

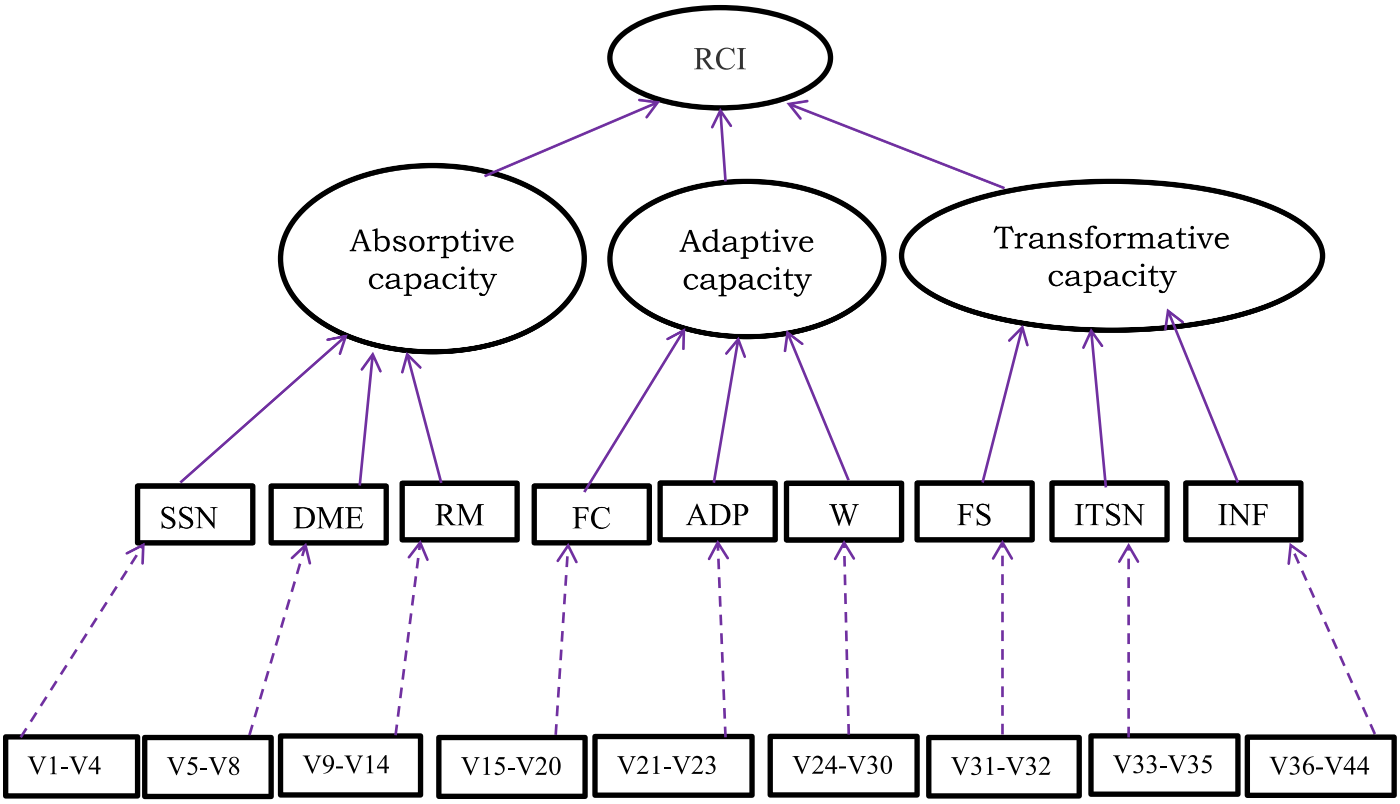

Figure 3: Path diagram of resilience estimation
Source: Modified from Atara *et al*. 2020

To estimate RCI_i (the climate resilience capacity index of the i-th household), it is necessary to estimate it separately, as suggested and framed by Nadu *et al*. (2021), the IEDD (2022) and Teklu *et al*. (2023):

$ABPCi$ = f (SSNi, DMEWSi, RMi),

$ADPCi$ = f (FCi, ADPSi, Wi, FSi), and

$TRNCi$ = f (ITSNi_j, INFRAi) (3)

Following Alinovi *et al*. (2008) and Teklu *et al*. (2023), this study models that households' resilience to climate change-induced shock is a function of its dimensions/indicators. Accordingly,

RCI = f (RMi, SSNi, DMEWSi, ADPSi, Wi, FSi, IT, SNi, INFRA), (4)

where RCI is the climate resilience capacity index of household i, RM = risk management, SSN = social safety net, DMEWS = disaster mitigation and early warning system, ADPS = adaptation strategies, W = wealth, FS = food security, IT = information and training, SN = social network, and (INFRA) = use of infrastructure of household i for i = 1 … n.

However, resilience is not directly observable, and we cannot directly estimate the resilience or resilience dimensions. To overcome such challenges, this study utilised PCA over factor analysis for dimensional and composite resilience estimation (Alinovi *et al*. 2008). We focused on variance and dimensionality reduction, i.e., simplifying data for further analysis and running with PCA, whereas factor analysis is more suitable for exploring underlying relationships, i.e., the underlying factors influencing resilience capacity.

Using PCA, the estimation was performed hierarchically by first estimating each of the resilience dimensions separately and then combining them to estimate the resilience scores for each household. Each indicator was estimated via observable household-level variables. Therefore, in the first step, resilience blocks/indicators were estimated via observed variables. Thereafter, the resilience dimension for each household was estimated separately via indicators of resilience.

As proposed by Kaiser (1960), the criterion of an eigenvalue being greater than 1 was applied to select components. Indices were estimated for each dimension as a product of the component score and weight (explained variation) of the components (Adane, 2018). In addition, a varimax rotation technique was used to produce these constructs. Therefore the values of the continuous variables were standardised. Accordingly, the model in Equation (1) was transformed into the one in Equation 5. The dimensional index (CI_i) of each individual household was computed as follows:

$$CIi = \mathrm{w1} \times \mathrm{CS1} + \cdots + \mathrm{wj} \times \mathrm{CSij}, \tag{5}$$

where CIi is the index of a dimension or component, w_j is the percentage of variance explained by the i^{th} component (weight), and $CSij$ is the component score of the ith household on the jth component.

In the second stage, PCA was applied to the resilience dimension or indicators (alternatively), which was derived from the first-stage exercise. Finally, the resilience capacity index (RCi) was estimated for each household as a product of the component score and weight (explained variation) of a component (Adane 2018), via Equation (6).

$$\mathrm{RCI} = \frac{\sum_{i=1}^{11} wjCIj}{\sum_{i=1}^{11} wj}, \tag{6}$$

where RCI is the climate resilience capacity index and w_j is the weight of the ith component/ dimension.

The estimated continuous resilience scores were normalised to a scale ranging from 0 to 1. These normalised values were then rescaled into three categories: scores between 0 and 0.33 were classified as low resilience, scores from 0.34 to 0.66 as medium resilience, and scores above 0.67 as high resilience.

2.4.3 Multinomial endogenous switching regression

The literature presents models for analysing impact evaluation, such as propensity score matching (PSM) and endogenous switching regression (Gebru *et al*. 2020). However, PSM has a significant limitation: the existence of unmeasured confounding variables leads to biased results. Specifically, PSM may not fully account for unobserved variables that affect both treatment and outcome (Nuttall & Houle 2008), and it is also unsuitable for scenarios with more than two treatment groups. To address these limitations, we employed the multinomial endogenous switching regression (MESR), which is recommended in the literature (Abdulai & Huffman 2014; Jaleta *et al*. 2016; Kassie *et al*. 2017; Aseres *et al*. 2019; Biru *et al*. 2020). The MESR addresses endogeneity in the selection process, which can lead to biased estimates if unobserved factors influence both the treatment choice and the outcome (Khanal & Mishra 2018).

We then used MESR to estimate the impacts of different adoption levels of climate-smart agriculture (CSA) practices on the climate resilience of rural households. MESR is a statistical model designed to analyse the choices made by individuals when confronted with multiple alternatives (more than two treatments), while considering the potential endogeneity between the selection of alternatives and the outcomes associated with those choices.

The estimation of the MESR model follows a two-step procedure. The first stage involves estimating the probability of households adopting different levels of CSA practices via a selection equation, which aims to identify factors that affect the level of CSA adoption. This was done via a multinomial logit estimation model. The intensity of CSA practices is measured by the number of CSA practices adopted by farm households (Ojoko *et al*. 2017; Musafiri *et al*. 2022). The probability of being in a particular regime is modelled via a multinomial logit, typically as a function of observable covariates, which is specified as follows:

$$\boldsymbol{P\ (Y = j/X) = Y = \frac{e^{BjX}}{\sum_{k=1}^{J} 1 e^{BkX}}}, \tag{7}$$

where P(Y=j|X) is the probability that the outcome is category j given the predictor variables X, βj is the vector of coefficients associated with category j, and X represents different household socioeconomic characteristics. Thus, in this study, the variable Y is a multinomial choice variable, measured as the number of climate-smart practices adopted by a given household on its farmland, which are categorised as follows: non-adoption, single adoption, partial adoption and multiple adoption.

The MESR estimation model assumes that farmers who adopt climate-smart agriculture (CSA) practices may systematically differ in characteristics from those who do not adopt these practices. Furthermore, their decision to adopt may have been influenced by the expected outcomes they anticipated, resulting in selection bias. Unobservable characteristics of farmers may affect both the adoption decision and its outcome, resulting in inconsistent estimates. For example, if only skilled or motivated farmers choose to adopt and the analysis fails to control for these factors, then upward bias will occur. Thus, the study accounts for the endogeneity of the adoption decision, i.e., controlling the effect of factors on the adoption decision and its outcome, by estimating a simultaneous equation model of the adoption of CSA practices and its impact via the MESR estimation method. This implies that the MESR model is specifically designed to address selection bias, based on the core assumption that adoption is not random but endogenous. To control for this selection bias, using MESR jointly models the adoption decision and outcome equations, assuming correlated error terms to correct for unobserved heterogeneity where outcome equations vary by treatment status.

The MESR model was used for the outcome variables (resilience capacity index), in which farmers face two regimes: Regime 1, to adopt, and Regime 2, not to adopt. Moreover, selection and endogeneity bias were addressed by incorporating a selectivity correction term, commonly known as the inverse Mills ratio (λ). Following the methodology outlined in Wekesa *et al*. (2018), the inverse Mills ratio was calculated after conducting a multinomial logistic regression, therefore assuming that no adoption of a particular CSA practice (Z = 0) is a reference category. Following Aseres *et al*. (2019) and Ayenew *et al*. (2020), the outcome equation adjusted for the selectivity correction term is specified as follows:

Regime 1: $Y_{0i} = \Gamma_0 X_{0i} + \Theta_0 \hat{\lambda}_{0i} + U_{0i}$ if $Z = 0$,

Regime j: $Y_{ji} = \Gamma_j X_{ji} + \Theta_j \hat{\lambda}_{ji} + U_{ji}$ if $Z = j$, (8)

where Y_{0i} … Y_{ji} is the expected outcome variable of the study (climate resilience). U0 … Uji are independently and identically distributed random disturbance terms with a mean of zero and constant variance. X_{ji} is a vector of explanatory variables indicating the socioeconomic characteristics of households. Γ_0 and Θ_0 are parameters to be estimated, whereas $\hat{\lambda}_{0i}$ is the inverse Mills ratio, which is derived from the first stage of the selection equation.

According to Di Falco *et al*. (2011), for the outcome equation (Equation 8) to be identified, it is important to use selection instruments – not only those automatically generated by the nonlinearity of the selection model of adoption, but also other variables that directly affect the adoption of CSA practices, but not the outcome variable directly (except through its effect on the dependent variables). The study established the admissibility of these instruments by performing a simple falsification test: if a variable is a valid selection instrument, it affects the adoption decision, but it does not affect the capacity for climate resilience. Instrumental variables are used to mitigate bias that can arise when independent variables are correlated with the error term of the model. Distance to market was used as an instrumental variable to explain and predict variations in the adoption of agricultural practices.

The MESR can also be applied to derive the average treatment effect on the treated (ATT), which measures the actual impact of an intervention on the expected outcome of interest, considering only those that received these interventions. The average treatment effect on the untreated (ATU) measure, on the other hand, is the counterfactual effect of adopting CSA, i.e., the projection of potential outcomes in a target (sub)population (Nguyen Viet 2013). 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 (White & Raitzer 2017). In this study, ATT measures the impact of CSA practices on the climate resilience of adopters, whereas ATU measures the impact of CSA practices on the climate resilience of non-adopters.

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

$Y_j = E(Y_{ji}|Z = j; X_{ji}, \hat{\lambda}_{ji})$ for $j = 1$ (9)

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

$Y_0 = E(Y_{0i}|Z = 0; X_{0i}, \hat{\lambda}_{0i})$ (10)

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

$Y_{0j} = E(Y_{0i}|Z = j; X_{ji}, \hat{\lambda}_{ji})$ for $j = 1$ (2)

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

$Y_{j0} = E(Y_{ji}| Z = 0; X_{0i}, \hat{\lambda}_{0i})$ (3)

The MESR model can be used to compare the expected outcome variable of the farm households that adopt a particular level of CSA practices (Equation (9)) with respect to the farm households that did not adopt any practices (Equation (10)) and to investigate the expected outcome variable result in the counterfactual hypothetical cases (Equation (11)), namely that each level of farm households that adopted did not adopt, and Equation (12), that the farm households that did not adopt in fact adopted (see Table 2).

Table 2: Conditional expectations, treatment and heterogeneity effects

Adopter category	Adoption decision		Treatment effect
	To adopt	Not to adopt	
Adopters	$Y_j = E(Y_{ji}\| Z = j; X_{ji}, \hat{\lambda}_{ji})$	$Y_{0j} = E(Y_{0i}\|Z = j; X_{ji}, \hat{\lambda}_{ji})$	$ATT = Y_j - Y_{0j}$
Non-adopters	$Y_{j0} = E(Y_{ji}\| Z = 0; X_{0i}, \hat{\lambda}_{0i})$	$Y_0 = E(Y_{0i}\|Z = 0; X_{0i}, \hat{\lambda}_{0i})$	$ATU = Y_{j0} - Y_0$
Heterogeneity effects	$H_{1j} = Y_j - Y_{j0}$	$H_{2j} = Y_{0j} - Y_0$	TH = ATT-ATU

Notes: In this framework, (Y_j) and (Y_0) denote actual outcome values for adopters and non-adopters, respectively; (Y_{0j}) and (Y_{j0}) denote counterfactual outcome values for adopters and non-adopters, respectively; specifically, the outcomes for adopters had they not adopted, and for non-adopters had they adopted. $Z = j$ if farm households adopted CSA practices; $Z = 0$ if households did not adopt any CSA practices; ATT: this refers to the difference between the actual outcomes observed for households that adopted CSA practices. ATU: difference between the actual outcomes observed for households that did not adopt any CSA practices and the hypothetical outcomes they would have experienced if they had adopted them. H_{ij}: the effect of base heterogeneity for farm households that adopted practices ($i = 1$) and did not adopt the practices ($i = 2$); TH (transitional heterogeneity): the difference between the treatment effect for adopters and the potential effect for non-adopters.

We considered matching criteria for the treatment and control groups and model assumptions in the multinomial switching regression: (i) developed more than two discrete treatment groups, which are identified as single adopter, and partial, multiple and full adoption of CSA practices (Table 3); (ii) used observed covariates that influence both treatment assignment and outcomes.

Table 3: Variables used in the econometric analysis

Variables	Variable description (coding/units)
Outcome variables	
Resilience capacity	Continuous resilience score (normalised index 0–1)
Dependent variables	
Chemical fertiliser	1 if household applies chemical fertiliser efficiently, 0 if otherwise
Small-scale irrigation	1 if household has adopted small-scale irrigation, 0 if otherwise
Improved crop variety	1 if household practises crop diversity, 0 if otherwise
Agrochemicals	1 if household applies agrochemicals efficiently, 0 if otherwise
Compost	1 if household applies compost, 0 if otherwise
Intensity of CSA practices	0 (non-adopter): household adopted no CSA practices, 1 (single adopter): household adopted one CSA practice, 2 (partial adopter): household adopted two CSA practices, 3 (multiple adopter): household adopted three to four CSA practices, and 4 (full adopter): household adopted all five CSA practices
Explanatory variables	
Socioeconomic factors	
Age	Age of head of farm household (years)
Sex	Sex of the household head, 1 = male, 0 = female
Education	0 = if the household head is uneducated, 1 if informally educated, 2 if the head has a primary education, 3 if the head has a secondary education
Family size	Number of family members (count)
Dependency ratio	Household members aged below 15 and above 64 (count)
Livestock holding	Total livestock holding in TLU
Off farm	Participate in off-farm activity, 1 = yes, no = 0
Asset	Value of productive farm assets
Farm size	Area of cultivated land, in hectares
Institutional and biophysical factors	
Training	Household's participation in training on land management
Extension access	1 if the household accessed extension when they needed it, 0 if otherwise
Soil fertility status	0 if farm land soil status is perceived as poor fertility, 1 if otherwise
Climate change	1 if farmer perceives climate change, 0 if otherwise
Distance to market	Walking time to market in minutes
Membership	1 if the household head is a member of a RUSACCO, 0 if otherwise
Credit access	1if the household received credit when they needed it, 0 if otherwise

Notes: TLU = total livestock units; RUSACCO = rural savings and credit cooperatives
Source: Adapted from Ogola and Ouko (2021); Shiferaw (2021); Mossie (2022); Tilahun *et al*. (2023); Zeleke *et al*. (2024); Zeleke Tessera & Demeke Molla (2025)

3. Results and discussion

3.1 Results

This section primarily presents the key findings derived from the analysis of data collected through household surveys, key informant interviews and focus group discussions. It highlights the adoption rate of climate-smart agriculture (CSA) practices, the determinants of CSA adoption, and the status of household resilience capacity. Furthermore, the impacts of CSA on households' resilience capacity were estimated via a multinomial endogenous switching regression model. The results are presented and discussed in detail below.

3.1.1 CSA practices and determinants of adoption

In this study, 18 climate-smart agriculture (CSA) practices adopted by rural farmers in Gubalafto Woreda were evaluated. Among these methods, the most widely used practices include the use of inorganic fertilisers (50%), improved crop varieties (33%), and small-scale irrigation systems (27%). Notably, half of the respondents demonstrated effective use of inorganic fertilisers: applying them at the right time, in appropriate quantities, and using the proper method. These results are consistent with earlier research conducted in Ethiopia by Ahmed *et al*. (2023) and in Pakistan by Ul Haq *et al*. (2021).

About 23% of the respondents reported using agrochemicals such as pesticides and herbicides, 22% practised composting, and 18% adopted row planting**.** Other farming practices with notably lower adoption rates included intercropping (6%), seasonal or year-round cropping (5%), crop residue management (4%), farm-managed natural regeneration (2%), and the use of early-maturing crops (1%) (Figure 4). A study by Emmanuel and Oba (2019) reported that the most commonly adopted CSA practices among farmers were minimum or zero tillage (55%), mulching (53%), the application of organic manure (42%), and the use of improved seed varieties (35%). Overall, the findings indicate that the adoption of climate-smart agriculture (CSA) remains limited among farming households in Gubalafto Woreda, Ethiopia. This outcome aligns with the studies of Khanal and Mishra (2018) and Bekele *et al*. (2020), which also reported low levels of CSA adoption in their respective research areas.

Focused group participants highlighted key barriers to the adoption of farming practices. These barriers included ongoing conflicts, financial limitations, shortages of essential inputs and restricted access to resources. Such challenges were reported to significantly hinder farmers' ability to implement climate-smart agriculture (CSA) effectively. In addition, these factors may lead many farmers to use chemical inputs inappropriately on their farms. Furthermore, many farmers perceived the adoption of composting as time-consuming and believed it increases the risk of disease. This aligns with the findings of Emmanuel and Oba (2019), who identified limited government support and the absence of improved seed varieties as key barriers to the adoption of sustainable farming practices. These findings are also supported by Gashu *et al*. (2025) and Kidane *et al*. (2025).

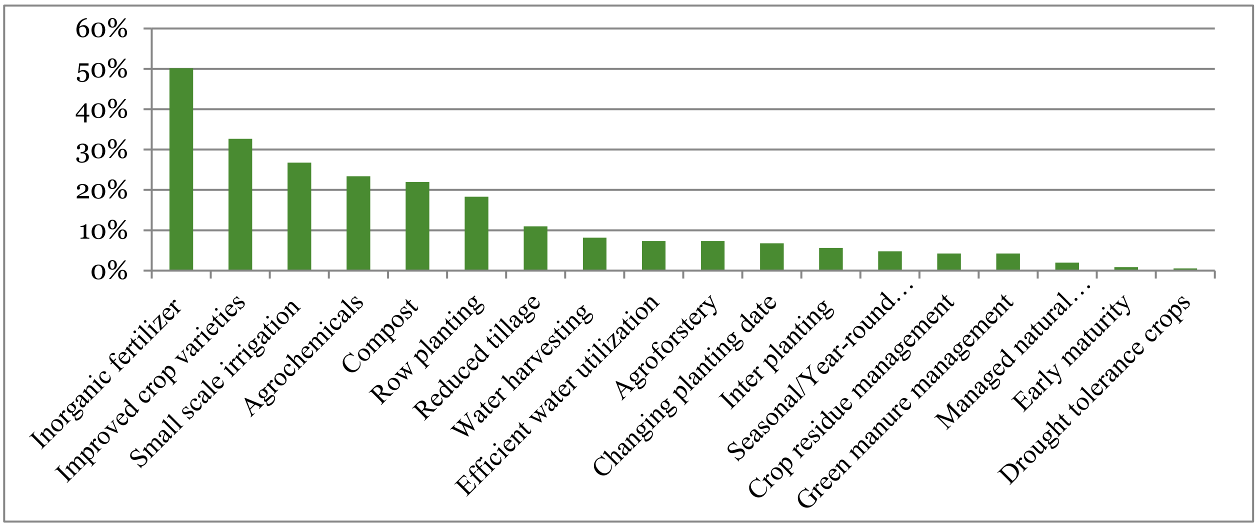

Figure 4: Adoption status of CSA practices
Source: Household survey, 2024

For further analysis, the five most widely adopted climate-smart agriculture practices chosen from a list of 18 were chosen, including the efficient use of inorganic fertilisers, improved crop varieties (pest-resistant and high-yielding), small-scale irrigation systems, agrochemicals and composting (Figure 4). As expounded in the method section, adaptation extent or adoption intensity was assessed via two complementary measures: (i) binary adopter/non-adopter per CSA practice and (ii) an adoption intensity score = count of CSA practices adopted. On the basis of the adoption intensity score, households were categorised into distinct groups according to the number of CSA practices implemented on their farmland. According to this analysis, approximately 30% of the total households did not adopt any of the top climate-smart agriculture (CSA) practices. Moreover, 21.4% of the respondents used two different farming CSA practices together and were categorised as partial adopters. Approximately 15% of the respondents were "multiple adopters", indicating that they implemented three to four CSA practices. Finally, approximately 10% of the total number of respondents adopted all the top practices on their farms (Table 4). Small portions of households had adopted full packages on their farms. This suggests that a relatively large proportion of households may prefer not to adopt any practices, whereas a few households prefer to adopt all practices. These results are consistent with earlier research conducted in Ethiopia by Ahmed *et al*. (2023) and in Pakistan by Ul Haq *et al*. (2021).

Table 4: Adopter categorisation on the basis of the intensity of adoption of CSA practices

Adopter groups	Description	Number	Adoption status (%)
Non-adopter	Farmer did not apply any of the top 5 CSA practices	107	30.14
Single adopter	» applying any one top practice	75	21.13
Partial adopter	» applying 2 top practices together	83	23.38
Multiple adopter	» applying 2 to 3 top practices together	54	15.21
Full adopter	» applying 5 to all practices	36	10.14

Source: Household survey, 2024

As shown in Table 5, age had a significant negative effect on compost adoption: each additional year reduced the probability of adoption by 10%, suggesting that older farmers were less inclined to adopt due to labour demands or resistance to change. Family size significantly influenced the adoption of inorganic fertiliser and improved crop varieties at the 5% and 10% levels, respectively, with each additional household member increasing the probability of adoption by 5%, likely due to the greater availability of labour.

The dependency ratio statistically affected the adoption of inorganic fertiliser and improved varieties at the 5% level of significance. Markedly, the marginal effect of the model indicates that, all other factors kept constant, a rise in the dependency ratio by one unit decreases the probability of adoption of inorganic fertiliser by 11% and improves crop variety by 7%. This implies that households with higher dependency ratios are less likely to adopt fertiliser and improved varieties. In combination with irrigation and agrochemical use, i.e., keeping other factors constant, a rise in TLU by one unit increases the probability of adoption of irrigation and agrochemicals by 6%, indicating that wealthier households invest more in CSA technologies, of which livestock owners adopt more. Similarly, logAsset significantly affected the adoption of inorganic fertiliser and irrigation at the 1% level. Specifically, when other factors are constant, increasing logAsset by one unit increases the probability of adoption of inorganic fertiliser and irrigation by 14% and 12%, respectively. These findings suggest that wealthier households (log assets) are more likely to adopt fertiliser and irrigation, reinforcing the role of economic capacity. In contrast, off-farm income activities negatively affect the adoption of inorganic fertiliser and improved crop varieties, possibly because of time constraints or reduced dependence on farming.

Households aware of climate change were significantly more likely to adopt inorganic fertilisers, with an 18% greater probability, indicating that climate risk perception promotes CSA uptake. RuSACCO membership positively influenced the adoption of improved crop varieties and compost at the 5% level, increasing the likelihood of adoption by 15% and 31%, respectively. Market access negatively affected the adoption of inorganic fertiliser, improved varieties, irrigation and agrochemicals, reducing probabilities by 30%, 20%, 20% and 30%, respectively – while compost adoption remained unaffected, likely due to its local availability. Households that perceived poor soil fertility were 19% more likely to adopt improved varieties and 15% more likely to use agrochemicals.

Table 5: Determinants of individual CSA adoption practices

Variables	Inorganic fertiliser		Improved crop variety		Small scale irrigation		Agrochemicals		Compost	
	Coef.	dy/dx	Coef.	dy/dx	Coef.	dy/dx	Coef.	dy/dx	Coef.	dy/dx
Sex (male)	-0.85**	-0.12**	-0.72*	-0.12*	-0.86	-0.08	-0.71	-0.1	0.04	-0.003
Age	-0.03	-0.01	-0.02	-0.01	0.01	0.01	-0.03	-0.01	-0.1**	-0.01**
Education: Informal ed.	-0.04	-0.04	0.37	0.07	0.31	0.03	1.27***	.21***	-1.16**	-0.15**
Primary »	-0.20	-0.04	-0.02	0.001	0.33	0.03	-0.04	-0.006	-0.56	-0.08
Secondary »	1.42*	0.18**	-0.06	-0.01	1.43	0.15	0.18	0.024	-0.48	-0.07
Family size	0.35*	0.05**	0.29*	0.05*	-0.32	-0.03	-0.12	-0.02	0.17	0.02
Dependency ratio	-0.79**	-0.11**	-0.44*	-0.07*	0.69**	0.07**	0.07	0.01	-0.28	-0.04
Livestock holding	0.06	0.01	0.11	0.02	0.65***	0.06***	0.45***	0.06***	0.03	0.01
logfarm size	0.77	0.12	0.46	0.07	-0.81	-0.08	-0.42	-0.06	2.82***	0.39***
logAsset	0.98***	0.14***	0.23	0.03	1.2***	0.12***	-0.01	-0.001	0.27	0.03
Off farm	-0.91*	-0.12*	-1.7***	-0.2***	0.43	0.04	-0.62	-0.07	-0.01	-0.01
Awareness of climate change	1.10***	0.18***	0.52	0.08	0.59	0.06	0.43	0.06	0.59	0.08
Training	0.22	0.04	0.67*	0.12	-0.61	-0.05	-0.31	-0.04	0.42	0.06
RuSACCOs membership	0.24	0.01	1.10*	0.15**	-0.67	-0.06	-0.03	-0.004	1.88**	.31**
Credit access	-0.47	-0.09	0.61	0.11	1.75**	0.21*	-0.01	-0.01	-1.86**	-0.2***
Extension access	0.27	0.02	0.19	0.03	0.04	0.004	-0.13	-0.02	0.56	0.08
Distance to market	-1.8	-0.3***	-1.5***	-0.2***	-2.4**	-0.2***	-1.9***	-0.3***	0.92**	0.12*
Soil fertility status	-0.38***	-0.07	1.36***	0.19***	0.68	0.06	1.31**	0.15***	-0.43	-0.06
_cons	-5.26		-2.99		-12.8		-0.03		-1.61	

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively
Source: Own household survey, 2024

3.1.2 Prevalence of household resilience capacity

As explained in the method section, the household resilience index was constructed as a composite index from the three dimensions of resilience capacity – absorptive, adaptive and transformative – by using PCA to derive weights and produce a continuous resilience score. Before constructing the composite resilience index, each dimensional capacity index was constructed from observable variables (see Appendix A, Tables 1 to 3). Finally, the composite resilience score was normalised to an index of 0 to 1 if the score was between 0 and 0.34, indicating a low resilience capacity; 0.34 to 0.66, indicating a medium resilience capacity; and 0.66 to 1, indicating a high resilience capacity. As shown in Table 6, the results of the Bartlett test of sphericity were significant (chi-square = 60.076, $p < 0.01$), indicating sufficient correlations of the variables with the corresponding components. The KMO test of sampling adequacy was 0.59. As a result, all the statistical criteria for the goodness of fit of the principal component analysis model were met. Following the Kaiser criterion, one component was retained because its eigenvalue was equal to or greater than one, accounting for approximately 50% of the total variance. As indicated in Figure 5, only the first principal component exceeds the Kaiser criterion threshold of 1, which is a value of 1.45, indicating that it captures a significant portion of the variance and can be used to construct a composite resilience capacity index.

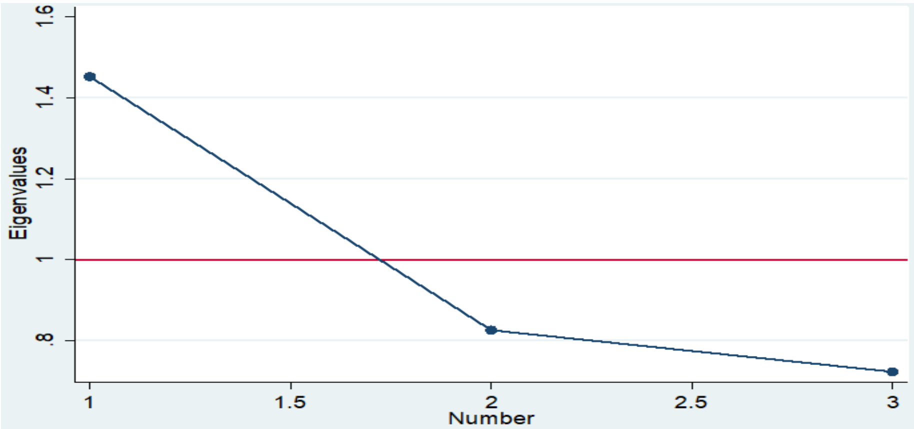

Figure 5: Screen plot of eigenvalues after PCA

The loading for absorptive capacity was 0.612, which is the highest among the three latent variables, indicating a strong correlation with the resilience capacity index. This suggests that the absorptive capacity is a key contributor to enhancing resilience in rural households. This finding aligns with work in Somalia by Dessie and Demsie (2024), who reported that absorptive capacity had the highest component loadings and largest contribution to household resilience.

The component loadings for adaptive capacity and transformative capacity were 0.5342 and 0.5832, respectively, indicating that these two latent variables play crucial roles in estimating household resilience capacity. Similarly, Dessie and Demsie (2024) reported that transformative capacity variables are pivotal in influencing household resilience. Moreover, these findings align with studies conducted in Tanzania and Uganda by Asmamaw *et al*. (2019), who found that adaptive capacity is the primary contributor to enhancing resilience capacity. However, d'Errico *et al*. (2018) also reported a negative correlation between transformative capacity and household resilience capacity.

Table 6: Eigenvalues for the components and loadings of the dimensions used to construct the composite resilience capacity index

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.45	0.63	0.48	0.48
Comp2	0.83	0.10	0.27	0.75
Comp3	0.72	.	0.24	1.000

Components/dimensions	Rotate, varimax
	Comp1
Absorptive capacity	0.612
Adaptive capacity	0.534
Transformative capacity	0.583
Variance: 0.484 Total variance explained/Rho: 0.484 Scale reliability coefficient/alpha: 0.409 Bartlett test of sphericity: Chi-square = 50.44, p = .01 Kaiser–Meyer–Olkin: 0.591	

Figure 6 shows the distribution of the resilience capacity of the sample households with respect to their intensity of adoption of climate-smart agriculture practices. Approximately 44% of the sample households were found to have low resilience capacity, whereas 37% and 19% were found to have medium and high resilience capacity, respectively. This indicates that most households had a low resilience capacity and that only a few households had a high resilience capacity. This finding indicates that a significant portion of the households experienced lower levels of resilience capacity.

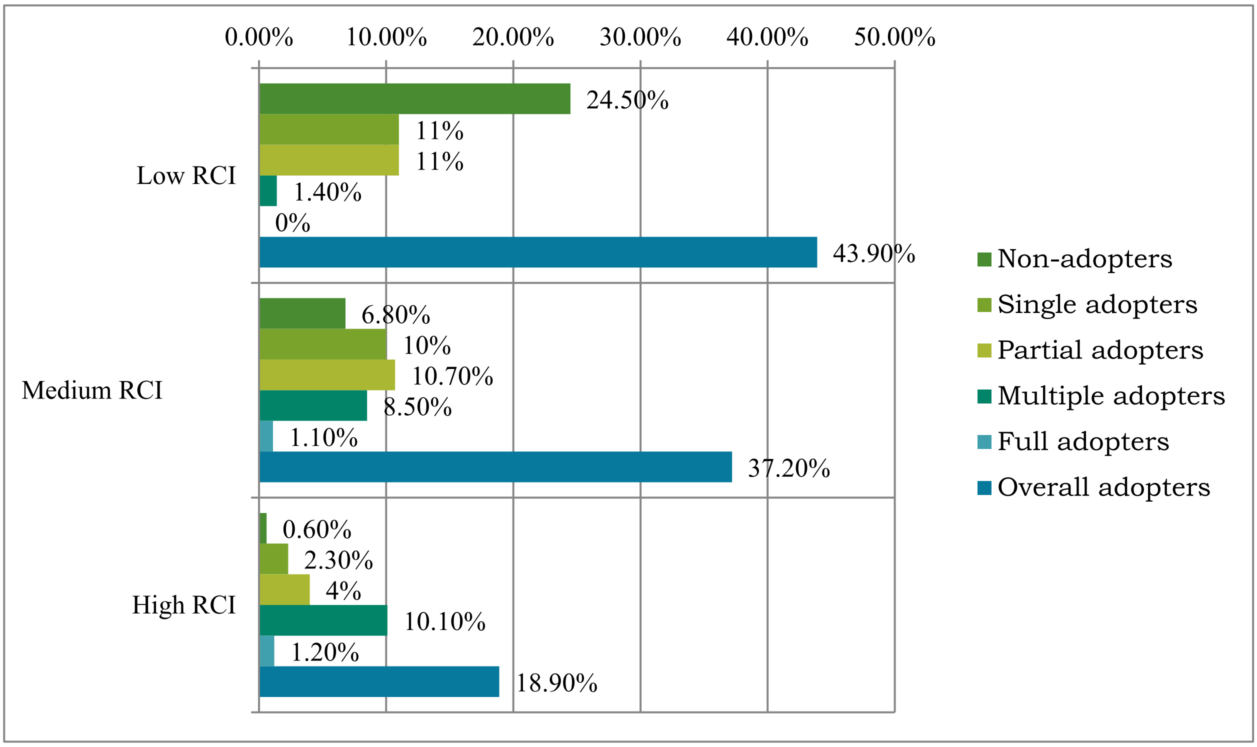

Figure 6: Resilience capacity distribution of households
Source: Authors' computation, 2024

Figure 7 shows the mean values of the composite resilience index and its dimensional capacities. Accordingly, the mean resilience score in terms of transformative capacity (0.239) was lowest for the other resilience capacities, whereas the mean absorptive capacity (0.465) was highest. This result is consistent with that of Asmamaw et al. (2019), who reported that transformative capacity is greater than other dimensions of resilience capacity.

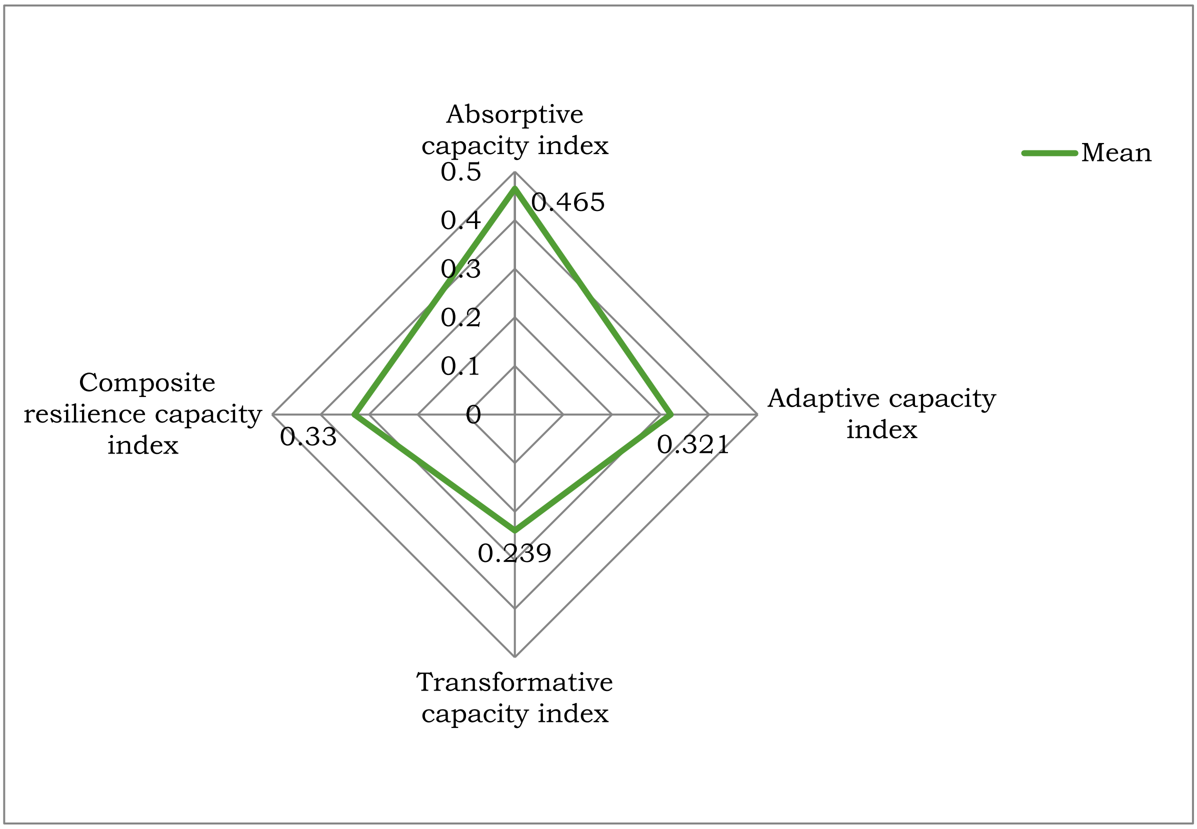

Figure 7: Mean resilience capacity
Source: Authors' computation, 2024

3.1.3 Impacts of CSA on household resilience

This section of the impact evaluation presents the second stage of the multinomial endogenous switching results of average treatment effects on the treated using outcome variables with comparisons of actual and counterfactual results. Hence, the impact of inorganic fertiliser, improved crop varieties, small-scale irrigation, agrochemicals and compost on household resilience capacity was estimated via the endogenous switching regression model. In addition, it assesses the effect of adoption intensity on resilience without providing an in-depth analysis of its underlying determinants. For clarity, the socioeconomic, institutional and biophysical variables that influence adoption intensity are reported in Appendix F.

Table 7 reveals that, on average, households that adopted inorganic fertiliser experienced a 49% increase in their resilience capacity index, whereas non-adopters experienced a 32% decline (-0.32) in the resilience capacity index. This difference was statistically significant at 0.01. Similarly, households that adopted improved crop varieties recorded a 42% increase in their resilience capacity index, whereas non-adopters experienced a 67% decrease (-0.67), with the difference also statistically significant at the 1% level. On average, adopters of small-scale irrigation indicated a 21% (0.21) increase in their resilience capacity index compared with their counterparts, who recorded a 75% (-0.75) decline in the resilience capacity index. In addition, households that adopted agrochemicals had a 4% (0.4) increase in the resilience capacity index, whereas non-users registered a 64% decrease (-0.64). This difference was also highly significant at the 1% level. The findings suggest that, on average, households adopting climate-smart agriculture (CSA) practices exhibit greater resilience capacity than their counterfactual scenario does – had they not adopted these practices. Likewise, non-adopters could achieve greater resilience if they adopted CSA practices. Therefore, CSA adoption has a positive and statistically significant effect on enhancing the resilience of rural farming households in the study area. These results align with the findings of Makate (2017), Radeny *et al*. (2018) and Wereta *et al*. (2025).

The findings from the group discussion and key informants show that agricultural practices play a critical role in building resilience to climate change. The conversation focused particularly on the extent of practice adoption, with consensus that farmers who implement a broader range of practices tend to achieve higher crop yields and have more varied food consumption, thereby increasing their resilience capacity. Participants specifically identified practices such as small-scale irrigation, composting, chemical fertilisers and improved seed varieties as key contributors to agricultural output. They noted that this diversification not only enhanced household diets, but also generated economic benefits that contributed to resilience. The group's insights were consistent with the existing literature, including findings by Kassie and Alemu (2021).

Table 7: Average treatment effect of the adoption of climate-smart agriculture on the resilience of the sample households

	Resilience (RCI)					
CSA practices	**Adopters (actual)**	**If they would not adopt**	**ATT**	**Non-adopters (actual)**	**If they would adopt**	**ATU**
Inorganic fertiliser	0.51	0.02	0.49***	0.14	0.47	-0.32***
Improved crop variety	0.54	0.11	0.42***	0.24	0.91	-0.67***
Small scale irrigation	0.57	0.35	0.21***	.22	0.97	-0.75***
Agrochemical	0.44	0.04	0.4***	0.29	0.93	-0.64***
Compost	0.49	0.5	-0.01	0.29	-0.28	-0.57***

Notes: *** indicates significant variables at1%. ATT = average treatment effect on the treated; ATU = average treatment effect on the untreated.
Source: Own household survey (2024)

Table 8 presents the impact of CSA adoption intensity on the resilience capacity of rural households. As a result, the ATT revealed that adopting two CSA practices had a notable effect on the climate resilience capacity of actual adopters, with statistical significance at $p < 0.1$. On average, households that partially adopted CSA practices experienced a 7.4% increase in their resilience index. This finding implies that households that implemented two CSA practices together experienced a positive increase in their resilience. Furthermore, the positive sign of the transitional heterogeneity effect (THE) indicates that the impact of partial adoption is more pronounced among adopters than among non-adopters. Thus, this suggests that partial adopters gain more benefits than remaining non-adopters. Similarly, the adoption of three to four CSA practices had a statistically significant effect on the resilience capacity of actual adopters ($p < 0.01$). On average, households that adopted multiple CSA practices experienced a 12% increase in their resilience index. These findings demonstrate that engaging with several CSA practices can lead to meaningful improvements in household resilience. In contrast, their counterparts (non-adopters) might have decreased their resilience index by 17 compared to if they had adopted multiple CSA practices. On the other hand, households that did not adopt multiple CSA practices would have experienced a significant positive increase in resilience if they had adopted multiple CSA practices. This implies that, if households do adopt (but do not) they possess greater potential for climate resilience than do those who actually do not; this finding highlights the potential benefits that non-adopters miss by not adopting these practices. Interestingly, the negative sign of THE indicated that adopting multiple CSA practices is less pronounced for actual multiple adopters than for non-adopters. Here, the effect is slightly negative, i.e. resilience would be slightly lower for those who would have adopted multiple options.

As indicated in Table 8, households that adopted five or more climate-smart agriculture (CSA) practices had a statistically significant improvement in their resilience capacity ($p < 0.01$). On average, full adopters indicated a 17% increase in their resilience index, indicating that those who fully adopted CSA practices benefited from a substantial and positive boost in resilience. According to ATU, non-adopters would have experienced a 50% lower resilience index than if they had fully adopted CSA practices. In other words, had these households fully engaged with the intervention, their resilience capacity would likely have increased significantly. These findings suggest that these households lack the necessary strategies to effectively cope with climate-related challenges other than the adoption of CSA practices. Furthermore, this finding is supported by key informants, who stated that merely adopting agricultural practices did not guarantee household resilience. They reported that non-adopting households experienced poor economic conditions, relatively small farm sizes and limited livestock, all of which influenced their capacity for resilience. Moreover, the positive sign of THE indicated that the adoption of full CSA practices had a more pronounced effect for full adopters than for non-adopters. This substantial positive effect suggests that promoting full adoption among households significantly enhances resilience for those who are full adopters.

Table 8: Average treatment effect of adoption intensity of CSA on household resilience

CSA adoption intensity	Households	Adoption decision: to adopt	Adoption decision: not to adopt	Treatment effect
Single adoption	Adopter	0.27	0.25	ATT = 0.026
	Non-adopters	0.05	0.11	ATU = -0.05
	BHE	0.22***	0.15 ***	THE = 0.029
Partial adoption	Adopter	0.38	0.31	ATT = .074*
	Non-adopters	0.10	0.04	ATU = 0.05
	BHE	0.28	0.27	THE = 0.024
Multiple adoption	Adopter	0.64	0.51	ATT = 0.12***
	Non-adopters	0.27	0.11	ATU = - 0.17 ***
	BHE	0.36***	0.41 ***	THE = 0.29
Full adoption	Adopter	0.73	0.55	ATT = 0.17*
	Non-adopters	-0.39	0.11	ATU = -0.5 ***
	BHE	1.1***	0.44***	THE = 0.67

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. BHE = base heterogeneity effect; THE = transitional heterogeneity effect

3.2 Robustness test

In this study, we conducted robustness tests to confirm the results obtained from the cross-sectional one-time survey data. These tests assess the reliability of our findings. The common strategies employed include: checked outliers of variables (see Appendix B), handling missing data, and using alternative estimation techniques to estimate the same relationships, such as ANOVA and multinomial endogenous switching regression. We also validated our findings with existing literature by comparing them to previous studies.

In addition, we conducted various statistical tests to evaluate the significance of our estimates through hypothesis testing. This included checking the normality of variables using (see Appendix C) and testing for multicollinearity[1] by employing the pwcorr command and calculating the variance inflation factor (VIF) to measure the degree of linear relationships among the continuous explanatory

[1] Means that check to ensure reliable estimation by indicating whether covariates correlated with each other or not.

variables (see Appendix D). Furthermore, we ran the multinomial endogenous switching regression and performed endogeneity[2] and instrumental variable[3] tests by conducting a simple falsification test (see Appendix E).

Measurement error was addressed by employing experienced enumerators for data collection, providing them with training, and pretesting the survey tools to reduce misinterpretation and recording errors. Cronbach's alpha was used to assess the internal consistency of the survey items measuring the same construct.

3.3 Discussion

The study revealed that approximately half of the surveyed households exhibited low resilience capacity, as reflected in their resilience index. This indicates that a significant portion of the population remains vulnerable to climatic shocks, limiting their ability to adopt and sustain climate-smart agriculture (CSA) practices. These findings are consistent with those reported by Demisse *et al*. (2024), because rural farmers depend on rain-fed agriculture, have limited access to resources, experience low income levels, and have inadequate infrastructure. Furthermore, this finding aligns with insights from the focus group, which emphasise that poor infrastructure and economic constraints hinder rural households' ability to adapt to climate change. In contrast, the finding that only a small proportion of households achieve a high resilience capacity highlights a critical development gap in rural adaptation systems. This limited resilience suggests that most farming households remain highly susceptible to climate-related shocks. This result is in agreement with work in the Central Rift Valley of Ethiopia by the IEDD (2022), in the central highlands of Ethiopia by Demisse *et al*. (2024), in southern Ethiopia by Atara *et al*. (2020), and in Bungoma by Siminyu *et al*. (2020). These authors state that many households are encountering challenges related to climate resilience, indicating that they are non-resilient.

The significant disparity in the adoption of CSA practices, where 30% of respondents did not adopt any practices, while only 10% fully adopted five or more practices, highlights critical gaps in awareness, capacity and institutional support. This uneven uptake suggests that a substantial portion of farming households either lack access to CSA knowledge, or face constraints that prevent implementation. These findings slightly agree with work done in Ethiopia by Ahmed *et al*. (2023), who reported that 16% of households were highly adopted. As reported in the group discussion, financial barriers, along with shortages of inputs and available resources, can significantly prevent farmers from adopting the practice; on the other hand, many farmers perceive that adopting the practice is time-consuming, which is in line with the findings of Gashu *et al*. (2025) and Kidane *et al*. (2025).

The evidence from this study reveals that CSA adoption is significantly affected by various socioeconomic and institutional factors. The observed negative association between age and compost adoption suggests that older farmers may face specific barriers, such as labour constraints, risk aversion, or limited access to training that reduces their likelihood of adopting labour-intensive practices such as composting. This finding aligns with those of previous studies (Asrat & Simane 2017; Kurgat *et al*. 2020; Ul Haq *et al*. 2021; Tilahun *et al*. 2023). Farmers with greater labour availability, fewer dependants and stronger economic capacity (livestock holdings (TLU) and asset ownership) are more likely to adopt labour- and input-intensive CSA practices. Notably, higher

[2] Occurred when unobservable characteristics of farmers affect both the adoption decision and its outcome.

[3] The instrumental variable is directly affected by the adoption of CSA practices, but not the outcome variable directly (except through its effect on the dependent variables). Instrumental variables are used to mitigate bias that can arise when independent variables are correlated with the error term of the model.

dependency ratios reduced the adoption of inorganic fertiliser, improved varieties and small-scale irrigation, reflecting household resource constraints. This suggests that households with more dependants often have limited labour and financial flexibility, which restricts their ability to invest in productivity-enhancing technologies. In contrast, a larger family size positively influenced the uptake of fertilisers and improved crop varieties, likely due to greater labour availability. The positive associations between a larger family size and the adoption of fertilisers and improved crop varieties suggest that they may have labour availability. Households with more working-age members are better positioned to adopt labour-intensive CSA practices. Similarly, wealth indicators, such as livestock holdings (TLU) and asset ownership (logAsset), were positively linked to the adoption of irrigation and fertiliser. These findings indicate that economic capacity plays a critical role in enabling CSA uptake. This suggests that households with greater financial and productive assets are better positioned to invest in input-intensive technologies, manage risk, and sustain long-term agricultural improvements. These findings are consistent with those of Zeleke *et al*. (2024). Moreover, climate change awareness significantly increased the likelihood of fertiliser adoption, suggesting that access to reliable information on current and projected temperature and rainfall patterns may enable farmers to select appropriate agricultural inputs. This finding is consistent with those of previous studies (Sisay *et al*. 2023; Teklu *et al*. 2023). Furthermore, membership of RuSACCOs positively influenced the adoption of both improved crop varieties and compost, likely due to increased access to financial and informational resources. Perceived soil infertility also emerged as a key driver, increasing the probability of adopting improved varieties and agrochemicals. These results align with earlier evidence (Wekesa *et al*. 2018; Ahmed *et al*. 2023).

Empirical evidence from the endogenous switching model highlights the transformative impact of climate-smart agriculture (CSA) practices on household resilience**.** Compared with non-adopters, farmers who adopt CSA practices exhibit significantly greater resilience capacity. Specifically, inorganic fertilisers significantly increase farmer resilience because this practice improves soil fertility and stabilises crop yields. Similarly, the adoption of improved crop varieties enhances resilience, suggesting that this practice helps reduce the risk of crop failure and ensures a more reliable food supply. Households employing small-scale irrigation also demonstrate marked improvements in resilience relative to their counterparts. This suggests that small-scale irrigation substantially bolsters households' capacity to cope with climate variability, maintain consistent crop production, and reduce vulnerability to drought and erratic rainfall. These findings are consistent with those of prior studies by Makate (2017) and Radeny *et al*. (2018). The findings suggest that CSA adoption supports Sustainable Development Goal 13 by strengthening household resilience to climate change. This aligns with the evidence reported by Makate (2017).

As households progress from partial to full adoption of CSA practices, the average treatment effect on the treated (ATT) increases markedly – from 0.07 for partial adoption to 0.17 for full adoption – indicating a strong positive correlation between adoption intensity and resilience capacity. Partial adopters can increase their resilience by approximately 7%, whereas full adopters can achieve gains of up to 17%. These findings underscore that combining multiple CSA practices enhances household resilience more effectively than does applying individual practices in isolation. This could be because using combined practices has a positive effect on improving soil nutrient use, soil moisture retention, fertility, and the adaptation of crops to moisture, pest and disease stress. These findings align with those of previous studies conducted in Ethiopia by the IEDD (2022) and Teklu *et al*. (2023), in India by Samuel *et al*. (2024), in Zambia by Khonje *et al*. (2018), and in sub-Saharan Africa by Okoronkwo *et al*. (2024), which reported that the adoption of agricultural technologies in combination improves resilience.

4. Conclusion and recommendations

The current study assessed the adoption of CSA services and examined their impacts on rural household resilience capacity in Gubalafto District, Ethiopia. Approximately 50% of the rural households exhibited low resilience capacity, while only 19% had a high resilience capacity. This distribution indicates that a significant majority of households are facing challenges in resilience, which may hinder their ability to adapt to climate-related stresses. In response, rural households are adopting various CSA practices to counteract the negative impacts of climate change on reliance capacity. The findings indicate that various CSA practices were adopted by rural households. Among the 18 CSA practices assessed, inorganic fertiliser, improved crop varieties, small-scale irrigation, agrochemicals and compost were the most widely adopted by rural households. Inorganic fertiliser ranked highest in adoption, indicating that farmers place strong emphasis on enhancing soil fertility. Moreover, the results show that one-fourth of the total households were full and multiple adopters, indicating that, among the surveyed households, only a few households implemented five climate-smart agricultural practices in combination. Thus, it is important to develop tailored outreach programmes that promote integrated CSA adoption, focusing on households currently using only one or two practices.

The results of the logit model underscore that the adoption of climate-smart agriculture (CSA) practices is strongly influenced by socioeconomic and institutional factors. High dependency ratios and limited market access pose significant barriers, whereas wealth indicators such as livestock holdings, household assets and farm size, as well as institutional factors such as RuSACCO membership and soil fertility, positively drive CSA uptake. These findings highlight the critical role of economic capacity and institutional support in enabling innovation. Therefore, targeted interventions that strengthen livestock ownership expand access to agricultural assets, RuSACCO membership and financial initiatives that improve credit access, which significantly promote the adoption of irrigation, improved crop varieties, inorganic fertilisers and agrochemical practices that collectively can significantly increase resilience outcomes in Gubalafto. Moreover, reducing implementation barriers by lowering dependency ratios, establishing local CSA marketplaces, and improving coordination among the government, donors and communities will be vital for scaling CSA and overcoming adoption constraints.

The results from the multinomial endogenous switching regression model indicate that integrating multiple CSA practices substantially enhances the resilience of rural households in the face of climate change. The evidence suggests that households adopting more diverse combinations of CSA practices can increase their resilience capacity. Overall, the study confirms a positive relationship between the intensity of CSA adoption and household resilience. Moreover, households that adopt inorganic fertilisers, improved crop varieties, agrochemicals and small-scale irrigation demonstrate greater improvements in resilience capacity than do non-adopters. Therefore, policymakers and development partners should prioritise these practices as core climate-smart agriculture (CSA) interventions and design extension programmes and input subsidy schemes that promote integrated CSA packages, rather than isolated technologies, to strengthen household resilience capacity.

Despite its valuable insights, this study has several limitations. The cross-sectional nature of the data constrains the ability to assess the long-term impacts and sustainability of CSA practices. Furthermore, the reliance on self-reported data for yields and income may be subject to recall bias, affecting the accuracy of the resilience assessment. To enhance validity, future research should triangulate these findings with extension records, where available, and investigate the long-term impacts of CSA practices through multiyear longitudinal data.

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Appendices

Appendix A

Table 1: Component loadings of the variables used to estimate the absorptive capacity

Variables	**Rotate, varimax**			
	Comp1	**Comp2**	**Comp3**	**Comp4**
Productive safety net				0.6104
Friend support			0.5796	
Formal aid (NGO & GO)				-0.698
Remittances		-0.386		
Informal social insurance	0.3041			
Access to weather information	0.5413			
Mobile phone communication	0.4146			
Ownership of radio and TV	0.5107			
Decrease size of meals			0.3306	
Decrease number of meals		0.623		
Decrease diversity of meals		0.6247		
Borrow grain from neighbours			0.5326	
Sales of livestock	0.3349			
Provision of farm labour			0.3607	
Proportion of variance explained	0.2337	0.1187	0.1024	0.0954
Total variance explained/Rho: 55.03%				
Scale reliability coefficient/Cronbach's alpha: 0.5436 Bartlett test of sphericity: Chi-square = 1061.84, p = .000				
KMO measure of sampling adequacy = 0.706				

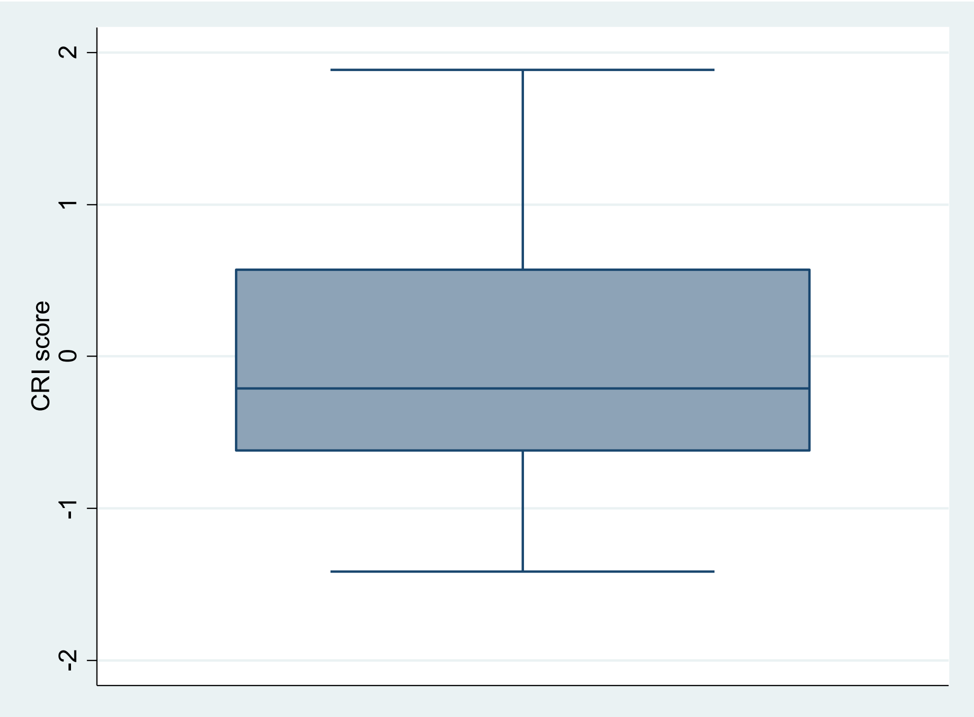
Table 2: Component loadings of the variables used to estimate the adaptive capacity

Variables	**Rotate, varimax**					
	Comp1	**Comp2**	**Comp3**	**Comp4**	**Comp5**	**Comp6**
Sex household head			-0.665			
Marital status			0.6661			
Education level of HH		0.463				
Farming experience		0.6006				
Labor availability						0.3991
Age of household head		0.6006				
Different crops planted	0.3863					
Improved verities				0.3633		
Water harvesting technologies				0.329		
Working non-farm	0.3066					
Working off-farm						0.8392
Physical asset	0.4547					
Average annual income	0.4002			0.6009		
Cash saving	0.4495					
Multidimensional food security					0.777	
Food consumption score				0.5136		
Proportion of variance explained	0.2314	0.1426	0.0946	0.0792	0.0623	0.0602
Total variance explained/Rho: 67%						
Scale reliability coefficient/alpha: 0.7041 Bartlett test of sphericity: Chi-square = 2 138.058, p = .000						
Kaiser–Meyer–Olkin measure of sampling adequacy: 0.719						

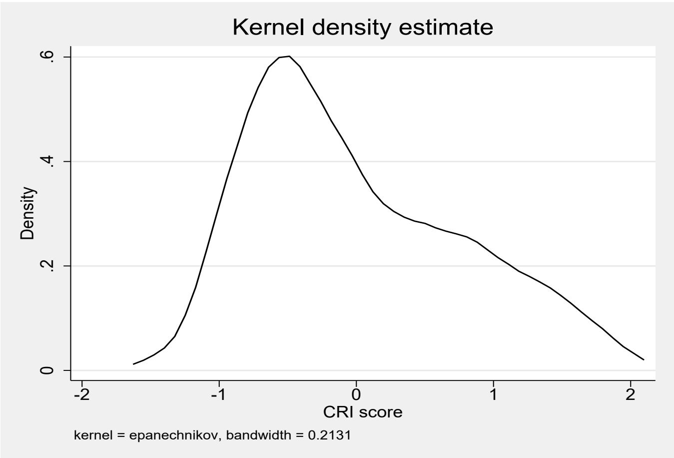
Table 3: Component loadings for the variables used to estimate transformative capacity

Variables	Rotate, varimax			
	Comp1	Comp2	Comp3	Comp4
Access to extension				0.6758
Access to agricultural training				0.5369
Membership in iqub		0.4953		
Membership RUSACO		0.6093		
Access to credit		0.5857		
Access to irrigation				0.4098
Distance to nearest school	0.5805			
Distance to nearest market	0.5547			
Distance to nearest health institution	0.5936			
Distance to drink water			0.4899	
All-weather road			0.5091	
Clear drinking water and sanitation			0.358	
Electricity			0.5879	
Proportion of variance explained	0.3076	0.1536	0.1264	0.0773
Total variance explained/Rho: 66.5%				
Scale reliability coefficient/alpha: 0.7460 Bartlett test of sphericity (Chi-square = 1 617.5, P = .000				
Kaiser–Meyer–Olkin measure of sampling adequacy: 0.783				

Appendix B: Examples of 'Check outlier variables'



Appendix C: Examples of 'Check normality'



Appendix D: Multicollinearity via vif

Variable	VIF	1/VIF
logAsset	2.88	0.347193
RUSACOm	2.09	0.477872
Credit	2.05	0.487381
Eds1	2.00	0.499268
Fclimate1	1.90	0.526156
Extension	1.84	0.542605
TLU	1.84	0.542780
Trianing1	1.83	0.546566
logTLS	1.74	0.574998
Age	1.66	0.600765
TFS	1.61	0.622530
Dr	1.39	0.719711
Sex1_01	1.31	0.763173
Market_dis~e	1.24	0.808887
Soil_ferti~2	1.12	0.894796
Offfarm1	1.11	0.897889
Mean VIF	1.73	

Appendix E: Test endogeneity and instrumental variable

```
estat endog

Tests of endogeneity
H0: Variables are exogenous

Durbin (score) chi2(1)          =  54.7638  (p = 0.0000)
Wu-Hausman F(1,337)             =  61.4696  (p = 0.0000)

estat firststag

First-stage regression summary statistics
```

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(1,338)	Prob > I
CSA_from_5~e	0.5248	0.5023	0.1278	49.5443	0.0000

```
Minimum eigenvalue statistic = 49.5443

Critical Values                       # of endogenous regressors:    1
H0: Instruments are weak              # of excluded instruments:     1
```

	5%	10%	20%	30%
2SLS relative bias	(not available)			
	10%	**15%**	**20%**	**25%**
2SLS size of nominal 5% Wald test	16.38	8.96	6.66	5.53
LIML size of nominal 5% Wald test	16.38	8.96	6.66	5.53

```
. estat overid
no overidentifying restrictions
```

Appendix F: Determinants of adoption intensity of CSA practices

CSA_from_5_lable	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Non_adopter	(base outcome)					
Single_adopter						
Age	-.0920874	.0317019	-2.90	0.004	-.154222	-.0299529
Sex1_01	.031577	.5208943	0.06	0.952	-.9893572	1.052511
Eds1	-.3964736	.2720635	-1.46	0.145	-.9297082	.136761
Labor	.9972684	.3378797	2.95	0.003	.3350363	1.6595
TLU	-.3582746	.1749528	-2.05	0.041	-.7011758	-.0153733
Offfarm1	-1.838916	.7037888	-2.61	0.009	-3.218317	-.4595156
Awether1	.1316655	.7703624	0.17	0.864	-1.378217	1.641548
logAsset	.3213098	.3167402	1.01	0.310	-.2994896	.9421091
logTLS	.0085271	.8899567	0.01	0.992	-1.735756	1.75281
Trianing1	1.659386	.9334942	1.78	0.075	-.1702286	3.489001
Extension	-.2882452	.5302185	-0.54	0.587	-1.327454	.750964
Soil_fertility2	.8869598	.505226	1.76	0.079	-.103265	1.877185
Fclimate1	.9408192	.6332004	1.49	0.137	-.3002307	2.181869
Credit	-1.572707	1.474605	-1.07	0.286	-4.46288	1.317466
logIncome	3.607474	.7977875	4.52	0.000	2.043839	5.171108
RUSACOm	1.837705	1.070832	1.72	0.086	-.2610877	3.936498
Market_distance	-2.181932	.6479183	-3.37	0.001	-3.451829	-.9120358
_cons	-36.1905	8.130725	-4.45	0.000	-52.12643	-20.25457
partial_adopter						
Age	-.0759422	.0342086	-2.22	0.026	-.1429898	-.0088945
Sex1_01	-.8409672	.556032	-1.51	0.130	-1.93077	.2488355
Eds1	-.2922864	.3035559	-0.96	0.336	-.887245	.3026723
Labor	.7555512	.3776349	2.00	0.045	.0154004	1.495702
TLU	-.443326	.1910174	-2.32	0.020	-.8177132	-.0689389
Offfarm1	-2.676787	.8351426	-3.21	0.001	-4.313636	-1.039938
Awether1	.2957898	.8174842	0.36	0.717	-1.30645	1.898029
logAsset	.52819	.342777	1.54	0.123	-.1436406	1.200021
logTLS	.1898407	1.000591	0.19	0.850	-1.771282	2.150964
Trianing1	1.72358	.9678537	1.78	0.075	-.1733786	3.620538
Extension	-.2595884	.5695454	-0.46	0.649	-1.375877	.8567001
Soil_fertility2	1.710033	.6371018	2.68	0.007	.4613367	2.95873
Fclimate1	1.102563	.6961872	1.58	0.113	-.2619384	2.467065
Credit	-1.518036	1.516252	-1.00	0.317	-4.489835	1.453763
logIncome	4.806022	.8790698	5.47	0.000	3.083077	6.528967
RUSACOm	1.714771	1.211273	1.42	0.157	-.6592811	4.088823
Market_distance	-3.448486	.7537395	-4.58	0.000	-4.925789	-1.971184
_cons	-50.36356	8.94028	-5.63	0.000	-67.88618	-32.84093

Multiple_adopter						
Age	-.0803954	.0411027	-1.96	0.050	-.1609553	.0001644
Sex1_01	-.9286047	.8061755	-1.15	0.249	-2.50868	.6514703
Eds1	-.6531088	.3721979	-1.75	0.079	-1.382603	.0763856
Labor	.7159718	.41731	1.72	0.086	-.1019407	1.533884
TLU	-.1149667	.2133618	-0.54	0.590	-.5331481	.3032146
Offfarm1	-4.30865	1.334438	-3.23	0.001	-6.924101	-1.6932
Awether1	.9736838	.9297217	1.05	0.295	-.8485373	2.795905
logAsset	.7406961	.3915063	1.89	0.059	-.0266422	1.508034
logTLS	-1.17212	1.179344	-0.99	0.320	-3.483592	1.139352
Trianing1	2.49566	1.0285	2.43	0.015	.4798373	4.511483
Extension	-.8821171	.6870279	-1.28	0.199	-2.228667	.4644328
Soil_fertility2	1.379832	.7072368	1.95	0.051	-.006327	2.76599
Fclimate1	1.012903	.8632764	1.17	0.241	-.6790881	2.704893
Credit	-2.039211	1.592085	-1.28	0.200	-5.15964	1.081219
logIncome	7.147688	1.031575	6.93	0.000	5.125837	9.169538
RUSACOm	.8391496	1.327842	0.63	0.527	-1.763373	3.441672
Market_distance	-3.970925	.9322239	-4.26	0.000	-5.79805	-2.1438
_cons	-77.29878	10.57117	-7.31	0.000	-98.0179	-56.57966
Full_adopter						
Age	-.1759194	.1036664	-1.70	0.090	-.3791018	.0272631
Sex1_01	-4.173076	3.061394	-1.36	0.173	-10.1733	1.827147
Eds1	-1.587445	.9348585	-1.70	0.089	-3.419734	.2448441
Labor	.5700362	1.00516	0.57	0.571	-1.400042	2.540115
TLU	-.294058	.3643737	-0.81	0.420	-1.008217	.4201013
Offfarm1	-16.83524	1887.381	-0.01	0.993	-3716.033	3682.363
Awether1	1.070255	1.725728	0.62	0.535	-2.31211	4.45262
logAsset	1.619951	1.04577	1.55	0.121	-.4297195	3.669622
logTLS	-9.757883	3.931249	-2.48	0.013	-17.46299	-2.052776
Trianing1	.6497129	1.721385	0.38	0.706	-2.724139	4.023565
Extension	-1.534633	1.698636	-0.90	0.366	-4.863899	1.794633
Soil_fertility2	17.44586	1452.949	0.01	0.990	-2830.282	2865.174
Fclimate1	17.36422	755.0602	0.02	0.982	-1462.527	1497.255
Credit	2.067394	2.745394	0.75	0.451	-3.313479	7.448266
logIncome	16.24832	3.411408	4.76	0.000	9.562079	22.93455
RUSACOm	.0484458	2.402887	0.02	0.984	-4.661125	4.758017
Market_distance	-.2555811	2.491727	-0.10	0.918	-5.139277	4.628115
_cons	-215.8152	1637.95	-0.13	0.895	-3426.139	2994.508