Adoption of Climate Smart Agricultural Practices by Smallholder Farmers in Ethiopia: Evidence from Spatiotemporal Analysis

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Abstract

Climate-smart agriculture (CSA) practices are serving as a fundamental element for achieving sustainable agricultural development while maintaining food security against the challenges of climate change. So far, the adoption of these practices by smallholder farmers has remained low. Hence, this study used panel data from two waves of the Ethiopian Living Standards Measurement Survey (LSMS), conducted in 2018/19 and 2021/22, to explore the determinants of CSA adoption, particularly soil and water conservation, agronomic practices, and livelihood diversification among smallholder farmers in Ethiopia. The determinants that facilitate or hinder the adoption of these CSA practices were identified using a multivariate Probit model. The results indicated that adoption rates were patently low: only 17.5% for soil and water conservation, 7% for agronomic practices, and 31% for livelihood diversification. The study found that female-headed households were less likely to adopt soil and water conservation and agronomic practices but more likely to diversify livelihoods. Education, extension services, mobile ownership, and drought shocks consistently promoted adoption across practices. Larger landholdings positively influenced soil and water conservation and agronomic practices but discouraged livelihood diversification. In contrast, family size, livestock holdings, and slope exhibited varied effects across the three practices. Greater distance to markets constrained the adoption of agronomic practices, while agroecological conditions also played a role in shaping both agronomic practices and livelihood diversification strategies. The findings suggest that strengthening access to

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extension services, promoting education, and enhancing CSA information distribution are critical for enhancing CSA adoption. Policies should also address gender disparities by providing targeted support to female-headed households. Improving market access and tailoring interventions to specific agroecological contexts would further facilitate adoption. Integrating land management with livelihood support could help reconcile the trade-offs posed by land size, livestock holdings, and household composition in shaping CSA adoption.

Keywords: Adoption, Climate Change, Climate-smart Agriculture, Panel, Multivariate Probit, Ethiopia

JEL Classification: Q540

1. Introduction

Climate change is now one of the biggest challenges of our time, with the world's most vulnerable communities bearing the heaviest burden (Saleem et al., 2024). As temperatures rise and weather patterns become more unpredictable, the challenge of simply putting food on the table has grown incredibly difficult (Rani and Reddy, 2023; Rosegrant et al., 2024; Toromade et al., 2024). Specifically, for the most vulnerable populations, climate change undermines food systems, livelihoods, and overall well-being (IFPRI, 2022). Recent estimates indicate that 2.3 billion people were estimated to have been affected by either moderate or severe food insecurity globally in 2024, which is 335 million more than before the COVID-19 pandemic, with climate change and extreme events among the key drivers in vulnerable regions (FAO *et* al., 2025).

As the primary source of the world's food and provider of critical ecosystem services, agriculture constitutes a key lever for achieving the Sustainable Development Goals (FAO *et al.*, 2025). Despite agriculture being vital to the global economy and food security, its capacity to meet growing nutritional needs is highly vulnerable to climate change, which negatively impacts food systems, nutrition, and human well-being (Cheo and Tapiwa, 2021; Malhi *et al.*, 2021; Hansen *et al.*, 2022; IPCC, 2022; Semeraro *et al.*, 2023). Sub-Saharan African (SSA) countries, including Ethiopia, are predominantly susceptible because of their heavy reliance on rain-fed agriculture and restricted coping mechanisms (Ayanlade *et al.*, 2022; Kone *et al.*, 2024). For many rural communities, this reliance on traditional farming methods has already meant smaller harvests and not enough food to last the year (Wudil et al., 2022).

Climate change is now making this struggle even harder, hitting smallholder farmers the hardest and making it increasingly difficult for them to get by. As conditions grow more unpredictable, the path toward the Sustainable Development Goals becomes steeper, making it even harder for those who depend on the land to build a better future (Rahut et al., 2021).

Climate-smart agriculture (CSA) is a promising solution, offering farmers a practical way to adapt to a changing climate while maintaining sustainable food production (FAO, 2010, 2019). At its core, CSA boosts crop yields, reduces greenhouse gas emissions, and builds resilience simultaneously. It is a comprehensive approach that integrates improved farming techniques, supportive policies, strong local institutions, and access to funding. The premise behind CSA is that food security, climate change, and emissions are deeply connected (IPCC, 2018; FAO, 2019). This necessitates a broad perspective, from introducing new technologies and improving weather forecasting to ensuring farmers have the information and financial resources necessary to take risks. It also entails strengthening markets and creating effective policies for the people on the ground (FAO, 2013). This is not merely about isolated changes on individual farms; it is about rethinking the entire food system, from local fields and communities to national policies (FAO, 2013).

Recognizing the vital role of CSA in achieving food security and building resilience against climate change, the Government of Ethiopia has implemented a range of policies and strategies to promote its adoption. For example, Ethiopia's climate and development policies, including the National Adaptation Plan (2017), the Climate-Resilient Green Economy (CRGE) Strategy (2011), the Growth and Transformation Plans I and II (2011 and 2015, respectively), the Climate-Smart Agriculture Investment Plan (2024), and the current 10-Year Prosperity Plan, build on existing interventions to reduce climate vulnerability by enhancing adaptive capacity and resilience (FDRE, 2010, 2011, 2015, 2017; Alliance of Biodiversity International and CIAT, 2024). These initiatives aim to enhance agricultural productivity, improve farmers' adaptive capacity, and reduce the sector's vulnerability to climate shocks.

Key measures include the integration of CSA practices into national agricultural extension programs, the provision of climate information services, promotion of sustainable land and water management techniques, and support for access to credit and innovative financing mechanisms. Additionally, Ethiopia's policies emphasize capacity building, research and development, and the creation of enabling institutional frameworks to support the expansion of CSA technologies across diverse agro-ecological zones. However, the adoption of climate-smart agricultural

(CSA) practices in Ethiopia remains low (Jirata, *et al*., 2016; Berhe *et al*., 2017; Zerssa *et al*., 2021; Alemayehu *et al*., 2024). Therefore, it is crucial to analyze the determinants of CSA adoption using two waves of nationally representative panel data to fully understand both the adoption levels and the factors influencing the uptake of these practices (Berhe *et al*., 2017; Sileshi *et al*., 2019; Alemayehu *et al*., 2024; Tariku and Kebede, 2024).

Several studies assess the determinants of CSA practices in Ethiopia and other Sub-Sahara African countries (Belay *et al*., 2017; Berhe *et al*., 2017; Amare and Simane, 2018; Asrat and Simane, 2018; Dinku *et al*., 2019; Sileshi *et al*., 2019; Kurgat *et al*., 2020; Marie *et al*., 2020; Demissie *et al*., 2021; Kudama, 2021; Lungu, 2021; Diro *et al*., 2022; Negera *et al*., 2022; Mume *et al*., 2023; Sisay *et al*., 2023; Alemayehu *et al*., 2024; Geda *et al*., 2024; Masha *et al*., 2024; Lankamo *et al*., 2025). These studies have primarily focused on identifying factors that influence adaptive capacity, considering economic, social, institutional, and technological conditions that constrain the implementation of adaptive strategies at both macro and micro levels. While these studies provide valuable insights for policy development, they also have notable limitations that suggest areas for further research. Most prior studies examined specific climate-smart agricultural (CSA) practices in isolation or treated different practices as independent, often assuming that the adoption of CSA measures is mutually exclusive, with little consideration of interdependencies among practices. However, in reality, farmers often adopt multiple CSA practices simultaneously, and different factors may influence each practice differently (Diro *et al*., 2022; Alemayehu *et al*., 2024; Geda *et al*., 2024). These studies generally overlooked the potential interdependencies between practices, even though the adoption of CSA practices represents interdependent household decisions that should ideally be analyzed simultaneously. Moreover, most past research has focused on specific geographic areas or agro-ecological zones and suffer from reliance on cross-sectional data, limiting the ability to capture temporal dynamics and broader national patterns in CSA adoption. Consequently, these studies may not fully reflect regional variability or changes in farmers' behavior over time.

The present research aims to bridge this gap in the literature by examining the determinants of climate-smart agriculture (CSA) adoption among farm households in Ethiopia. It focuses on three major categories of CSA practices: soil and water conservation, agronomic practices, and livelihood diversification. To achieve this, the study uses the two most recent waves (2018/19 and 2021/22) of nationally representative Living Standards Measurement Study (LSMS) panel data, which cover all regions and agro-ecological zones, enabling both spatial and temporal analysis. Beyond identifying determinants, the study also explores the interdependencies among different CSA practices by applying a multivariate probit (MVP) model. The findings are expected to provide a comprehensive national-level picture of CSA adoption dynamics over time, offering vital evidence to help policymakers design and strengthen strategies that encourage wider adoption, which in turn improves productivity, food security and livelihoods, and environmental sustainabili**ty.**

The findings of the study must be contextualized within its scope and limitations. Primarily, the short temporal span of the panel data limits our ability to observe long-term trends, potentially affecting the generalizability of the results beyond the observed period. Furthermore, the sample size, while adequate for initial exploration, restricts the statistical power for more complex subgroup analyses. These limitations present clear pathways for future research. Subsequent studies would benefit from employing a longer panel to validate and extend our findings over time. Furthermore, a mixed-methods approach, incorporating qualitative interviews, could be deployed to triangulate these quantitative results and provide deeper insight into the underlying mechanisms observed.

2. Methodology

2.1. Description of the Study Area

This study utilizes two rounds of data from the Living Standards Measurement Study (LSMS) Ethiopia Socioeconomic Survey (ESS), which was collected from all regions of the country. Ethiopia, with a population exceeding 109.5 million (ESS, 2025), is the second most populous nation in Africa, next to Nigeria. Agriculture remains a cornerstone of the Ethiopian economy, contributing more than 30% to the GDP (World Bank, 2022). Smallholder farmers constitute the backbone of this sector, comprising 95% of agricultural producers and providing employment to over 85% of the workforce (CSA, 2021). Agriculture drives a substantial portion of Ethiopia's export revenue, primarily from key commodities like coffee and livestock (World Bank, 2022). While the country possesses substantial arable land, only about 20% is currently cultivated (CSA, 2021). Moreover, rapid deforestation over the past three decades has significantly reduced forest cover, with only 10–15% of the land area now covered by forests (CSA, 2021).

Ethiopia's agro-ecology is divided into three main agro-ecological zones. The Dega zone, located at an altitude above 2,600 meters, experiences temperatures ranging from near freezing to 16°C. The Woinadega zone, found between 1,500 and 2,500 meters, is home to over 90% of the country's population, with temperatures ranging from 16°C to 30°C. Lastly, the Kolla zone, which includes both tropical and arid areas, has higher temperatures, ranging from 27°C to 50°C (World Bank, 2022). Beyond these broad categories, Ethiopia's agro-ecology is further classified into more specific sub-zones: tropic-warm/arid, tropic-warm/semiarid, tropic-warm/subhumid, tropic-cool/arid, tropic-cool/semiarid, tropic-cool/subhumid, and tropic-cool/humid.

2.2. Type and Source of Data

The study employed secondary data from the Living Standards Measurement Study Integrated Surveys on Agriculture (LSMS-ISA) initiative of the World Bank, conducted in collaboration with the Ethiopian Statistical Service (ESS), formerly the Central Statistical Authority (CSA). For this research, two survey waves were used: the fourth wave (ESS4), the 2018/19 Ethiopian Socioeconomic Survey, and the fifth wave (ESS5), the 2021/22 Ethiopian Socioeconomic Panel Survey. ESS4 covered all nine regional states and the two chartered cities, Addis Ababa and Dire Dawa, and was conducted in 565 enumeration areas (EAs), of which 346 were rural and 219 were urban. ESS5, however, excluded Tigray due to the security situation and conflict in the region at the time of data collection. This wave interviewed households from 438 enumeration areas, providing nationally representative estimates for both rural and urban areas. For the purposes of this research, the analysis focused exclusively on rural households. The datasets provide detailed information on household welfare, agriculture, and socioeconomic characteristics, including land use, crop and livestock production, input use, consumption, prices, labor, and household demographics.

2.3. Sampling and Sample Size

The survey employed a two-stage stratified probability sampling method. In rural areas, the enumeration areas (EAs) were selected as a subsample from the Agricultural Sample Survey (AgSS) EA sample. This process involved the first stage of sampling, where EAs were randomly chosen using simple random sampling (SRS) from the 2018 AgSS enumeration areas. For urban areas, the first stage of sampling involved selecting EAs directly from the urban frame within each region using systematic probability proportional to size (PPS) sampling. This approach ensures that the urban sample is proportionally allocated by zone within each region.

In the second stage of sampling, households are selected using systematic random sampling. In rural EAs, 10 agricultural households and 2 non-agricultural households are chosen, with non-agricultural households selected similarly. If fewer than 2 non-agricultural households exist, the total number of agricultural households remains 10. In urban areas, 15 households are selected per EA, irrespective of economic activity, using systematic random sampling. ESS5 retained most of the ESS4 samples, excluding those from Tigray and a few other locations. In ESS4, 6,894 households from 541 EAs were interviewed, but due to security issues, only 4,999 households from 438 EAs were surveyed in ESS5. However, since the core objective of the present research is to investigate the adoption patterns of CSA practices among smallholder farmers, the analysis excludes the urban sample. Therefore, this study concentrates solely on rural areas, drawing on approximately 3,183 rural households consistently surveyed across both waves. Since the survey of ESS5 does not include data for the Tigray region due to security problems, the data for that region is excluded from both waves (ESS4 and ESS5) in the current study to make the data appropriate for analysis and maintain consistency. The exclusion of Tigray introduces a potential source of regional selection bias and limits the generalizability of the findings. However, the results are more representative of the other regions of Ethiopia and should be interpreted with this data limitation in mind. Table 1 presents the sample distribution across regions.

Table 1: Sampling distribution across regions of Ethiopia

Region	Number Households		Total
	ESS4 (2018/19)	ESS5 (2021/22)	
Afar	246	100	346
Amhara	280	213	493
Oromia	304	235	539
Somali	276	242	518
Benishangul Gumuz	119	56	175
SNNPR	249	245	494
Gambela	249	245	494
Harari	139	128	267
Dire Dawa	57	52	109
Total	1,796	1,387	3,183

Source: Authors' calculation from ESS4 (2018/19) and ESS5 (2021/22).

2.4. Method of Data Analysis

Random utility theory offers a methodology for studying the choices of individuals, firms, and organizations. It deals with value, worth, satisfaction, and allied judgmental and preference notions (Fishburn, 1968). Choice-making, according to this theory, adheres to the utility maximization rule, in which the best option is that which provides the maximum amount of utility to the choice-maker. In this case, the decision-maker is the smallholder farmer who decides how much of each of the available options of climate change adaptation to utilize in order to maximize their total level of overall utility in terms of income, prices, and other determining factors.

The random utility model describes the decision process in which the individual *(i)* selects an alternative *(j)* from a choice set. The theory is based on the principle that an individual gains utility by choosing among several alternatives (Waibel *et al.*, 2018; Deffersha *et al.*, 2024). A representative farm household will, therefore, implement a measure if the expected gains outweigh those of inaction. However, the utility received from such strategies of adaptation cannot be directly observed and is inferred from the adaptation decision made by the farmer.

Let us depict the disparity of the utility or gain achieved because of accommodating climate change (U_A) compared to the utility or net benefit of not adapting (U_N). The linear random utility model is given by:

$$U_A = {\alpha_A}' Z_i + \varepsilon_A \quad \textbf{(1)}$$

$$U_N = {\alpha_N}' Z_i + \varepsilon_N \quad \textbf{(2)}$$

In this model Z_i represents a set of covariates that affect the perceived benefits of adaptation, ${\alpha_A}'$ and ${\alpha_N}'$ are vectors of parameter estimates for selecting alternative strategy and for not adapting respectively. Additionally, ε_A and ε_N are error terms assumed to be independent and identically distributed. The correlation of error terms between the adaptation equations whether correlated or not guides the kind of qualitative choice model to be implemented in the study. Therefore, households will choose to adopt climate-smart agricultural practices if:

$$A^* = E(U_{iA}) - E(U_{iN}) > 0 \quad \textbf{(3)}$$

Where $E(U_{iA})$ and $E(U_{iN})$ are the estimated utilities of adopting an alternative choice and not adopting, respectively.

This research uses a mixed-methods approach to analyze data on climate-smart agricultural practices (CSA). Descriptive statistics are utilized to characterize and present the prevalence of CSA among farmers. This includes summarizing key variables such as mean, median, and standard deviation. To investigate the determinants of adoption behavior among farmers, a multilevel mixed-effects multivariate probit model is applied. The econometric model is further detailed in the subsequent sections.

The multivariate probit model allows for the possibility of correlation among different climate-smart agricultural practices, assuming that there is covariance in the adoption of these practices. If the correlation in adoption is ignored and the equations are estimated independently, it would lead to biased and inconsistent standard error estimates, resulting in incorrect inferences (Greene, 2003). The model estimates multiple probit equations for M-adaptation practices, which can be analyzed using the full information maximum likelihood (FIML) method. For observation i and equation m, the multivariate probit model is expressed as:

$$y_{im}^{*} = \beta_m x_{im}^{*} + \varepsilon_{im} \qquad \textbf{(4)}$$

$$y_{im} = \pi(y_{im}^{*} > \tau_m) \qquad \textbf{(5)}$$

Where $i=1,2,..,n$ denoting household and ($m= 1,2,.., M$) representing different CSA practices. The outcome variable $y_{im} = 1$ *if* $y_{im} > \tau_m$ and 0 otherwise, where x_{im} is vector of explanatory variables that influence the level of CSA practice. For each i, there are diverse CSA practices. The parameter β_m represents the coefficients to be predicted where τ_m is the cut-off point of the m^{th} alternative practice, and ε_{im} are the error terms. The error term, ε_{im} incorporates an unobserved effect α_{im} which can be expressed as $\varepsilon_{im} = \alpha_{im} + \eta_{im}$. Here η_{im} is an error term, which follows a multivariate normal distribution with a conditional mean value of zero and variance covariance matrix.

The mixed effect multilevel multivariate probit model for the purpose of this study is specified as follows. For a household i in region j, and for outcome m (where $m = 1, ..., M$), the latent variable is given as:

$$Y^*_{ijm} = X^T_{ijm}\beta_m + Z^{(2)T}_{ijm} b^m_j + \epsilon_{ijm} \tag{6}$$

Where Y^*_{ijm} is latent propensity for outcome m; XT_{ijm} is fixed effect covariates for outcome m; βm is fixed effect coefficients for outcome m; $Z^{(2)T}{}_{ijm}$ is region level random effect covariates; b_j^m is random effects coefficient and ϵ_{ijm} is the error vector. Region level random effects: $b_j^m \sim MVN(0, \Psi^{(2)})$, where $\Psi^{(2)}$ is a covariance matrix that captures the variances and covariances of the region level random effects across the *k* outcomes. The error vector across the k outcomes is given as:

$$\epsilon_{ijm} = \left(\epsilon_{ijm1}, \cdots, \epsilon_{ijM}\right) \sim MVN(0, \Sigma) \tag{7}$$

Where **Σ** is a correlation matrix (with 1's on the diagonal) because we are using the probit link. The random error terms follow a multivariate normal distribution with a mean of zero and unit variance. The components of covariance matrix which are not on diagonal, as outlined in Equation (8), capture the correlation (unobserved) between the error terms associated with different CSA adoption practices.

$$\begin{matrix} \varepsilon_{1i} \\ \varepsilon_{2i} \\ \varepsilon_{3i} \end{matrix} \approx N\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}\begin{pmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{21} & 1 & \rho_{23} \\ \rho_{31} & \rho_{32} & 1 \end{pmatrix}\right] \tag{8}$$

When the off-diagonal components of the covariance matrix take nonzero values, indicating correlations among the error terms, the appropriateness of the MVP model is confirmed over univariate Probit models. In this study, the off-diagonal elements were nonzero, implying that the dependent variables are interdependent. Various socioeconomic, institutional, and biophysical variables are included in the model as independent variables.

The observed binary outcome Y_{ijm} is:

$$Y_{ijm} = \begin{cases} 1 \; if \; Y_{ijm} > 0 \\ 0 \;\; otherwise \end{cases} \tag{9}$$

The likelihood for the multilevel multivariate probit model is complex because it involves integrating over the random effects at each level. The marginal likelihood for the observed data is:

$$L(\beta, \Sigma, \Psi^{(2)}) = \prod_{m=1}^{M} \int \left[\prod_{j=1}^{J} \int \left[\prod_{i=1}^{N_j} P(Y_{ijm} = y_{ijm} \mid b_{jm} \right] \phi(b_{jm}; 0, \Psi^{(2)}) db_{jm} \right] \quad \textbf{(10)}$$

Where M is the number of alterative CSA adoption practices; J is the number of regions; N is the number of households in region j; $Y_{ijm}=(Y_{ijm},\ldots,Y_{ijM})^T$ is the vector of observed binary outcomes for households; $P(Y_{ijm} = y_{ijm}/b_{jm})$ is the conditional probability of the observed outcomes given the random effects, which is a multivariate normal cumulative distribution function (CDF) with mean vector given by the linear predictor and correlation matrix Σ. The description of all variables in the model with their expected signs is presented in Table IV (Annexed).

In this study, climate-smart agriculture (CSA) practices are categorized into three broad groups: soil and water conservation (SWC), agronomic practices (AP), and livelihood diversification (LHD). Each category encompasses a range of specific techniques and strategies that farm households adopt to enhance productivity, build resilience to climate change, and sustain their livelihoods.

According to the World Bank (2010), soil and water conservation (SWC) practices encompass a range of measures aimed at preserving soil fertility and promoting efficient water use. Farm households adopt practices such as irrigation, the application of organic fertilizers (e.g., compost and manure), watershed management, mulching, and minimum tillage (CSA, 2020). Farmers often implement a combination of two or more SWC practices, recognizing that their integrated use enhances soil moisture retention and reduces erosion.

Agronomic practices (AP) refer to crop management and cultivation techniques designed to improve agricultural productivity and resilience (CSA, 2020). These practices include crop rotation to maintain soil health, crop diversification to reduce risks associated with monocropping, the planting of leguminous crops to enhance soil nitrogen content, and the use of improved seed varieties that are more resistant to pests and adverse climatic conditions (CSA, 2020).

Livelihood diversification (LHD) is another critical strategy that farm households use to mitigate the impacts of climate change (World Bank, 2010). Engaging in non-farm income-generating activities reduces households' dependence on agricultural income, thereby enhancing economic stability. This strategy not only serves as a coping mechanism during periods of agricultural downturns but also provides additional resources that can be reinvested in farm activities, further promoting the adoption of CSA practices.

3. Result and Discussion

3.1. Descriptive Statistics

Before directly diving into the econometric results, it is essential to provide general insight into the nature of the data and the distribution of key variables used in the analysis. Hence, in this section, descriptions and summary statistics of key variables, and a comparison of socioeconomic and demographic characteristics of adopters and non-adopters are extensively discussed.

3.1.1. Description of key variables

Key socioeconomic, demographic, institutional, and community-level variables are rigorously examined within a panel data framework to gain a comprehensive understanding of the data's underlying structure. Examining the distribution, mean, standard deviation, and other properties of these variables is instrumental in revealing patterns and variations both within individual units and across different units over time. Such an approach not only highlights the inherent variability but also strengthens the robustness and credibility of the study's findings by providing a solid empirical foundation for further analysis. This scrutiny ensures that any observable trends or relationships are well-grounded in the data's characteristics.

The summary statistics for the continuous and categorical variables used in the analysis are presented in Table II and III (Annexed). These tables summarize the overall distribution and variation of the variables across all observations, both between and within households over the survey periods. The results show notable differences between households in total income, TLU, and land size, indicating a high degree of heterogeneity in economic characteristics, resources, and access to services. Within-household variation is generally smaller than between-household variation, suggesting that most changes occur between households rather than within households over time. Exceptions include variables such as non-farm income and livestock holdings, which fluctuate more. Binary and categorical variables such as female-headed household, access to credit, adoption of SWC, AP, LHD, marital status, agro-ecology, drought, flood, and mobile ownership tend to be more stable over time for individual households.

For instance, the large standard deviation of total income between individuals, amounting to 331,156.8 ETB, indicates substantial variation across individuals and, likewise, within households. For the majority of variables, the household-level differences are larger than the over-time variations. This implies that household characteristics hardly change over time. This is because some variables are stable by nature over time, such as sex, agro-ecology, and distance to market. The other reason is that the period considered is relatively short, so households may not exhibit significant change over this period.

The output of the two-sample t-test (Table 2) shows a comparison of the means of independent variables between adopters and non-adopters of climate-smart agriculture (CSA) practices. There is a statistically significant mean difference between adopters and non-adopters for several variables, including sex, total income, family size, age, distance to market, drought, land size, access to extension services, non-farm income, access to credit, agro-ecology, and slope.

The two-sample t-test also further illuminates patterns of CSA adoption. For instance, family size shows a positive association with adoption, with adopters having slightly larger households on average (5.51 vs. 5.30), which may reflect greater labor availability for labor-intensive CSA practices. Age also differs modestly between adopters and non-adopters (45.16 vs. 44.33 years), suggesting that slightly older household heads are more likely to adopt, possibly due to greater experience or accumulated knowledge in farming.

Education levels, while not significantly different, remain an important variable to consider, as adopters and non-adopters have similar mean schooling years (6.95 vs. 7.17). This indicates that formal education may not be the key driver of CSA adoption in this context, highlighting the potential importance of practical knowledge and access to extension services. In fact, access to extension services shows a significant difference, with 57.6% of adopters receiving support compared to only 7.5% of non-adopters, demonstrating that access to technical knowledge is key to scaling climate-smart agriculture.

The local environment and geography play a big role in shaping how one household's situation differs from another's. Adopters are generally closer to markets (61.4 km vs. 98.0 km), which may reduce transaction costs for inputs and output sales. Exposure to drought is significantly lower among adopters (11.4% vs. 29.2%), while slope is higher (15.15% vs. 8.85%), suggesting that households in more marginal or erosion-prone areas may be more encouraged to adopt CSA practices to mitigate environmental risks. Agro-ecological differences are also pronounced, with adopters more likely to reside in Kolla, Weina Dega, or Dega zones, reflecting the role of local environmental conditions in shaping the feasibility and benefits of CSA interventions.

Table 2: T-test for Mean Difference between Adopters and Non-adopters

Variables	Adopters	Non-adopters	Mean Difference
Female headed	0.177	0.354	-0.175***
	(0.008)	(0.010)	(0.014)
Family size	5.506	5.301	0.205**
	(0.055)	(0.06)	(0.083)
Total income	266081	179209	86872***
	(1013)	(699)	(122)
Education	6.954	7.171	-0.216
	(0.258)	(0.241)	(0.353)
Age	45.16	44.33	0.832 *
	(0.320)	(0.322)	(0.454)
Dist. Market	61.4	98.01	-36.604***
	(1.271)	(2.078)	(2.459)
Drought	0.114	0.292	-0.178 ***
	(0.007)	(0.010)	(0.012)
Flood	0.027	0.030	-0.004
	(0.003)	(0.003)	(0.005)
Mobile owned	0.465	0.486	-0.021
	(0.012)	(0.011)	(0.016)
Land size	0.958	0.244	0.714***
	(0.026)	(0.044)	(0.051)
Extension	0.576	0.075	0.501***
	(0.011)	(0.006)	(0.01)
TLU	2.398	4.685	-2.288
	(0.068)	(0.171)	(0.187)
Nonfarm income	9446	17310	-7864***
	(1607)	(1824)	(2438)
Credit use	0.753	0.936	-0.183 ***
	(0.0101)	(0.0056)	(0.011)
Kolla	0.095	0.058	0.064***
	(0.013)	(0.004)	(0.011)
Weina Dega	0.326	0.211	0.308***
	(0.009)	(0.018)	(0.008)
Dega	0.131	0.053	0.077***
	(0.006)	(0.01)	(0.016)
Slope	15.15	8.849	6.302***
	(0.220)	(0.212)	(0.305)

Note: *the asterisks *, ** and *** denotes 10%, 5% and 1% level of significance, respectively; Standard errors in parenthesis.*

NB.: *Figures are rounded to three decimal places in all tables, and the results shall be understood with this caveat in mind*

Source: Authors computation, 2024

Livelihood and resource variables provide further insights. Total income and land size are substantially higher among adopters, reinforcing the role of resource endowments in enabling adoption. Interestingly, non-farm income is higher among non-adopters (17,310 ETB vs. 9,446 ETB), suggesting that households relying on off-farm income may have lower incentives to invest in CSA. Livestock holdings, measured in TLU, are higher among non-adopters (4.685 vs. 2.398), indicating that resource allocation toward livestock may compete with the adoption of crop-based CSA practices. Mobile phone ownership and access to credit also differ between groups, reflecting the importance of information access and financial resources in supporting adoption decisions.

3.1.2. The adoption of climate-smart agriculture (CSA)

The adoption of CSA practices among rural households in Ethiopia shows notable variation across practice types and over time. Table 3 presents the categories of CSA practices and the adoption rates by the sampled farm households. In 2018/19, approximately 16 percent of the households adopted SWC practices, which increased slightly to 19 percent in 2021/22. The overall adoption rate for SWC is around 17.5 percent, slightly higher than that of AP, but lower than LHD. The average adoption rate for AP stands at 6.7 percent, with rates of 7 percent and 5 percent in 2018/19 and 2021/22, respectively. The adoption of livelihood diversification decreased from 31.5 percent to 30.8 percent over those years.

Table 3: Categories of CSA practices

CSA practices	Description	Frequency by percentage		
		2018/19 (n=1,796)	2021/22 (n=1,387)	Total (N=3,183)
SWC	Soil and water practices	16.26	19.32	17.59
AP	Agronomic practices	7.18	5.98	6.66
LHD	Livelihood diversification	31.57	30.86	31.26

Source: Authors' own estimate, 2024

Generally, these figures indicate a slight increase in the adoption of SWC over the two years, while the adoption of agronomic practices and livelihood diversification has declined slightly. The moderate adoption levels across all CSA practices suggest that, while farmers recognize their benefits, several barriers continue to hinder wider adoption. Therefore, it is crucial to identify the factors that facilitate or constrain the adoption of CSA practices. Understanding these determinants can help design interventions that promote the simultaneous adoption of multiple CSA practices, ultimately contributing to more resilient and sustainable agricultural systems. The next section presents the determinants of CSA practices among rural households in Ethiopia.

3.1.3. CSA adoption rate across regions

Ethiopia is one of the countries hit hardest by climate change. Because its economy relies so heavily on rain-fed agriculture and other weather-dependent sectors, even small shifts in climate can have outsized consequences, especially for communities already grappling with poverty and limited resources. Household vulnerability to climate change is mainly related to the occurrence of drought, lack of infrastructure facilities, and weak institutional support, including financial sectors (Gemeda et al., 2023). This study revealed that there is a significant disparity in climate change vulnerability across different regions. In line with studies by Deressa et al. (2008) and Gemeda et al. (2023), Afar, Somali, Oromia, and Tigray are identified as being at significantly higher risk, while the SNNP region exhibits notably lower vulnerability. This is strongly associated with the comparative advantages of the region: greater access to technology and markets, a higher potential for irrigation, and a more educated population with a higher literacy rate (Deressa et al., 2008). The evidence found from the current study on the adoption rate of CSA practices among the regional states indicates that the most vulnerable regions still have the lowest uptake of CSA practices (Figure 1).

The regions with the lowest adoption indices—Somali, Afar, and Gambela—are also among the most vulnerable to climate change. They are predominantly lowland areas characterized by arid and semi-arid climates, where livelihoods are highly reliant on pastoralism and rain-fed agriculture. These regions face existential threats from increased temperature, recurrent and severe droughts, and erratic rainfall, which decimate pasture and water resources. The extremely low adoption score (6.37) in the Somali region reflects a near-total disconnect from CSA practices. This is not due to a lack of need but immense structural barriers: limited government and NGO extension services, deep-seated poverty that prevents investment in new technologies, mobile pastoralist communities that are hard to reach, and a justifiable risk-aversion where failed experiments can mean starvation. Their vulnerability is heightened because they lack the tools to adapt.

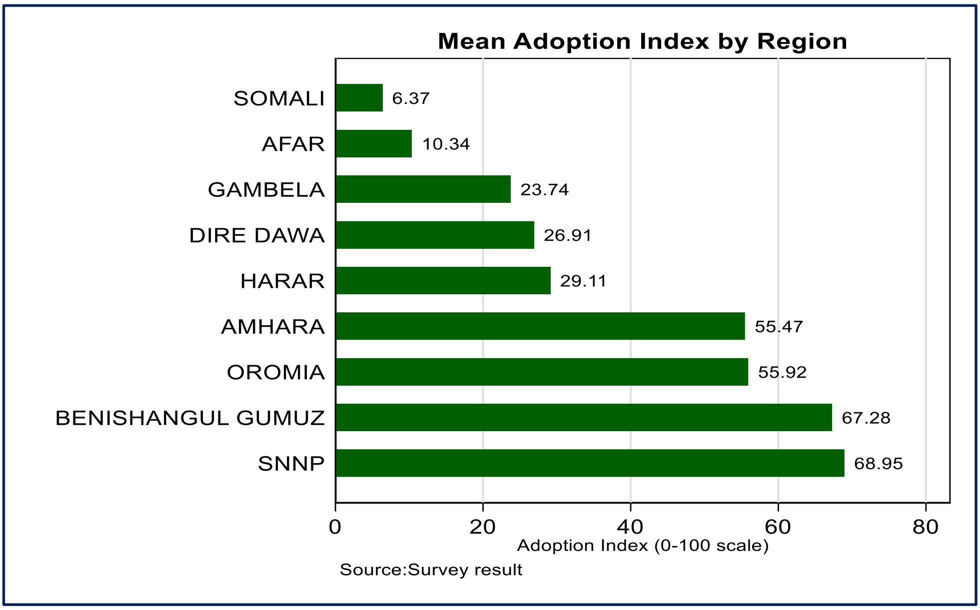

Figure 1: Average Adoption Index by Region

Source: Authors' own estimate, 2024

Conversely, the highland regions with higher adoption scores—Amhara, Oromia, SNNP, and Benishangul-Gumuz—face different but still severe climate threats, primarily land degradation, rainfall variability, and soil erosion. Their relatively higher adoption rates (55–69%) can be attributed to better infrastructure, higher population density, more established agricultural extension systems, and projects promoting practices like soil conservation, compost, and improved seeds. However, even a score of 69% indicates that adoption is far from its potential, with significant room for improvement. The challenge here is not just adoption but sustained adoption and the scaling up of practices to effectively counteract intensifying climate pressures. The data suggests that while these regions have a stronger foundation for building resilience, current adoption levels are still insufficient to fully mitigate their vulnerability, indicating a nationwide struggle against the pervasive barriers of limited resources, knowledge transfer, and access to credit that hinder widespread CSA uptake.

3.2. Factors Affecting the Adoption of Climate-Smart Agricultural Practices

Factors influencing the uptake of CSA practices among farmers were assessed using a multilevel mixed-effect multivariate probit model, which accommodates the analysis of more than two alternative practices along with the interdependency among different alternative climate-smart agricultural practices. This model is a type of mixed-effects model that comprises fixed effects and random effects. Moreover, the model allows multilevel analysis so that CSA adoption at the household level and regional level is undertaken in the current research. To estimate the model, the CMP (conditional mixed process) package of Stata software was used. Prior to estimating the model, explanatory variables were tested for multicollinearity problems using the Variance Inflation Factor (VIF) and found no significant collinearity that affected the estimate of the model (Table IV in Annex). Robust standard errors are used to account for any heteroscedasticity problem. The likelihood ratio test for the null hypothesis of independence between CSA practices is significant *($\chi2$ (36) = 593.29, p-value = 0.0000 < 0.01)*, suggesting that the use of multiple CSA practices is interdependent rather than mutually exclusive. Therefore, the null hypothesis (H0), which postulates that all correlation coefficients (ρ) are jointly equal to zero, is rejected, indicating that the model fits well and supports the appropriateness of the MVP modeling approach.

The model incorporated a range of demographic, economic, institutional, climatic, and geophysical factors that potentially influence farmers' decisions to adopt CSA practices. The results, presented in Table 4, indicate that variables such as sex, age, education, family size, land size, TLU, mobile ownership, access to extension services, drought, agroecology, and slope significantly affect the adoption of at least one of the practices.

The sex of the household head (FHH) has a significant and negative effect on SWC and AP but a positive effect on LHD. This means that being in a female-headed household decreases the likelihood of adopting SWC and AP, respectively. The reason for this is that female-headed households are often constrained by resources and have limited access to services and information, which leads to a lower capacity to adopt climate-smart agricultural practices. Conversely, being in a female household increases the likelihood of adopting LHD because most female-headed households tend to diversify their income rather than exclusively practice farming activities. This finding is consistent with researchers Amare and Simane (2018), Asrat and Simane (2018), and Waibel *et* al. (2018).

The results also indicate that households with more members are more likely to practice SWC than households with fewer members, whereas the relationship is inverse for LHD. In general, larger households tend to adopt more CSA practices overall (Chavula *et* al., 2023). This can be attributed to the greater availability of family labor, which serves as an important resource for implementing labor-demanding CSA practices such as terracing, bund construction, mulching, and irrigation management (Ali and Erenstein, 2016; Abrham *et* al., 2017). In contrast, farmers often struggle with limited labor, which can make it harder to take on labor-demanding practices. As a result, these households may turn to non-farm sources of income, helping to explain the negative link with adopting livelihood diversification strategies. Ultimately, this shows just how important household labor availability is in shaping whether farmers can embrace practices that demand more hands-on work.

Table 4: Average Marginal Effect from Mixed Effect Multivariate Probit Model

Independent Variables	SWC	AP	LHD
Female headed hh	-0.337 *** (0.068)	-0.362 *** (0.076)	0.222*** (0.063)
Total income	0.015 (0.012)	0.0141 (0.013)	0.019 (0.012)
Family size	0.134 *** (0.031)	0.054 (0.035)	-0.091*** (0.03)
Education	0.092*** (0.027)	0.098 *** (0.031)	0.098 *** (0.027)
Age	-0.077 *** (0.027)	-0.006 (0.029)	0.036 (0.026)
Distance to market	-0.039 (0.042)	-0.123** (0.052)	0.032 (0.039)
Drought	0.153 * (0.089)	0.166 (0.104)	0.142** (0.081)
Mobile ownership	0.133 ** (0.059)	0.121* (0.064)	0.144*** (0.056)
Land size	0.241 *** (0.049)	0.388 *** (0.046)	-0.431*** (0.057)
Extension service	0.772*** (0.063)	0.682*** (0.063)	0.552*** (0.064)
TLU	-0.008 (0.007)	-0.023* (0.012)	0.013** (0.006)
Slope	0.007 ** (0.004)	0.000 (0.003)	-0.006* (0.003)
_Iagro_ecol_3 (Kolla)	-0.4227 * (0.239)	0.364 (0.403)	-0.035 (0.234)
_Iagro_ecol_6 (Weina Dega)	0.217 (0.2)	0.9189** (0.380)	0.415** (0.188)
_Iagro_ecol_7 (Dega)	0.289 (0.22)	0.816** (0.397)	0.364* (0.213)

*Note: the asterisks *, ** and *** denotes 10%, 5% and 1% level of significance, respectively; Standard errors in parenthesis*

Source: Authors' own estimate, 2024

Among the different factors considered in the study, the education level of the household head, measured simply by years of schooling, turned out to have a statistically significant effect. This aligns with earlier work by Ayenew and Tilahun (2022) and Diro et al. (2022), who found that more educated households are often better equipped with knowledge and access to information, making them more open to trying new methods and innovations in response to climate change. On the other hand, the age of the household head had a negative effect on the adoption of soil and water conservation practices, suggesting that older farmers are less inclined to take up these climate-smart measures (Diro et al., 2022). This could be because older farmers tend to be more cautious, less interested in adopting unfamiliar techniques, or simply face physical limitations when it comes to labor-intensive practices like building terraces, constructing bunds, or applying mulch.

Land size had a clear positive effect on the adoption of climate-smart agricultural practices. This lines up with what Diro et al. (2022) and Ayenew and Tilahun (2022) found: that farmers with more land are more likely to adopt these practices, simply because land is a key resource that makes it feasible to invest in soil and water conservation, agronomic practices, and other interventions that require space and effort. Interestingly, though, the picture changes when it comes to livelihood diversification strategies. In that case, larger landholdings were linked to lower adoption rates. A likely explanation is that farmers with more land tend to pour their labor and resources into farming itself, leaving less time and energy for non-farm income-generating activities, which lowers their chances of taking up LHD strategies.

Access to extension services turned out to have a strong and highly significant positive influence on the adoption of climate-smart practices, a result consistent with the findings of Amare and Simane (2018) and Ojo and Baiyegunhi (2019). Households that receive extension support are more inclined to adopt SWC, AP, and LHD strategies, largely due to the technical guidance, training, and practical demonstrations provided through such services.

Furthermore, mobile phone ownership was positively associated with CSA adoption, as mobile technology enhances access to timely information regarding climatic conditions, adaptation strategies, and market opportunities. This finding underscores the critical role of information access in facilitating the uptake of climate-smart agricultural practices.

Distance to markets also emerged as a significant barrier to the adoption of CSA. Greater distances from markets increase the cost of transporting agricultural inputs, thereby raising overall production costs and discouraging farmers from implementing these practices. This finding is consistent with Alemayehu et al. (2024), who underscored the importance of market accessibility in facilitating the adoption of climate-smart agriculture. The results further reveal that livestock ownership, measured in tropical livestock units (TLU), exerts a differentiated influence on the adoption of various CSA practices. Specifically, larger livestock holdings were negatively associated with the adoption of SWC and AP, while showing a positive relationship with LHD strategies (Diro et al., 2022; Chavula et al., 2023; Alemayehu et al., 2024). This pattern likely reflects the tendency of households with larger herds to prioritize labor and resources toward livestock management over crop production. As a result, they may be less inclined to engage in crop-focused CSA practices, while simultaneously pursuing diversification into livestock-related or other non-farm income sources.

Empirical evidence suggests that farmers with prior exposure to climate-related shocks tend to adopt more adaptive strategies in response (Amare and Simane, 2018; Waibel et al., 2018; Pandey et al., 2019). Consistent with these observations, the findings of the current study reveal a positive and statistically significant coefficient for drought, indicating that households affected by this climatic shock are more inclined to adopt climate-smart agricultural (CSA) practices than those who have not experienced drought. This pattern may be attributed to the heightened awareness among drought-affected households of the risks associated with climate variability, having already endured production and income losses. Consequently, they face stronger incentives to adopt practices that enhance resilience. Practices such as soil and water conservation, crop diversification, and improved agronomic techniques help reduce vulnerability to erratic rainfall and contribute to safeguarding household food security.

The positive association between drought exposure and the adoption of climate-smart agricultural practices can thus be interpreted as both a reactive and a proactive form of adaptation. Having directly experienced the adverse effects of climatic shocks, these farmers are more motivated to modify their practices in order to protect their livelihoods. In contrast, those who have not yet faced such events may underestimate the risks associated with climate variability and continue relying on traditional methods. This finding implies efforts to promote CSA adoption could be made more effective by integrating climate risk awareness campaigns and experiential learning opportunities. Such approaches could help farmers who have not yet experienced shocks recognize the potential benefits of adopting resilient practices before they are severely affected.

The slope of the farmland was found to have a positive and statistically significant effect on the adoption of soil and water conservation (SWC) and agronomic practices (AP). This can be attributed to the greater vulnerability of sloping lands to erosion and land degradation, which compels farmers to adopt climate-smart agricultural practices that address these specific biophysical constraints. This interpretation is supported by Alemayehu et al. (2024), who identified slope as a critical determinant of CSA adoption, noting that households cultivating steeper plots face stronger incentives to implement measures that protect against soil erosion and productivity decline. As a result, steeper slopes were associated with a higher likelihood of adopting practices such as soil bunds, terraces, and other conservation structures.

The agro-ecology variable, specified as a categorical variable comprising seven distinct zones, further underscores the importance of environmental and ecological context in shaping the adoption of climate-smart agricultural practices. Although the coefficients for some agro-ecological zones did not achieve statistical significance, the results indicate that households situated in the Tropic-warm/subhumid (Moist Kolla), Tropic-cool/subhumid (Weina Dega), and Tropic-cool/humid (Dega) zones were more likely to adopt practices such as agronomic practices (AP) and livelihood diversification (LHD). This pattern suggests that households in relatively favorable agro-ecologies characterized by more reliable rainfall and cultivable land are more inclined to adopt CSA practices compared to those in more marginal environments. These findings are consistent with earlier studies by Teklewold et al. (2019) and Bryan et al. (2013), which similarly highlight that agro-ecological conditions influence both the feasibility and the perceived benefits associated with adopting climate-smart practices. In contrast, the nomadic or semi-nomadic nature of pastoralism in warm/arid (Kolla) agro-ecologies limits the adoption of CSA practices. Pastoralist households are more mobile and less engaged in settled crop production, making the implementation of practices such as SWC and AP less compatible with their production system. This finding resonates with Amare and Simane (2018), who emphasized that CSA adoption is highly context-specific and may face structural constraints in pastoral systems due to mobility, limited access to extension, and reduced incentives for long-term land-based investments.

The findings point to the need for slope- and agro-ecology-specific interventions to promote the adoption of climate-smart agricultural practices. In areas characterized by steep slopes, policy efforts should prioritize erosion control measures such as terrace construction, watershed management, and targeted incentives for soil and water conservation investments. In more humid and subhumid agro-ecologies, extension services could place greater emphasis on diversified practices such as crop–livestock integration and agroforestry, which are particularly well-suited to these environments. For arid pastoralist systems, a different approach is warranted that aligns with the mobility and livelihood patterns of pastoral communities. This might include promoting drought-resilient livestock breeds, supporting rangeland management, and delivering extension services through mobile- or community-based platforms. Taken together, these findings underscore the importance of differentiated strategies that are responsive to both topographical and agro-ecological contexts, which are essential for enhancing CSA adoption and building resilience across diverse farming systems.

Table 5 presents the estimated correlation coefficients between the error terms of three different adoption equations at the household and region level; cross-equation correlation of random effect intercepts and random effect coefficients at the regional level. The random intercepts represent the unobserved factors that vary across regions and influence the outcomes of SWC, AP, and LHD. These random intercepts allow each region to have its own baseline level of the outcome, accounting for regional differences that are not captured by the fixed predictors.

Equations 1, 2, and 3 in the multivariate probit model estimate the adoption of SWC, AP, and LHD, respectively. The correlation between the error terms of equations 1 and 2, equations 1 and 3, and equations 2 and 3 at the region level is measured by *atanhrho_12, atanhrho_13, and atanhrho_23*. A positive and significant error correlation between SWC and AP at the household, as well as the region level, indicates that the farmers use the two practices together or that the practices complement each other. Similarly, the cross-equation random intercept correlation for SWC and AP shows a positive relationship between them. On the other hand, a negative and significant correlation between the error terms of equations 1 and 3 as well as 2 and 3 indicates that adopting SWC and AP has an inverse relationship with adopting LHD, with the same result observed on cross-equation random intercept correlation.

Regional-level random effect parameters and standard deviations show that there is significant variation among regions in terms of the unobserved factors that affect the adoption of CSA practices. Furthermore, *lnsig_1_1 (SWC), lnsig_1_2 (AP),*and*lnsig_1_3 (LHD)*indicate log-transformed standard deviations of random effects for the three equations. This figure is highest for SWC and AP but relatively lowest for LHD. The likelihood ratio test rejects the null hypothesis that states all correlation coefficients are zero, which confirms that there are significant correlations between the error terms and random effects of the three equations. The presence of significant correlations between the error terms and random effects suggests that the adoption decisions for SWC, AP, and LHD are interrelated, and the unobserved factors influencing the adoption decisions are not independent.

The analysis also revealed a significant and positive correlation between soil and water conservation (SWC) and agronomic practices (AP), indicating that these two sets of practices are complementary and frequently adopted together by households. This finding implies that policy interventions should avoid promoting them in isolation. Rather, there is a strong case for bundling SWC and AP into integrated CSA packages—for example, combining soil management techniques with improved crop production practices. Such an integrated approach could enhance adoption rates while reinforcing the synergistic effects of these practices in building household resilience.

Table 5: Cross Equation Correlation and Random Effect Parameters

Cross-equation random intercept correlation	**Household level**	**Region level**
SWC_AP	0.405 (0.035)	0.593 (0.233)
SWC_LHD	-0.339 (0.035)	-0.789 (0.178)
AP_LHD	-0.409 (0.052)	-0.401 (0.353)
Cross-equation error term correlation		
/atanhrho_12 (Corr_SWC_AP)	0.429*** (0.042)	0.682** (0.359)
/atanhrho_13 (Corr_SWC_LHD)	-0.353*** (0.039)	-1.067** (0.471)
/atanhrho_23 (Corr_AP_LHD)	-0.434*** (0.062)	-0.425 (0.421)
Region level Random effect coefficient		
SWC	0.448 (0.062)	
AP	0.496 (0.060)	
LHD	0.307 (0.092)	
Region level random effect variances		
/lnsig_1_1 (SWC)	-0.824*** (0.139)	
/lnsig_1_2 (AP)	-0.702*** (0.122)	
/lnsig_1_3 (LHD)	-2.84*** (0.305)	
Log likelihood	-2611	
Likelihood Ratio test	*chi2(36) = 593.29 Prob > chi2*	*= 0.0000*

Standard errors in parenthesis

Source: Authors' estimate, 2024

In contrast, the negative and statistically significant correlation observed between soil and water conservation (SWC) practices, agronomic practices (AP), and livelihood diversification (LHD) points to a trade-off between on-farm and off-farm livelihood strategies. Households that allocate substantial labor, time, and financial resources toward SWC and AP may have limited capacity to engage in non-farm income-generating activities, while those pursuing livelihood diversification may depend less on farm-based climate-smart practices. This finding suggests that efforts to promote CSA must be attentive to the resource constraints households face. Accordingly, support programs should consider sequencing interventions or bundling them with complementary measures, such as linking CSA adoption with access to credit or income from off-farm sources, thereby enabling households to more effectively balance both strategies.

The regional heterogeneity captured in the random effect parameters provides further evidence that adoption decisions are shaped by unobserved, location-specific factors, including infrastructure availability, extension service coverage, and market access. This finding underscores the necessity of designing regionally tailored CSA strategies rather than applying uniform approaches across diverse contexts. For instance, regions characterized by strong non-farm employment opportunities may require policies that explicitly integrate livelihood diversification with CSA interventions, whereas more agrarian regions might benefit from intensified support for farm-based CSA practices.

Finally, the rejection of the null hypothesis that all correlation coefficients are zero provides empirical confirmation that CSA adoption decisions are not made independently but are, in fact, interdependent. This carries both methodological and policy implications. From a methodological standpoint, the use of multivariate models is essential to adequately capture these complex interlinkages. From a policy perspective, the findings suggest that CSA interventions should be designed as integrated packages that deliberately account for both complementarities, such as those observed between SWC and AP, and trade-offs, including the tension between farm-based CSA practices and livelihood diversification. Adopting such an approach can enhance the efficiency of adoption, minimize unintended substitution effects, and contribute to building more robust household resilience in the face of climate change.

4. Conclusion and Recommendation

Farmers face the triple challenges of increasing food production, adapting to the changing climate, and reducing greenhouse gas emissions to achieve sustainable development. CSA practices provide farmers with the key to tackling these challenges and building a climate-resilient economy. This study aimed to identify the major CSA practices and determine the factors influencing their adoption by farmers in Ethiopia, using nationally representative two-wave panel data. In this study, CSA practices were categorized as SWC, AP, and LHD. Adoption of these practices is not mutually exclusive, meaning farmers may consider adopting two or more combinations of practices simultaneously. The evidence from this study shows that the change in adoption over time is small or insignificant. The model results showed that sex, age, and TLU affect the adoption of CSA practices negatively and significantly. Other variables like education, family size, land size, mobile ownership, access to extension services, drought, agroecology, and slope were found to positively and significantly affect the adoption of at least one of the CSA practices. Specifically, the study found that female-headed households had a lower probability of adopting soil and water conservation (SWC) and agronomic practices (AP) but were more likely to engage in livelihood diversification (LHD). Factors such as education, access to extension services, mobile phone ownership, and exposure to drought shocks consistently promoted adoption across all CSA practices. Land size positively influenced the adoption of SWC and AP but had a negative effect on LHD. Other factors, including family size, livestock holdings, and slope, exhibited mixed effects depending on the specific practice. Additionally, greater distance to markets constrained the adoption of agronomic practices, and agro-ecological variations significantly affected both agronomic practices and livelihood diversification.

Based on the results of the study, the findings indicate that enhancing access to extension services, promoting education, and improving the dissemination of CSA-related information are critical for increasing adoption among smallholder farmers. Extension services provide technical guidance and practical demonstrations, while education and mobile technologies enable farmers to access timely climate forecasts, adaptation strategies, and market information. Addressing gender disparities is also important, as female-headed households were less likely to adopt labor- or resource-intensive practices, suggesting the need for targeted support such as credit access, labor-saving technologies, and capacity-building programs. Improving rural infrastructure, market linkages, and tailoring interventions to local environmental conditions can facilitate uptake. Additionally, integrating land management and livelihood strategies is essential, as household characteristics like land size, livestock holdings, and family composition have mixed effects on CSA adoption.

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Annex

Table I: Variables with measurements and expected signs

Variables	Measurement	Expected signs
Dependent variables		
Soil and water conservation	Dummy (1 = adopter, 0 = non-adopter)	
Agronomic practices	Dummy (1 = adopter, 0 = non-adopter)	
livelihood diversification	Dummy (1 = adopter, 0 = non-adopter)	
Independent variables		
Female headed hh	Dummy (1 = female headed, 0 = male headed)	Positive / negative
Total income	Total household income (Birr)	Positive
Family size	Number of family members	Positive / negative
Education	Year of schooling	Positive
Age	Year	Positive / negative
Distance to market	Kilometres	Positive / negative
Drought	Dummy (1 = occurred, 0 = not occurred)	Positive
Mobile ownership	Dummy (1 = owned, 0 = not owned)	Positive
Land size	Hectare	Positive / negative
Extension service	Dummy (1 = accessed, 0 = not accessed)	Positive
TLU	Tropical livestock unit	Positive / negative
Slope	Percent	Positive
Agro-ecology	Categorical (1=warm/arid; 2=warm/semiarid; 3=warm/subhumid;4=cool/arid;5=cool/semiarid;6=cool/subhumid ;7= cool/humid)	Positive / negative

Source: Authors' preparation from literature

Table II: Summary statistics for continuous variables

Variable	Variations (Std. deviation)			Mean
	Overall	Between	Within	
Total income	376192.4	331156.8	244718.2	221727
Household size	2.54	2.44	0.70	5.40
Education	10.81	9.25	5.93	7.06
Age	13.90	13.24	5.04	44.73
Distance to market	77.33	71.77	9.82	80.08
Land size	1.62	1.24	0.99	0.59
Livestock Holding	5.84	4.45	3.43	3.57
Non-farm income	74617.30	54123.19	47748.72	1341
Output (kg)	1210.95	1133.14	450.11	669.14
Area planted (ha)	0.934	0.859	0.34	0.575
Labor (man days)	152.46	147.79	53.50	104.97
Seed (kg)	241.85	165.71	163.04	57.84
Fertilizer (kg)	217.92	202.78	109.53	153.09
Total cost (Birr)	20635.99	18231.73	9460.46	11624.56
Land cost (Birr)	12204.08	10750.33	5831.97	5470.36
Labor cost (Birr)	8428.13	7295.94	4235.28	4712.53
Seed cost (Birr)	2510.95	2361.13	1149.43	1702.07
Fertilizer cost (Birr)	1585.27	1485.67	599.42	677.30

Source: Authors' own estimate, 2024

Table III: Summary statistics for Binary and Discrete variables

Variable	Values	Overall		Between		Within
		Freq.	Percent	Freq.	Percent	Percent
Marital status	Never Married	396	12.44	381	17.71	74.54
	Married (Mono)	2126	66.79	1572	73.08	91.13
	Married (Poly)	175	5.50	156	7.25	69.23
	Divorced	112	3.52	99	4.60	76.77
	Separated	54	1.70	50	2.32	69.00
	Widowed	316	9.93	259	12.04	82.24
Fhh	Yes	823	25.86	594	27.62	93.18
Drought	Yes	610	19.16	505	23.48	74.85
Flood	Yes	94	2.95	93	4.32	67.74
Mobil ownership	Yes	1513	47.53	1196	55.60	85.29
Extension access	Yes	1135	35.66	928	43.14	85.88
Credit access	Yes	2619	82.28	1766	82.10	100.00

Source: Authors' computation, 2024

Table IV: Multicollinearity test result

Variable	VIF	1/VIF
Female headed hh	1.14	0.875
Total income	1.10	0.906
Family size	1.26	0.792
Education	1.05	0.951
Age	1.05	0.955
Distance to market	1.24	0.807
Drought	1.23	0.811
Mobile ownership	1.11	0.904
Land size	1.27	0.788
Extension service	1.34	0.747
TLU	1.21	0.826
Slope	1.36	0.735
Agro-ecology	1.89	0.529
Mean VIF	1.25	

Source: Authors' computation, 2024