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Impacts of Climate-Smart Agricultural Practices on Crop Productivity in North Wello Administrative Zone, Northern Ethiopia

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Abstract: *In most Sub-Saharan African countries, the agriculture sector drives the economy. However, this sector primarily relies on rain-fed farming practices, which are highly vulnerable to climate change-related risks. Different agricultural technologies have been introduced to increase agricultural production in the changing climate. However, it has not yet been sufficiently documented which technologies will provide better crop yields when used in isolation or combination. As a result, the current study is intended to examine the impact of climate-smart agricultural practices on crop productivity in Northeast Ethiopia.The study followed a cross-sectional research design, with data collected through survey questionnaires from randomly selected rural household heads.A multinomial endogenous switching regression model was employed to estimate the adoption of multiple climate-smart agricultural practices and their impacts on crop yield. For this purpose, 411 farm household heads were surveyed across three agro-ecological zones of the North Wello Administrative zone, Northern Ethiopia. The result reveals that farmers who implemented a single or full package of climate-smart agricultural practices had a higher crop yield per hectare than those who did not. Adopting multiple climate-smart agricultural practices produces more crop yield than a single practice. Adopting input-based crop management practices combined with water management practices achieved a greater yield per hectare than any other practice, either in isolation or in combination. However, when climate risk reduction measures such as early warning weather information and adjusting planting dates are used in conjunction with other packages, they have no significant impact on crop yield. The non-significant effect of climate-risk reduction measures in all cases suggests that agricultural risk reduction measures may not be climate-smart.*

Keywords: Climate-smart agricultural practices, multinomial endogenous switching regression model, crop productivity, crop management, water management

I. INTRODUCTION

Climate change is a global problem affecting food security in many developing countries (Alemu and Mengistu, 2019; Kassie et al., 2017).The problem is more acute in Sub-Saharan Africa, where 62 percent of the population lives in rural areas and is primarily dependent on rain-fed agriculture (Calzadilla et al., 2013).Despite its importance to the overall economy, agricultural production in Sub-Saharan Africa is being hampered by increasing temperatures and varying precipitation (Ferede et al., 2013).Climate extremes particularly seasonal droughts areundermining the economies of Horn of Africa countries, with agriculture hardly hit (Lipper et al., 2014; Shiferaw et al., 2018).East African countries are arguably the most at risk from climate change impacts, and land degradation exacerbates the negative impacts on agricultural production (Evangelista et al., 2013; Wubie, 2015).

Agriculture dominates the Ethiopian economy (Alemu and Mengistu, 2019; Alemu et al., 2003; Yalew et al., 2018); which contributes, on average, 44 percent of the GDP and employs over 80 percent of the population (Shiferaw2017;Gebreegziabher et al., 2016; Wubie, 2015).Crop production accounts for more than 60% of agricultural GDP, while livestock accounts for the remaining 20% (Solomon et al., 2021).Ethiopian agriculture is rainfed, with irrigation agriculture accounting for less than 1% of total cultivated land (Di Falco et al., 2012;Robinson et al., 2013).The vast majority (95 percent) of cropped area is under small-scale rain-fed farming, which accounts for 95 percent of national annual crop production (EPCC, 2015; Solomon et al., 2021).

Ethiopia's agriculture is highly vulnerable toclimate change-related risks (Di Falco et al., 2012).Evidence suggests that the average annual temperature rose by 1.3 ^{O}C, or 0.28 ^{O}C, between 1960 and 2006(Gashaw et al., 2014; Wubie, 2015). In terms of precipitation, Ethiopia experiences inter-annual and inter-decadal variability (Admassie et al., 2008;Debalkie and Solomon, 2014;Bewket, 2009; Zelekeet al., 2013).The country is also frequently hit by extreme events like droughts and floods, in addition to rainfall variability and increasing temperatures, which contribute to adverse impacts on livelihoods (EPCC, 2015; World Bank, 2021).Recently, drought caused by climate change-induced El Niñoresulted in food insecurity for 10 million people in 2015/16(Alemu and Mengistu, 2019).Unpredictable climate variability contributes increasingly to low agricultural productivity and production (Deichert et al., 2017). Previous studies at the national level show that the impacts of climate change on crop production have been negative in Ethiopia (Bryan et al., 2009; Kassie et al., 2014; Wubie, 2015; Yalew et al., 2018). According to the World Bank (2010) report, climate change-related risks could reduce the national GDP by 2-6% by 2015 and up to 10% by 2045 when compared to a baseline scenario in Ethiopia.This means that climate variability hurts agricultural production systems in Ethiopia, where the climate-sensitive sector is the primary source of income.

The agriculture sector has a significant potential to contribute to the solution, assisting people not only in feeding themselves but also in adapting to and mitigating the effects of climate change (FAO, 2013; Fenta et al., 2019).Adopting climate-smart agriculture appears to be an appropriate strategy for increasing agricultural productivity while mitigating and adapting to climate-related risks(FAO, 2013).Ethiopia's government now emphasizesclimate-smart agriculture (CSA) for enhancing resilient and adaptive systems to climate change (Yirgu et al., 2013).Sustainable intensification practices that build on existing agricultural lands, as one example of CSA technologies, have significant adaptation potential. Because they reduce cropland expansion at the expense of forestland and shrubland, they improve livelihoods as well as mitigation potential (Lipper et al. 2014).There are also in situ and ex situ water harvesting technologies; integrated soil fertility management through the use of legumes to improve nitrogen fixation and the efficient use of mineral fertilizers; precision agriculture, which optimizes soil and water management to locally specific conditions; and the incorporation of conservation agriculture (CA) into in situ crop residue management (Hadguet al., 2019).To increase crop production, local demand and context-specific CSA technologies and practices, such asdrought tolerant, early maturing, and drought resistant crops and incorporating multipurpose tree/shrub species that provide multiple benefitspracticed in northern Ethiopia (Georgise et al., 2019).Climate-smart practices are critical for reducing land degradation, mitigating the effects of climate change and variability, and improving crop productivity and nutrient availability (Araya, 2019).

Empirical studies from Ethiopia have shown that CSA technologies can increase agricultural productivity and farm income.For instance, the decision to practice row planting, use of chemical fertilizers, crop diversification, soil and water conservation, improved crop seeds,integrated soil fertility management, minimum tillage, cereal-legume intercropping, small-scale irrigation, and improvedlivestock management practices have a significant positive impact on agricultural productivity and farm income (Sedebo et al., 2022;Tesfaye et al., 2020; Asrat&Simane, 2017; Komarek et al., 2019; Teklewold et al., 2019; Habtewold, 2021).Similarly, other studies from various regions of Ethiopia show that CSA practices and technologies improve soil fertility and organic carbon levels(Araya, 2019; Tadesse et al., 2021;Teklewold et al., 2017). However, when estimating the crop yield effects of CSA technologies in most of these studies, adopters are defined as having used at least one of the identified CSA technologies (Adego et al., 2019; Sedebo et al., 2022; Fentie&Beyene, 2019; Sedebo et al., 2021).Empirical evidence suggests that the benefits of combining agricultural technologies increase when compared to adopting technologies alone (Di Falco & Veronesi, 2013; Kassie et al., 2015; Teklewold et al., 2017; Teklewold et al., 2019).As a result, rather than a piecemeal approach, a package approach is required to maximize the synergies implicit in various climate-smart practices in Ethiopia (Teklewold et al., 2017).

It is critical to consider locally demanded CSA technologies and practices in the study area, such as drought tolerant, early maturing, and drought resistant crops, as well as integrating multipurpose trees that provide multiple benefits to crop productionsystems (Georgise et al., 2019).Empirical evidence on the impacts of these new agricultural practices will help in the filling of knowledge gaps in the areas of CSA technology implementations. Because of differences in topography, microclimate, and socioeconomic factors, the adoption of CSA practices and their impact on crop productivity varied across geographical settings. Therefore, a context-specific study of CSA adoption and its impact on crop productivity is required considering the varied agro-ecological conditions.Though important evidence has been provided more recently about the effect of row planting on teff yield in the study area (Fentie&Beyene, 2019), it was only focused on the method of sowing (Teff row planting) instead of evaluating the effectsof improved seeds, fertilizer, soil, and water conservation, agroforestry, crop diversification, small-scale irrigation, and integrated pest management adoptions in isolation or in combinations.

As a result, the objective of this study is to provide rigorous empirical evidence for the effect of a set of climate-smart agricultural practices implemented in isolation as well as in combination on crop productivity using a multinomial endogenous switching regression model.The following two research questions were addressed by this study: How do climate-related and socioeconomic factors influence farmers' decisions to adopt climate-smart practices, either individually or in combination, and what effect does this have on crop productivity in the North Wello Zone?The authors of this study do this by controlling for selection bias using a multinomial endogenous switching (ESR) treatment effects model.

II. RESEARCH METHODOLOGY

Description of the Study Area

The study was conducted in the North Wello Administrative Zone because the North Wello region is one of the most drought-prone and populated areas in Ethiopia.The area is located lies between 11°30′0′′ to 12°30′0′′ N latitude and 38°30′0′′to 40°0′0′′ E longitude (Figure 1).Its elevation ranges from 900 to 4265 meters above sea level, and there are three major agroecological zones: hot (lowland), temperate (middle), and cool (highland). The North Wello zone is distinguished by a distinct bimodal precipitation pattern, Belg in April-May prior to the primary wet season, Kermit, from July to September (Conway 2000).The temperature varies depending on the season, with average minimum temperatures ranging from 9.5°C to 15.6°C during the rainy season and from 30°C to 33°C during the dry season.May and June are the hottest months in the study area.Dominant soils include Cambisols, Luvisols, Vertisols, Xerosols, Leptosols, Regosols and Nitisols.

The agricultural system of the study area is a mixed farming system. Cereals represented 85.06% of all cultivated land in the study area (1865.27 ha). Teff, wheat, sorghum, barley, and maize accounted for 30.48% (approximately 56,859.09 hectares), 25.41% (approximately 47,412 hectares), 25.39% (47,350.99 hectares), 15.3% (28,499.58 hectares), and 3.41% (6,406.00 hectares) of the grain crop area, respectively. In 2020–21, pulses represented 14% of the total area under cultivation. The most common pulses include beans, peas, lentils, and chickpeas (CSA, 2021). Livestock is inextricably linked to the farming system and is mainly used for plowing and transportation.

Sampling design and procedures

The study relied on primary data sets gathered from rural households via cross-sectional survey methods. We used a multistage sampling method to select household heads who could participate in the study and to select the kebeles from which data would be collected. First, rural administration districts are classified according to their agroecology. Second, three representative districts were purposefully chosen to represent the three dominant agroecological areas: Habru in the lowlands, Gubalafto in the midlands, and Gidan in the highlands.Third, in consultation with agronomic experts in the study area, the kebeles that had the dominant characteristics of each sampled district were identified and aggregated.This third step is crucial to exclude kebeles that do not share the prevailing micro-climatic and agricultural characteristics of the sampled districts.Following this, six kebeles, which were two kebeles from each sampling district, were selected using a stratified sampling technique.About 421 randomly selected farm households in the three districts using proportional sampling methods were interviewedfrom March to May 2024.However, we used only 411 of the survey participantswhofilled in the questionnaires correctly and used them for the data analysis.

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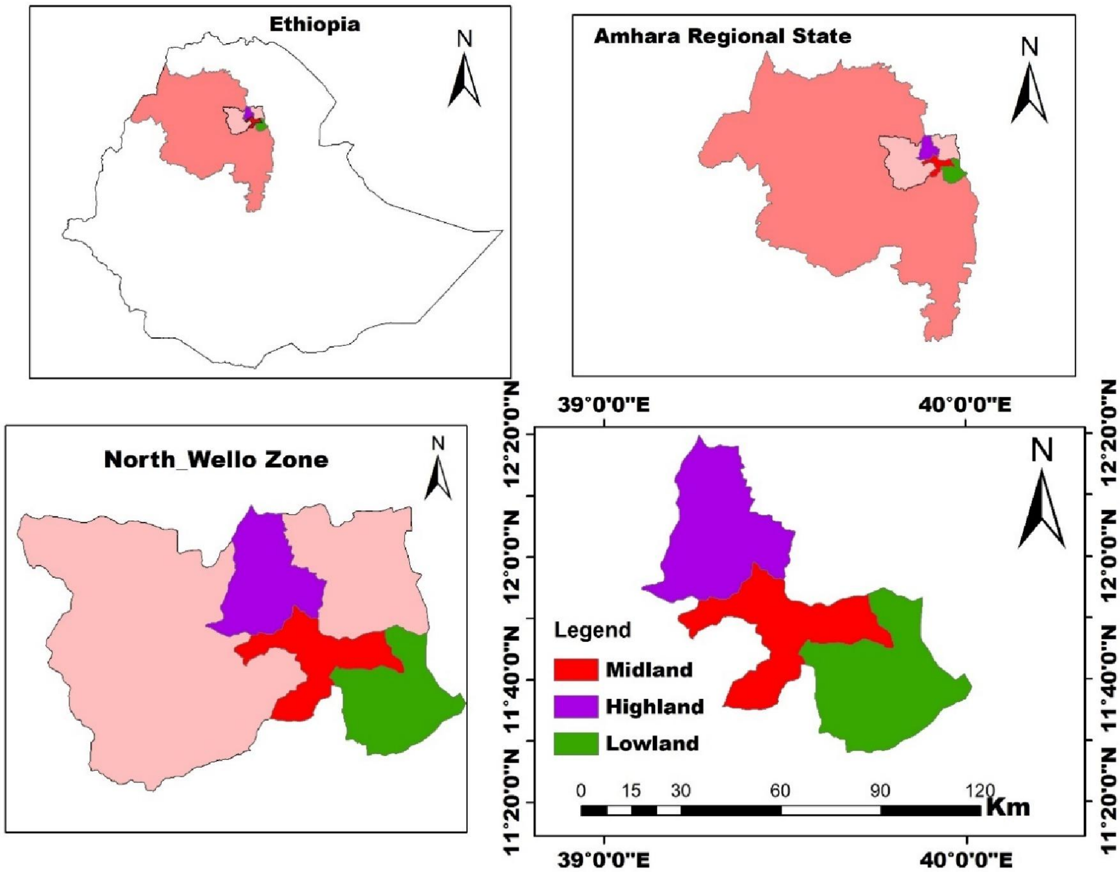

Figure.1: Location of Study Area (source: author,2024)

Data Sources and CollectionMethods

Cross-sectional data for the study were collected from the randomly selected households in various agro-climatic zones of the North Wello administrative zone using open and closed-ended questionnaires.The household and plot level data collected through a structured questionnaire provides household demographic and socio-economic characteristics and different typologies of climate-smart agricultural practices. The plot level data included biophysical characteristics of a plot, crop production level per plot, and the types of climate-smart agricultural practices applied to each plot. These data were mainly used to analyze the impact of climate-smart agricultural practices on crop productivity based on household-level information.

To identify the CSA practices used in the study area, the authors first compiled a list of all CSA practices by consulting with agronomic experts in each sampled district before including all CSA practices used by farmers in the questionnaire. As well, to supplement the quantitative data, a series of in-depth group discussions and interviews were conducted. A total of six focused group discussions (FGDs) were conducted, one in each sampled kebele. The discussants were farm household heads selected in consultation with agricultural extension experts working in each kebele, considering their farm experiences, active participation in farmers' associations in the kebele, and implementing agricultural technologies introduced in the kebele. At every FGD meeting, participants were restricted to 6–8 persons. A total of 45 participants in the focus group were present in the six kebeles, of which only three were women, indicating that men were dominant. The first author led each focus group using a checklist.

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Description of variables

Farm households in the study sites have undertaken a number of CSA practices, including improvedcrop varieties, organic and inorganic fertilizers, agroforestry, adjusting the cropping calendar, using early warningweather-related information,adopting soil conservation measures, and adopting water strategies such as water harvesting and small-scale irrigation (Table 1).

Table 1: Identified climate-smart agricultural practices in the study sites

Climate-smart agricultural practices	Frequency	Percent
Crop diversification	159	38.69
Improved crop varieties	80	19.46
Organic fertilizers (compost, and or manure)	150	36.5
In-situ water conservation practices (infiltration ditches, soil/stone bund)	384	93.43
Small-scale irrigation practices	97	23.60
Minimum tillage practices	68	16.55
Agroforestry	45	10.95
Rainwater harvesting practices (pond construction and geomembrane)	36	8.76
Inorganic fertilizers	272	66.18
Crop rotation	176	42.82
Use of early warning weather information (crop harvesting)	157	38.2
Adjusting planting dates (cropping calendar)	115	27.98

Source: Authors survey, 2024

The explanatory variables in this study were chosen using a random utility framework and empirical literature on CSA practices and factors of agriculture technology uptake (Deressa& Hassan,2009; Asrat&Simane, 2017; Asfaw et al.,2018; Fentie&Beyene, 2019; Teklewold et al.,2017; Tsige et al.,2020; Beyene et al.,2017; Miheretu&Yimer, 2017; Kassie et al.,2015; Pender & Gebremedhin,2008). These include demographic factors (education, age, gender, and household size), plot characteristics (plot number, farm distance, slope, soil, and tenure), asset-related (farm size, TLU, and irrigable land), and other CSA-related training, extension, infrastructure, and institutional support variables. The descriptions of the selected variables and descriptive statistical measures are presented in Table 2 below.

Table 2: Explanatory variables included in The Endogenous Switching Regression Model

Variable	Description	Measurement	Mean	SD
Yield/ha	Crop productivity (value of crop production per hectare) in ETB	Continuous	41,067.17	19,673.47
Gender	Sex of the household head	Dummy = 1 if male 0 = female	.87	-
Age	Age in years of the household head	Continuous	46.9	9.74
Education	Education status of the household head	Dummy =1 if literate 0= illiterate	0.35	-
Family size	Household size of the respondents	Discrete	5.56	2.02
Social Membership	Household head membership of social organization (Edir, Equb, etc.)	Dummy =1 if member 0= not	.88	-
TLU	Livestock herd size in tropical livestock unit	Continuous	4.01	2.18
Farm size	Total farm size that the farmers owned in hectares	Continuous	1.10	.56
Parcel number	Number of plots of cultivated land	Discrete	2.94	1.18
Gentle slope	The slope of farmland is perceived as moderate in ha	Continuous	.37	.35
Steep slope	The slope of farmland is perceived as very steep in ha	Continuous	.12	.24
Land rent	Sharing of cropland from another farm	Dummy = 1 if yes 0= not	.314	-

Farmdistance	Walking distance from home to farmland in minutes	Continuous	37.7	19.38
Media access	The presence of a radio in the home	Dummy =1 if yes 0 = not	.817	-
Extension	Distance from home to extension services in minutes	Continuous	47.62	36.91
Market	Distance from home to nearest market in minutes	Continuous	99.64	125.24
Credit	Credit services available to households	Dummy = 1if yes 0= otherwise	.70	-
Training	Access to agricultural training for household heads	Dummy = 1 if yes 0= not	.42	-
Climate information	Climate information is obtained from extension services and other media	Dummy = 1 if yes 0= no	.25	-
Age dependency ratio	The proportion of household members under 15 and over 64 compared to those between 15 and 64.	Ratio	2.08	1.52
Soil fertility	Farmland soil fertility is perceived to be low	Dummy = 1 if yes 0 otherwise	.11	-
Belg rainfall	Belg (short rain season) rainfall (mm) of the year 2019	Continuous	135.26	60.09
Meher rainfall	Mehere (long rain season) rainfall (mm) of the year 2019	Continuous	294.11	15.85

Source: Authors survey, 2024

Data analysis

Using both household and plot-level data, the researchers investigated how multiple climate-smart agricultural practices affect crop productivity.The authors primarily used quantitative data, which they analyzed using basic descriptive statistics, principal component analysis methods, and an econometric model.Descriptive statistics were used to summarize the respondents' socioeconomic, demographic, plots, assets, and institutional characteristics.When a large and extensive database is available, Principal Component Analysis (PCA) is used to investigate CSA practices (Wekesa et al., 2018). PCA was applied in this study to standardize variables and condense all of the data from the original interconnected variables into a smaller set of factors known as principal components (Chatterjee et al., 2015). To place fewer highly correlated variables under each factor and make interpretation easier, factors were rotated using orthogonal rotation (varimax method) (Wekesa et al., 2018). All factors with eigenvalues greater than one were retained and interpreted using Kaiser's criterion (Kaiser, 1958). Following Kaiser's criterion, four principal components out of a possible eight were extracted with eigenvalues greater than one (Kaiser, 1958). Table 3 shows how the identified CSA practices were grouped using a principal component analysis.

The econometric model was used to estimate the CSA technology adoption decision on crop productivity. Using the full information maximum likelihood (FIML) estimation technique, we used the ESR model to determine who was more likely to benefit from the adoption of CSA practices.

A. EconometricFramework and Estimation Strategy

A micro-econometric structural Ricardian model was employedto assess the impact of CSA technology on crop productivity, assuming that farmers use a combination of CSA practices to maximize their expected profits. However, estimating the impact of technology adoption on crop productivity based on non-experimental observations is difficult because we do not observe the outcome of plots with CSA technologies if they did not have CSA technologies, or we do not observe the counterfactual(Asfaw et al., 2012; Kassie et al., 2007; Kassie et al., 2008).Furthermore, farmers' decisions to implement or not implement CSA technologies on their farm plots are voluntary and may be based on individual self-selection (Di Falco et al., 2011; Asfaw et al., 2012), and farmers who decide to implement multiple CSA technologies may have different characteristics than those who do not.Besides that, unobservable characteristics of farmers and their farms may influence both the adoption of climate-smart agricultural technologies and the farm outcome, resultinginconsistent estimates on the effect of climate-smart agricultural technology practice on crop productivity(Di Falco et al., 2011; Asfaw et al., 2012; Kassie et al., 2008).All of this implies that using observational data to assess the ex-post effects of CSA technology adoption is difficult due to possible selection bias fromobserved and unobserved plots and household characteristics (Kassie et al., 2008; Kassie et al., 2007).Unless sample selection bias is taken into account, this leads to an incorrect estimate of the adoption effect on crop productivity (Teklewold et al., 2019; Teklewold et al., 2013).Hence, estimating the impact of CSA technology users with ordinary leastsquares leads to biased estimates.

There are several econometric models for addressing sample selection bias, such as using the Instrumental Variable (IV), the Heckman two-step method, or a non-parametric estimator (propensity score matching) method (Abebe & Bekele, 2014;Heckman et al., 2004; Zingiro et al., 2014), and each has its own set of limitations.Heckman selection and IV methods, for example, enforce a functional form assumption by assuming that farmers' decision to use CSA technologies only causes an intercept shift in the outcome variables rather than a slope shift (Tambo &Wünscher, 2016).Though propensity score matching (PSM)addresses the above issue by avoiding functional form assumptions, it assumes selection is based on observable variables, but there is likely to be unobserved heterogeneity because farmers' decisions to adopt CSA technologies are likely to influence by their expected benefits from the technologies.When there are unobservable factors influencingboth agricultural technology adoption decisions and outcome indicators, PSM produces biased results (Tambo&Wünscher,2016).

We used the endogenous switching regression (ESR) model to address these issues. Based on the selection equation, the ESR method specifies separate outcome equations for each regime.The ESR model estimates a two-outcome equation corresponding to users and non-users in a two-stage framework. Using a random utility conceptual model, it is assumed that farmers are risk-neutral, and their decisions to use CSA or non-use are based on their expected net benefits. As a result, decisions to use or not to use CSA practices in crop production systems are made based on their expected maximum net benefits.The net benefit in this study is defined as a latent variable (μ_i^*) capturing the difference between crop yield derived from CSA practices ($\mathcal{Y}_{1i}$) and without CSA practices ($\mathcal{Y}_{0i}$). It is assumed that the i^{th}household will use a combination of CSA practices or a single CSA practice if the net crop yield difference withCSA practices and Without CSA practicesis positive, described as:

μ_i^*=$\mathcal{Y}_{1i}$-$\mathcal{Y}_{0i}$ > 0eq(1a)

Where, μ_i^* is determined by observable factors (such as socio-economic conditions of the household, the biophysical conditions of the farm plot, and institutional factors) and unobservable factors (such as farmers'farm management ability, soil fertility, risk preference, etc.).The CSA use decisions in the latent variable framework are specified following Kassie et al. (2014);Adego et al., (2019) as: (ε_{ij}):

$$U_i^* = \mathcal{X}_i\beta_j + \varepsilon_i, \qquad eq(1b)$$

Where ($\mathcal{X}_i$) is observed exogenous variables (socio-economic conditions of farmers and biophysical characteristics of farm plot); β is the vector of the parameters to be estimated, and $\varepsilon_{ij}$is unobserved characteristics. As previously stated, a switching regression model was used to estimate the impact of CSA technology adoption on crop yield or productivity while accounting for sample selection bias in CSA technology adoption participation.The researcher does not observe U_i^* , rather the actual adoption status can be only observed (U_i), expressed as:

$$U_i = \begin{cases} 1, & if U_i^* > 0 \\ 0, & if U_i^* < 0 \end{cases} \qquad eq\ (2)$$

Where U_i is a binary dummy variable, which equals 1 for CSA uses by the i^{th}household, and zero, otherwise. Furthermore, due to the household decide to use CSA or not, the yield benefits of with CSA and without are specified as an endogenous switching regime model conditional on μ_i, like that:

$$CSA\, users\, regime: \quad \mathcal{Y}_{1i} = \beta_1\mathcal{X}_{1i} + \mu_{1i}, \quad if \quad \mu_i = 1 \qquad eq(3a)$$

$$CSA\, non-users\, regime: \mathcal{Y}_{0i} = \beta_0\mathcal{X}_{0i} + \mu_{10}, \quad if \quad \mu_i = 0 \qquad eq(3b)$$

The left-hand side variables $\mathcal{Y}_{1i}\, and\, \mathcal{Y}_{0i}$ refers the crop yield amount per hectare expressed in the regional price in Ethiopian Birr (ETB) corresponding to the two regimes users of CSA and non-users of CSA respectively. The right-hand side, $\beta_1$and β_0 are vectors of parameters to be estimated; $\mathcal{X}_{1i}$ and $\mathcal{X}_{0i}$ are vectors of determinants of crop yield for

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the i^{th}household, μ_{1i} and μ_{0i} are the error terms. The error terms ε in $eq(1b)$, and the two (μ_{1i}, μ_{10}) in $eq(3a)$ and $eq(3b)$have a trivariate normal distributions with zero mean and a non-singular covariance matrix (Adego et al.,2019) expressed as follows:

$$Cov(\varepsilon_i, \mu_{1i}, \mu_{0i}) = \begin{bmatrix} \sigma_1^2 & \sigma_{10} & \sigma_1\varepsilon \\ \sigma_{10} & \sigma_0^2 & \sigma_0\varepsilon equ \\ \sigma_1\varepsilon & \sigma_0\varepsilon & \sigma_\varepsilon^2 \end{bmatrix} (4)$$

Where σ_1^2= var (μ_1),σ_0^2= var (μ_0),σ_{10}= cov $(\mu_{1i}.\mu_0)$, $\sigma_1\varepsilon$= cov $(\mu_1.\varepsilon)$, $\sigma_0\varepsilon$= cov $(\mu_{0.}\varepsilon)$, and σ_ε^2=1. the regimes $\mathcal{Y}_{1i}$ and $\mathcal{Y}_{0i}$ outcomes cannot be simultaneously observed for a farmer and hence the covariance(σ_{10}) is assumed zero (Madalla,1983; Amadu et al.,2020).

Moreover, due to the presence of selection bias, the expectations of the error terms in$eq(3a)$ and $eq(3b)$are different from zero. Applying ordinary least squares (OLS) regression would therefore result in biased estimations of $\mathcal{Y}_{1i}$ and $\mathcal{Y}_{0i}$ (Amadu et al.,2020).bracketsve assumption, the truncated error terms $[{\mu_{1i}}/{U_i} = 1]$and $[{\mu_{0i}}/{U_i} = 0]$ have the following expected values:

$$E\,[{\mu_{1i}}/{U_i} = 1]=\sigma_1\varepsilon\frac{\phi[\beta\mathcal{X}_i]}{\Phi[\beta\mathcal{X}_i]}=\sigma_1\varepsilon\lambda_{1i} equ(5a)$$

$$E\,[{\mu_{0i}}/{U_i} = 0]=-\sigma_0\varepsilon\frac{\phi[\beta\mathcal{X}_i]}{1-\Phi[\beta\mathcal{X}_i]}= \sigma_0\varepsilon\lambda_{0i} equ(5b)$$

Where $\lambda_{1i} = \frac{\phi[\beta\mathcal{X}_i]}{\Phi[\beta\mathcal{X}_i]}$and $\lambda_{0i} = \frac{\phi[\beta\mathcal{X}_i]}{1-\Phi[\beta\mathcal{X}_i]}$;

Where, ϕ is the standard normal probability distribution and Φ is the standard normal cumulative distribution.λ_{1i}andλ_{0i} are interpreted as the inverse mill's ratios (Heckman, 1979) evaluated at $\beta\mathcal{X}_i$ and used in $eq(3a)$ and $eq(3b)$ to correct for selectivity bias through the two stage estimation techniques. But this technique produces the heteroscedastic residuals that is not efficient in generating consistent standard errors (Lokshin and Sajaia, 2004).The two-stage instrumental variable procedure is a widely used method for estimating self-selection (Maddala, 1983). However, this technique is incorrect and heavily criticized because it requires some adjustment to derive consistent standard errors and performs poorly when the covariates of the selection equation and the covariates of the outcome equation are highly multi-collinear (Maddala,1983).

The FIML technique is the most appropriate and efficient method for estimating the ESR model. In many cases, this technique is preferable to other approaches. Using the movestay command in STATA version 14, the FIML method estimates both the selection and outcome equations simultaneously (Lokshin and Sajaia, 2004). Furthermore, it allows for the use of restrictions to be applied and the construction of likelihood ratio tests on the restriction variable (Lokshin and Sajaia, 2004) when similar variables affect the adoption decision (Z) and subsequent outcome equations (X); the absence of model identification will be a problem. We used exclusion restrictions for identification, which means that we need at least one variable that influences farmers' adoption decisions but does not directly affect crop yield or productivity (Asmare et al., 2019; Lokshin and Sajaia, 2004).

The validity of the ESR requires exclusion restriction that is correlated with CSA adoption decision while it does not playa role in the productivity of farmers (Adego et al., 2019;Asfaw et al., 2012; Gorst et al.,2018). Thus, we use access to climate related information, extension services, access to information on CSA agricultural practices and farmers past experience of extreme weather eventsas selectioninstruments (selection variables) and are considered as instrumentalvariables.The authors assumed that these instrumental variables are critically importantin determining the adoption decisions to CSA technologies variables but did not directly determine the productivity of farm plots.Empirically, the validity of ESR instrumentsis tested. The first test is running a probit model for adaptationwith instruments and other variables. The instrumentsare jointly validated as strong predictors foradoption decisions. The second is falsification test that checkswhether the instruments played an important role in production.As indicated by Adego et al. (2019), this test indirectly checks whether instrumentsare correlated with the unobservable. The test confirmsthat the instruments are not jointly statistically significantdrivers of productivity for non-adapters.

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B. The effects of CSA technology adoptionon crop productivity

The effect of CSA adoption on the crop productivity was estimated by using endogenous switching regression model following the work of (Adego et al.,2019; Amadu et al.,2019, Kassie et al.,2014, Tekelewold et al, 2013). The multinomial endogenous switching treatment regression model can be used to compute the counterfactual and average adoption effects. The counterfactual is defined as the crop yield of CSA users which would have obtained if the returns(coefficients) on their characteristics had been the same as the returns (coefficients) on the characteristics of the non-users of CSA practices, vice versa (Kassie et al.,2014). From equation (6a and 6b), the following conditional expectations for each outcome variable can be computed:

user with CSA (actual): $E\left({Y_{1i}}/{U_i} = 1\right) = \beta_1 \mathcal{X}_{1i} + \sigma_{1i}\varepsilon\lambda_{1i}$ $\quad eq\ (6a)$

user without CSA (actual) $E\left({Y_{0i}}/{U_i} = 0\right) = \beta_0 \mathcal{X}_{0i} + \sigma_{0i}\varepsilon\lambda_{0i}$ $\quad eq\ (6b)$

where, as if those household had not used CSA (counterfactual case), will be specified as:

Users had they decided not to userCSA (counterfactual):

$$E\left({Y_{0i}}/{U_i} = 1\right) = \beta_0 \mathcal{X}_{1i} + \sigma_{1i}\varepsilon\lambda_{1i} \qquad eq\ (7a)$$

Non-user had they decided to apply CSA (counterfactual):

$$E\left({Y_{0i}}/{U_i} = 0\right) = \beta_0 \mathcal{X}_{0i} + \sigma_{0i}\varepsilon\lambda_{0i} \qquad eq\ (7b)$$

Then the average treated impact of yield for those is computed as:

$$\mathcal{ATT} = \mathcal{X}_{1i}(\beta_1 - \beta_0) + \lambda_{1i}(\sigma_{1i}\varepsilon - \sigma_{0i}\varepsilon) \qquad eq(8a)$$

where ATT – represents the average treatment for the treated (with CSA).

Similarly, the impact of the treatment on untreated (ATU) estimated that it actually did not adopt did adopt (6b and 7d).

$$\mathcal{ATU} = \mathcal{X}_{0i}(\beta_1 - \beta_0) + \lambda_{0i}(\sigma_{1i}\varepsilon - \sigma_{0i}\varepsilon) \qquad eq\ (8b)$$

III. RESULTS AND DISCUSSION

3.1. Characterization of Identified CSA practices

Table 3 displays the descriptive statistics for each component's composition (climate-smart agricultural practices). Water management practice was the first and most widely used component, with 97.32 % of farm households practicing this component. This component includes small-scale irrigation practices as well as in-situ water conservation practicessuch as soil/stone bund andinfiltration ditches.The second major component is crop management practices which is used by 68 % of farm households. Poor soil nutrient management and climate-related risks are the major constraints to crop production in Ethiopia. As a result, 66 percent of study participants reported as they haveapplied chemical fertilizers to reduce crop loss risks due to low soil fertility conditions in the study area. The third most used component was conservation agriculture practices for increasing crop income, used by 58% of farmers. This component comprised the use of crop rotations and crop diversities.Lastly, 49.4 percent of farm households practiced climate risk management strategies which includes adjusting planting dates and using early warning weather information to harvest crops, which are central to modern farming practices, and are essential in Ethiopian smallholder farmers' adaptation to climate change related-risks.

Table 3: Characterization of theidentified CSA practices

Practices	Users		Component	Percentage of users	
	Frequency	%		Frequency	Percentage
Efficient use of inorganic fertilizers	272	66.18	Inputbased crop management (I)	279	67.88
Improved cropvarieties	159	38.69			
Crop rotations	176	42.8	Conservation agriculture(C)	238	57.91
Crop diversifications	80	19.46			
Adjusting planting dates	115	27.98	Climate risk reduction	203	49.39

(cropping calendar)			measures on crop (R)		
Use of early warning weather information to harvest crops	157	38.2			
Small-scale irrigation	97	23.60	Water management(S)	400	97.32
Soil/stone bund, infiltration ditches)	384	93.43			

Source: Authors survey, 2024

Farmers in the study areadecided to adopt CSA practices in a wide range of different combinations, and this has implication on household's crop income. Given the set of available packages, understanding what drives an individual to select specific packages is important for policy direction.Table 4 presents different packages (combinations), whereby 14 out of 16 possible combinations/packages were used for further ESRM estimations.Few farmers (1.2%) did not use/adopt any CSA package.About 18.7 % of farmers used package $I_1C_1R_1S_0$, which contained Input based crop management practices, conservation farming practices and farm risk reduction measures. Approximately 18.3 % of farmers used package $I_1C_1R_1S_1$ with all the four groups of CSA strategies. Further, 28% of farmers used package $I_0C_1R_1S_1$, which contained conservation farming practices, farm risk reduction measures andwater management practices.About 28.5 % used package $I_0C_1R_1S_0$, which contained conservation farming practices and climate-risk reduction measures only.Moreover, 31 % of the respondents used package $I_1C_0R_1S_1$, which had input-based crop management practices, climate-risk reduction measures, and water management practices. About 31.6 % used package $I_1C_0R_1S_0$, which comprised input-based crop management and climate-risk reduction measures.Another 48.9% of them used package $I_0C_0R_1S_1$, which had climate risk reduction measures and water management practices. Moreover, 43 % used package $I_1C_1R_0S_0$, which had input-based crop management and conservation farming practices.

A significant number of household heads (49.5%) used package $I_0C_0R_1S_0$, which contains only climate-risk reduction practices.Another large share of farmers (57%) used package $I_0C_1R0S_1$, which had conservation practices and water management practices. About 58% used package $I_0C_1R_0S_0$, which had only conservation farming practices. Further, 66.4% of farmers used package I_1C0R0S_1, which contains input-based crop management and water management practices. Another 68 % of the farmers used package $I_1C_0R_0S_0$, which contains onlyinput based crop management practices. Almost all of the farmers in this study (97.32%) used package$I_0C_0R_0S_1$.This package included water management measures.Water management practices in this study refer to soil bund/stone bund, infiltration ditches and the applicationof small-scale irrigationpractices.In this study area, farmers primarily used water managementand fertilization practices to boost crop productivity in a climate-friendly manner.

Table 4: Specification of CSA strategy combinations

Choice	Binaryquadruplicate	Frequency			
		Yes		No	
		Frequency	%	Frequency	%
	$I_0C_0R_0S_0$	5	1.22	406	98.78
	I_0 C_0 R_0S_1	400	97.32	11	2.68
	I_0 $C_0R_1S_1$	201	48.91	210	51.09
	$I0C_1$ R_1 S_1	115	27.98	296	72.02
	I_1C_1R1 S_0	77	18.73	334	81.27
	I_1C_1 R_0 S_0	177	43.07	234	56.93
	I_1C_1 R_1 S_1	75	18.25	336	81.75
	I_1 C_0 R_0S_0	279	67.88	132	32.12
	I_0C_1 R_0S_1	234	56.93	177	43.07
	I_1C_0 R_1 S_0	130	31.63	281	68.37
	I_1C_0 R_0S_1	273	66.42	138	33.58
	$I0C_1$ R_0 S_0	238	57.91	173	42.09
	I_0C_1 R_1 S_0	117	28.47	294	71.53

	$I_0\ C_0\ R_1\ S_0$	203	49.39	208	50.61
	$I_1\ C_0\ R_1\ S_1$	128	31.14	283	68.86
	$I_1C_1\ R_0\ S_1$	173	42.09	238	57.91

Source: Authors survey, 2024

3.2. The Effect of CSA Practices on Crop Yield /Productivity

This section examines the impact of CSA practices on crop yield/productivity as determined by the FIML-ESR model estimation. Table 5 depicts the effect of climate-smart agricultural practices on crop productivity as measured by the value of crops produced per hectare using the endogenous switching regression model's full information maximum likelihood estimates. The ESR model includes a selection equation as well as separate outcome equations for users and non-users that are all evaluated at the same time (Di Falco et al., 2011; Tambo &Wünscher, 2016).The selection equation refers to the determinants of CSA adoption decisions (Table results are presented in appendix, Table 6).The Waldtest of independence is statistically significant at($p < .0000$). It indicates the presence of selection biasand the need to run separate models for users andnon-users.

3.2.1. Determinants of crop productivity

To gain a better understanding of the variables that affect the crop yield effects of CSA practices, we examined a broad set ofexplanatory variables including household demographic factors,asset holdings, plot level factors, and institutional related variables.As shown in Tables6, the effect of age is positive and statistically significant on crop yield for only the packages of $I_0C_1R_0S_0$ and $I_0C_1R_0S_1$.These results show that an increase in age is associatedwith a higher likelihood of productivity for $I_0C_1R_0S_0$ and $I_0C_1R_0S_1$ users and lower productivity for non-users, the differencemight originate from the availability of large family sizefor practicing sustainable land and water management practices and large farm size forpracticing crop rotationandcrop diversifications.Age also increases the likelihood of crop yield for non-usersof $I_1C_1R_0S_1$, $I_1C_0R_1S_1$, $I_0C_0R_1S_0$, $I_0C_1R_1S_0$, $I_1C_0R_0S_1$, $I_1C_0R_1S_0$,$I_0C_1R_1S_1$,$I_0C_0R_1S_1$,$I_1C_1R_1S_0$ and$I_1C_1R_1S_1$CSA packages.This is attributed to the fact that older farmers might have better experience or availability of labor for managing the farm.Regarding the gender of the respondents,being male creates more likelihood of yield as compared to being female for users of$I_0C_1R_0S_0$, $I_1C_1R_0S_1$, $I_1C_0R_0S_1$, and $I_0C_1R_0S_1$, which could be because males are better positioned to have better farm experiences and access to extension services, allowing them to respond more. Even though women are involved in agricultural practices, accounting for more than half of the labor required to produce food consumed in Ethiopia (Tegegne, 2012), it is worth noting the problem that a female farmer is frequently perceived as a co-farmer and plays a minor role in agricultural development, particularly by those with significant influence in extension and development activities.

Plot fragmentation is estimated todecrease crop yield whenthe packages $I_1C_1R_1S_0$ and $I_1C_1R_1S_1$ are used. This result might emanate from the probability that land fragmentation can reduce yields by affecting the efficiency of agricultural inputs. Similarly, Cholo et al. (2018) found that land fragmentation is an obstacle to climate change adaptation measures and reduces yields by changing the marginal outputs of agricultural inputs.The result also shows that farmers who rent land but do not use $I_1C_0R_0S_1$ are more likely to have lower crop yields.This implies that if farmers rent land and do not use various agricultural inputs that can improve agricultural production, there will be a negative effect on productivity.The model also revealed that farmers who rent land and use $I_0C_0R_1S_1$ have lower crop yields than farmers who do not, while farmers who do not use it have higher yields.

Farmers who have irrigable land and access to irrigation infrastructure are more likely to practice all types of agricultural technologies, and their productivity is mostly positive. The authors have noticed that farmers with irrigated land and infrastructure have a better experience of using agricultural technologies, and at the same time, their agricultural results are better.Distance from home to farmland, on the other hand, is negatively and significantly correlated with crop productivity for both adopters and non-adopters. Having media access has the likelihood of increasing yield for both adopters and non-adapters of agricultural technologies (Table 6).Consistent with the report byTeklewold et al. (2019), media access helps farmers to become familiar with different agricultural technologies and has a positive role in crop productivity.Farmers may become more aware of the changing climate conditions and new seeds and crop varieties, livestock breeds, irrigation applications, planting dates, pest and disease control, and livestock vaccinations as a result of radio and television access.

Distance from home to the input market is negatively and significantly associated with the crop yield of farmers who use $I_0C_0R_1S_0$ and $I_0C_0R_1S_1$ CSA packages.Longer distances to the market for insecticides and pesticides decrease the information on the appropriate utilization of these inputs and then decrease crop productivity.Because of the increased transportation cost, farmers usually send someone else to buy insecticides and pesticides, and they will not have enough information about the utilization of those inputs.Consistent with this result, Teklewold et al. (2013) noted that apart from influencing market access, distance can also affect the accessibility of new technologies and information, resulting in a negative relationship.

Another variable studied in this study is farm size, which has a mostly positive relationship with crop productivity for both adopters and non-adopters of CSA packages in the study area (Table 6).This suggests that larger farms are more productive than their smaller counterparts. However, this finding contradicted thatincreasing farm size has the likelihood of reducingyield for both adapters and non-adapters (Adego et al., 2019) and the argument small farm be more productive with their use of all resources (Helfand & Taylor, 2021).This may be due to the direct relationship between labor productivity and farm size, where Ethiopia has higher potential of labor productivity.Farmers who had poor soil fertility conditions had lower yields compared to those who perceived the soil as fertile for $I_0C_1R_1S_0$ package users only.This is due to farmers frequently cultivating non-fertile land with only certain types of grain each year, such as oil seeds, flax, and sorghum in rotation or intercropping, and frequently without using manure.

Farmers who use the $I_1C_1R_1S_0$ and $I_1C_1R_1S_1$ CSA packages on sloping farmland have very low crop productivity. As a result, even if the best agricultural method is used to cultivate sloping land, the efficiency is very low. This implies that using agricultural technology on sloping land has higher production costs because sloping land is prone to soil fertility loss.Conversely, livestock assets influence crop productivity positively in most cases without disaggregating CSA package users and non-users. Livestock plays an important role in crop productivity. This is because farming is done almost entirely using animal labor.In addition, the presence of many cattle is a typical solution to increase the productivity of the land beyond the food security of the cattle in times of crisis. This is because cattle serve as a source of organic fertilizer in the study area.

Summer rainfall increases crop productivity for those who used $I_0C_1R_0S_0$, $I_1C_1R_0S_1$, $I_0C_0R_1S_0$, $I_0C_1R_0S_1$, and $I_0C_0R_1S_1$ CSA packages, while it decreases yields for those who did not use $I_1C_1R_0S_1$, $I_1C_0R_1S_1$, $I_0C_0R_1S_0$, $I_0C_1R_1S_0$, $I_1C_0R_1S_0$, $I_0C_1R_1S_1$, $I_0C_0R_1S_1$, $I_1R_1C_1S_0$, and $I_1C_1R_1S_1$. The increasing summer rainfall has the likelihood of increasing crop productivity when farmers use a variety of soil and water conservation measures, herbicides, and conservation agricultural practices such as crop rotation and crop diversification. Conversely, when farmers do not use improved crop varieties, crop productivity is more likely to decrease under high summer rainfall.The finding is consistent with the previous finding by Yesuf et al. (2008) that too much or too little rainfall during the main growing season has a negative impact on crop production unless adaptation measures are implemented.However, while climate change is frequently estimated to have a negative overall impact on agriculture, the previous result reaffirms the critical roles that adaptation can play in enabling farmers to cope with, and even benefit from, long-term increases in rainfall (Etwire et al., 2022).The findings show that increases in rainfall have positive effect on the productivity of farmers who adapt to climate change, whereas farmers who do not adapt experience productivity losses when rainfall increases.

Ethiopian farmers lack access to and use of modern agricultural inputs due to insufficient government extension services. Under these conditions, rural social networks could facilitate information exchange, allow farmers to learn from their experiences, and bridge the information gap. The model result of this study suggests that stronger social interactions enable farmers to more efficiently use improved irrigation practices,water management practices, drought-tolerant crop varieties, and chemical fertilizers, resulting in increased agricultural land productivity. Therefore, farmers who do not accessed credit in order to use these technologies is negatively associated with crop yields.

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Table 5: Estimates of crop productivity (Yield in ETB/ha) Equations by Multinomial Endogenous Switching Regression Model

VARIABLES	$I_0C_1R_0S_0$		$I_1C_1R_0S_1$		$I_1C_0R_1S_1$		$I_0C_0R_1S_0$		$I_0C_1R_1S_0$		$I_1C_0R_0S_1$	
	Users	Non-users	Users	Non-users	Users	Non-users	Users	Non-users	Users	Non-users	Users	Non-users
Age	282.86*	192.97	183.33	347.28***	5.20	389.24***	209.81	246.51**	0.90	260.05**	159.77	593.9***
	-147.33	-126.56	-163.77	-123.11	-169.18	-117.98	-152.31	-124.56	-240.02	-105.28	-107.39	-164.99
Gender	13,406.55***	-5096.48	18,826.74***	-5096.19	2486.94	1853.14	-5885.01	4245.68	-2074.70	2215.14	6,238.36**	-2953.04
	-4506.60	-3175.89	-5089.46	-3145.53	-7471.78	-2936.80	-5256.32	-3188.59	-9671.81	-2643.03	-3117.44	-4219.74
Family size	-36.79	-347.80	752.78	-21.07	433.89	-525.37	438.34	100.92	-111.39	-312.59	-548.22	-423.58
	-909.86	-800.32	-1027.18	-767.11	-1118.07	-712.48	-949.78	-777.41	-1514.67	-648.04	-662.79	-1033.58
Plot Number	306.74	979.30	1101.33	591.86	-767.62	1607.65	-452.38	1408.26	-857.29	1655.12	324.07	2905.47
	-1370.01	-1343.59	-1512.21	-1281.39	-1217.94	-1343.60	-1189.67	-1440.11	-1603.68	-1143.95	-1050.27	-1990.55
Land leasing	1585.63	1915.21	4124.35	-3844.47	-917.36	99.94	-4,499	5,918.37	-3528.89	1909.99	2708.09	-11,634***
	-2810.69	-2702.47	-3166.26	-2669.42	-2875.26	-2455.76	-2314.86	-2824.82	-4976.85	-2190.04	-2205.16	-3580.67
Irrigable land	13,891.613***	327.09	15,587.946***	3160.94	11,464.447***	7,964.938*	11,785.361***	3222.91	10165.37	6,300.969*	7,310.248**	19,369.125**
	-4390.69	-4476.23	-4811.88	-4578.28	-4151.51	-4474.32	-3623.73	-4804.69	-6839.68	-3727.51	-3446.50	-8739.56
Irrigation -infrastructure	9,432.592**	14,014.182***	2523.67	20,263.715***	4439.41	14,044.127***	7,793.259*	7994.00	4424.02	12,335.981***	7,773.856**	10793.22
	-4590.89	-5216.65	-4873.45	-5123.31	-4364.88	-4733.86	-4079.23	-5164.23	-6065.42	-4148.85	-3720.21	-9324.89
Farmdistance	-14.40	-64.86	105.13	-43.49	-150.61*	-57.10	-37.47	-121.55	-89.46	-118.5**	-61.26	-84.97
	-73.16	-59.94	-86.57	-61.57	-79.85	-58.37	-66.97	-76.30	-120.00	-52.29	-60.30	-94.39
Give out	-5604.82	-1732.62	1764.23	-6,649**	5989.32	-7,748**	1628.22	-5335.99	11.91	-4290.16	-563.27	-15,785.8***
	-6009.22	-3390.72	-7101.20	-3355.49	-5262.70	-3636.67	-5090.71	-3786.17	-10642.7	-3090.79	-4023.05	-5160.24
Media	11,044.6***	2947.04	12,252.9***	4111.63	6707.67	4,914.5*	2322.85	6,607.78**	6674.34	5,051.19**	4741.47	9,156.16**
	-3922.39	-2923.41	-4666.38	-2781.66	-6485.87	-2816.79	-4231.40	-2974.93	-9037.10	-2506.25	-3225.22	-3959.49
Market	-6.50	-8.44	-7.00	-13.22	-38.55	-5.61	-59.98**	-7.66	-46.04	-7.53	-6.70	-2.24
	-9.85	-11.49	-11.38	-9.55	-33.57	-7.35	-28.20	-7.16	-50.74	-6.59	-8.77	-10.55
Farm size	18.25***	1.00	19.63***	6.03**	16.44***	6.770**	17.430***	-0.21	19.817**	5.76**	11.18***	7.96*
	-3.61	-3.08	-4.22	-2.97	-5.63	-2.84	-5.44	-4.46	-8.99	-2.71	-3.05	-4.21
Poor Soil fertility	2290.54	-1992.40	5055.78	-3200.50	-4355.18	644.57	-6183.55	2943.08	-10,130*	1806.36	-711.19	-3982.43
	-3981.93	-5384.09	-4490.19	-4489.53	-4630.39	-3547.35	-4153.77	-3692.41	-5982.30	-3303.67	-3241.57	-5356.01
Social Members	221.12	-1513.93	545.26	-2186.80	1407.41	-2180.51	2440.80	-3833.89	1822.84	-1186.00	1616.81	-8,736.963*
	-4700.27	-3091.98	-5600.91	-3075.12	-3987.62	-3603.15	-3291.18	-4584.06	-5741.29	-3070.88	-3271.61	-4558.43
TLU	892.71	1,392.826**	587.02	1,076.013*	2,456.656***	962.73	1,420.354**	1,388.646*	1334.50	1,336.952**	1,386.983**	1,232.316*
	-774.62	-599.38	-949.28	-573.30	-851.89	-608.94	-621.37	-811.29	-1085.75	-551.67	-661.83	-740.99
Steep slope	1922.00	2342.85	808.39	-884.55	-5140.75	-817.78	-3632.58	5732.28	-13584.9	3597.26	4048.35	-12014.57
	-6693.49	-6219.12	-7380.18	-6164.69	-6783.71	-5659.99	-6373.74	-6075.69	-13355.5	-4948.33	-4871.07	-9684.67
Meher rainfall	371***	-52.95	283.3**	-195.4**	-183.35	-164.1*	174.6*	-260.9***	-112.55	-150.5**	-122.37	-117.13
	-113.15	-97.33	-117.70	-81.91	-128.73	-95.93	-89.54	-91.17	-167.74	-66.94	-82.57	-157.98
Credit constraint	-5,474.5	-3031.06	3108.21	1898.55	-1183.49	2572.57	-83.87	1597.98	5504.20	171.51	2889.71	1878.70
	-2991.62	-2718.16	-3523.49	-2441.70	-4095.49	-2327.79	-2790.36	-2701.45	-5134.48	-2220.84	-2344.94	-3378.87
Age dependency	1332.14	968.32	628.17	305.65	-384.80	1171.56	-565.60	1,559.2	-201.36	1,491.26	1,692.9	-224.05
	-1038.06	-991.12	-1213.81	-910.27	-1228.80	-833.79	-1063.46	-916.33	-1778.99	-789.67	-841.31	-1247.07
Constant	73,967.5**	56,647.1*	28031.1	83,925.5***	76391.0	64,362.5**	77,405.4***	112,285.4***	58786.7	68,344.6***	45304.9	55614.78
	-32996.6	-30037.2	-37448.8	-25470.8	-47676.2	-29161.5	-28107.2	-31996.9	-48296.9	-22487.9	-32576.4	-46697.41

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VARIABLES	$I_1C_0R_1S_0$		$I_0C_1R_0S_1$		$I_0C_1R_1S_1$		$I_0C_0R_1S_1$		$I_1C_1R_1S_0$		$I_1C_1R_1S_1$	
	Users	Non-users	Users	Non-users	Users	Non-users	Users	Non-users	Users	Non-users	Users	Non-users
Age	9.07	389.54 ***	307.91 **	181.8	0.60	262.69 **	204.37	252.80 **	-51.70	340.85 ***	8.281	345.81 ***
	-167.69	-118.57	-150.24	-126.18	-254.22	-104.87	-153.27	-122.98	269.29	110.71	444.85	110.81
Gender	2515.36	1810.17	12,796.1***	-4630.75	-956.09	2211.16	-5865.80	4328.13	16,288.4	2,006.49	17,551.5	1,982.20
	-7419.75	-2948.52	-4565.24	-3132.95	-11130.2	-2630.63	-5303.10	-3176.20	10,732.5	2,679.86	11,499.2	2,670.3
Family size	434.87	-524.61	-169.25	-260.90	-232.27	-301.52	445.86	114.57	175.9367	-591.18	-34.80	-591.9
	-1108.48	-715.60	-928.30	-775.90	-1598.95	-644.73	-960.38	-774.39	1,538.15	648.59	1,576.5	646.80
Plot Number	-745.11	1586.94	504.80	815.17	-891.31	1642.41	-471.18	1383.47	-3,363.0 *	1,138.4	-3,477.0 *	1,141.16
	-1209.20	-1355.68	-1397.32	-1319.93	-1614.12	-1136.42	-1202.58	-1429.12	1,771.97	1,137.04	1,821.2	1,128.2
Land leasing	-782.79	82.96	2182.02	1648.38	-3239.58	1980.20	-4,632.2 *	6,087.3 **	2,203.4	92.99	3,493.41	199.56
	-2803.21	-2467.42	-2883.01	-2690.54	-6855.88	-2189.67	-2373.40	-2813.69	6,044.9	2,140.78	12,738.1	2,138.6
Irrigable land	11,582.8***	7,864.7*	13,364.0***	1059.07	10561.6	6,190.8 *	11,774.1***	2945.41	19,435.3**	8,594.69**	22,878.7	8,591.8 **
	-4080.64	-4610.23	-4479.28	-4290.12	-8096.63	-3645.06	-3722.59	-4678.92	9,266.32	3,811.23	19,712.6	3,716.
Irrigation - infrastructure	4364.05	14,058.7 ***	10,282.0**	13,284.8 ***	4856.50	12,526.6***	7,781.60*	8,534.48*	-2,834.5	15,508.9***	-4,514.1	15,618***
	-4210.51	-4839.89	-4689.20	-5123.05	-7597.56	-4120.62	-4241.46	-5075.41	5,591.57	4,070.20	7,012.3	4,015.3
Farmdistance	-144.5*	-56.74	-6.08	-71.05	-107.01	-118.6**	-39.48	-123.45	-177.65	-94.09*	-179.392	-92.9*
	-78.15	-58.80	-74.57	-59.44	-133.93	-51.87	-67.97	-76.19	130.76	50.47	153.75	50.1
Give out	6160.22	-7,754 **	-7513.50	-1106.94	-1153.80	-4299.05	1619.84	-5450.93	5,985.32	-6,734 **	4,917.54	-6,745 **
	-5202.79	-3647.48	-6302.07	-3373.93	-11824.5	-3080.73	-5138.14	-3768.35	13,586.6	3,172.98	15,226.2	3,166.9
Media	6819.21	4,856.92 *	10,450.7***	3565.86	7659.52	5,061.42**	2290.43	6,702.50**	36,870.9***	5,189.90**	41,038.5**	5,212.7**
	-6435.93	-2823.81	-3979.46	-2845.21	-10869.2	-2495.65	-4262.56	-2963.78	13,119.4	2,504.47	16,903.4	2,490.0
	-37.95	-5.67	-5.17	-10.09	-48.95	-7.50	-59.78**	-7.63	19.22	-6.69	12.54	-6.58
market	-32.45	-7.37	-9.98	-11.36	-52.41	-6.55	-28.72	-7.12	52.59	6.88	60.27	6.85
Farm size	15.83 ***	6.85**	17.4***	1.59	19.25	5.714**	18.018***	-0.42	18.67 ***	8.08 ***	17.25**	8.03 ***
	-5.42	-2.84	-3.67	-2.95	-12.19	-2.73	-5.65	-4.51	7.05	2.48	7.57	2.47
Poor Soil fertility	-4053.1	576.23	2468.09	-1826.4	-10147.	1840.32	-6414.10	3008.41	-1,100.22	-130.1	509.2	-36.3
	-4529.9	-3552.0	-4050.70	-5304.6	-6462.4	-3303.9	-4204.20	-3686.72	7,680.96	3,260.67	14,158.9	3,249.8
Social Member	1488.15	-2183.6	290.39	-1485.7	1811.05	-1254.34	2473.22	-4038.84	5,310.65	-1,687.1	5,625.74	-1,734
	-3954.5	-3614.5	-4766.9	-3068.3	-5830.2	-3062.45	-3312.73	-4569.56	7,185.19	2,958.46	8,629.6	2,952.4
TLU	2,422.9***	962.20	804.82	1,447.3**	1446.56	1,334.33**	1,437.27**	1,392.5*	5,303.15 ***	889.55 *	5,604.97***	882.82*
	-839.76	-611.76	-784.45	-593.12	-1138.5	-549.12	-626.52	-809.32	1,405.03	527.464	1,657.67	525.60
Steep slope	-5663.13	-750.79	2371.52	2151.67	-13365.0	3512.25	-3239.07	5604.74	-63,015 ***	-4,459.6	-70,313 *	-4,720.2
	-6633.06	-5680.49	-6816.18	-6106.05	-15786.5	-4938.50	-6444.22	-6029.79	23,418.6	8,428.6	40,327.2	8,411.79
Meher rainfall	-170.99	-168.13*	377.9 ***	-51.65	-129.36	-150.9 **	180.8 **	-257.2 ***	17.81	-140.60 **	47.66	-139.97 **
	-124.88	-95.18	-115.65	-96.05	-190.70	-66.73	-91.26	-90.76	161.80	67.30	213.76	67.13
Credit constraint	-1487.3	2544.9	-5,502.1	-3124.7	5405.2	103.40	153.96	1468.20	1,135.5	2,640.5	-117.81	2,581.1
	-4016.39	-2346.10	-3043.39	-2685.86	-6744.68	-2227.02	-2847.04	-2704.09	5,595.15	2,122.4	5,922.4	2,110.04
Age dependency	-305.49	1173.17	1284.27	985.21	-194.98	1,469.42	-625.99	1,503.93	1,576.82	1,193.14	2,445.72	1,200.989
	-1147.05	-849.40	-1062.32	-939.07	-2026.95	-771.65	-1111.91	-894.05	1,802.79	771.12	2,725.92	755.27
Constant	72807.4	65,427.3 **	77,288.1**	54,745.4 *	61712.5	68,594.8***	78,621.0***	111,780 ***	-54,137	59,740 ***	9.49 ***	9.6***
	-46635.5	-28980.2	-33598.8	-29838.4	-50229.8	-22477.2	-28412.1	-31777.2	75,987.8	21,573.5	0.23	0.04

*, **, and ***coefficients aresignificant at 10%, 5%, and 1% levels, respectively. In the parenthesis is standard error, Number of observations = 411

Source: Authors survey, 2024

The effects of CSA practices on crop productivity

The results from the conditional expected crop yield per hectare derived from an endogenous switching regression analysis for the actual (treated) and counterfactual (untreated) farm plots under different treatments are presented in table (Table 6).The last column (ATT) in the table (Table 6) presents the impact of each CSA package on crop production, which is the treatment effects, calculated as the difference between treated with treatment characteristics and the untreated with untreated characteristics. The estimation result provides a statistically significant positive impact on crop productivity inmost of thepackages whilestatistically non-significant impact on crop productivity was observed for the packages of $I_0C_1R_1S_0$, $I_1C_0R_1S_0$ and $I_0C_0R_1S_1$.Results also show that the decision to implement most of the CSA packages, whether jointly or in isolation contributes higher crop productivity per hectare compared with those who decide not to implement (Table6). In most of counterfactual cases, farm households who actually decides to implement CSA practices gained less crop yield if they had not decided to implement.

Deciding to use input-based crop management practices in isolation provides higher crop production than using other practices in isolation.The productivity-enhancing effect of input-based crop management practices issignificantly higher when conservation farming practices are included into thepackage. However, the decisions to implement the packages of input-based crop management practices with water management practices ($I_1C_0R_0S_1$) provides higher crop yield per hectare than any other packages in isolation or in combinations.For instances, practicing the packages of $I_1C_0R_0S_1$as a combination yieldthe highest benefit (11, 688.09ETB/ha) among all the other packages. In the counterfactual case $I_1C_0R_0S_1$,households who actually decided to use input-based crop management practices combinedwith sustainable soil and water conservation measures ($I_1C_0R_0S_1$)produced 32% less if they did not treat with $I_1C_0R_0S_1$treatments. In the counterfactual case, households that did not receive $I_1C_0R_0S_1$ treatments produced approximately ETB 4,597 (about 12%) more if they had. These results imply that input-based crop management practices and sustainable soil and water conservation measures significantly increase crop productivity in the study area. The transitional heterogeneity effect is positive; that is, the effect is larger for the households that practiced the package of $I_1C_0R_0S_1$relative tothose that did not practice the package.

The result implies complementarity among the three climatesmartpractices (Input based crop management (I), Conservation agriculture (C) and Sustainable Water management(S), which is in line with Di Falco and Veronesi (2013) and Teklewold et al. (2017), who suggest multiple agricultural practices to enhance the productivity of crop under the changing climate. However, households that decided to implement farm risk reduction measures in combination or isolation with other CSA practices yields less crop income per hectare in the study area. For instance, farm risk reduction measures $I_0C_0R_1S_0$ and $I_0C_0R_1S_1$ yields less crop production per hectare than any other combination of CSA practices. Furthermore, when input based crop management practices are decided to implement in isolation or in combination with other packages, yields the higher benefits. The estimation also revealed that the higher payoff is not achieved by implementing all four packages jointly. Implementing all four packages together would yield low crop income per hectare (8,127.5 ETB/ha) than implementing the packages $I_1C_0R_0S_1$and $I_1C_1R_0S_1$. The result implies that productivity decreases when the packages of farm risk reduction measures combined with others, which may be due to less accurate information provided from extension agents.Improving access to climate information and the speed with which it is communicated through agricultural extension experts will enable the early warning system to be more effective and efficient in planting and harvesting crops. However, due to weakinfrastructure for weather forecasting in Ethiopia, the early warning work is often not based on accurate information, so the effect on the farmers' crop productivity is equally low.Similarly, Choularton and Krishnamurthy (2019) observe that the lower accuracy of climate forecast data in northeastern Ethiopia affects the accuracy of early warning systems, which in turn affects their effectiveness on rural livelihoods, which are entirely dependent on rain-fed farming systems. Instead, implementing conservation farming practices and intensive farming practices are estimated to have a positive role in increasing productivity.

Table 6. Treatment effects by CSA package measured by regional price in ETB per hectare

CSA packages	Farm households that	Decisions stage		
		Treated characteristics	Un treated characteristics	Treatment effect (ATT)
$I_1C_1R_1S_1$	users	49529.33(1788.13)	41401.83(1337.91)	8,127.5 (2956.70) ***
	Non-users	44502.63 (2022.866)	40305.26 (647.08)	4,197.35 (1668.84) ***
$I_1C_1R_1S_0$	Users	50752.62 (1974.092)	42987.02 (1220.83)	7,765.6 (2676.92) ***
	Non-users	44296.52 (1735.58)	40322.53 (649.53)	3973.99 (1650.62) ***
$I_0C_0R_1S_1$	Users	50106.16 (1001.4)	49742.37 (1123.7)	367.79(1509.6) ***
	Non-users	42283.56 (798.0)	39897.17 (773.63)	2,386.56 (1111.2) ***
$I_0C_1R_1S_1$	Users	49007.79 (1232.3)	45648.52 (598.718)	3,359.79 (1753.1) ***
	Non-users	46914 (917.32)	44717.29 (1528.48)	2,196.71 (1229.521) ***
$I_0C_1R_0S_1$	Users	45506.99 (848.9)	40475.08 (812.9)	5,031.91(1205.3) ***
	Non-users	37254.95 (704.7)	35257.11 (661.1)	1,997.838 (993.6) **
$I_1C_0R_1S_0$	Users	47451.71(1322.5)	45191.87 (797.6)	2,259.84 (1408.5)
	Non-users	42010.41(1146.8)	40628.05 (710.4)	1,382.36 (1378.1) ***
$I_1C_0R_0S_1$	Users	47744.76 (1289.5)	36056.67(899.5)	11, 688.09 (1162.7) ***
	Non-users	42613.69 (690.3)	38016.51 (1367.5)	4,597.18 (2058.3) ***
$I_0C_1R_1S_0$	Users	49811.15 (916.34)	48631.5 (1216.98)	1,179.65 (1735.8) ***
	Non-users	44599.36 (1506.75)	39661.97 (601.42)	8,969.56(1223.7) ***
$I_0C_0R_1S_0$	Users	49391.76(791.1)	49209.5(1139.2)	182.24(513.9) ***
	Non-users	42238.02(992.9)	39918.2 (778.63)	2,319.82 (1110.0) ***
$I_1C_0R_1S_1$	Users	48058.23(1338.591)	45885.9 (793.6)	2,172.33(1415.1) ***
	Non-users	42077.92 (1161.43)	40606.9 (707.02)	1,471.02 (1383.7) ***
$I_1C_1R_0S_1$	Users	44749.61 (987.5)	36375.08 (762.49)	8,374.56(1228.25) ***
	Non-users	41826.77 (1173.1)	38109.13 (791.07)	3,717.64 (1364.1) ***
$I_0C_1R_0S_0$	Users	45449.84 (834.5)	41025.27(823.8)	4,424.57 (1204.8) ***
	Non-users	36642.2(709.9)	35185.22 (682.8)	1,457(1016.10) *
$I_1C_0R_0S_0$	Users	47022.3(1124.01)	42534.73 (543.08)	4488.3 (959.79) ***
	Non-users	41933.43 (793.2)	37927.33 (1087.8)	4006.1(1797.8) **
$I_1C_1R_0S_0$	Users	45004.93 (832.85)	38104.11(619.1)	6900.82(1065.5) ***
	Non-users	39892.69 (982.4)	38874.37(551.66)	1018.32(919.9) ***

*, **, and ***coefficients aresignificant at 10%, 5%, and 1% levels, respectively. In the parenthesis is standard error

Source: Authors survey, 2024

IV. CONCLUSIONS AND IMPLICATIONS

The present study was designed to determine the effect of CSA technology adoption on crop yield in the North Wello administrative zone. The study applied cross-sectional farm household-level data collected in 2024 from a randomly selected 411 sample households. The causal impacts of CSA practices are estimated by utilizing the endogenous switching regression model.This helps in estimating the productivity effects of CSA technologies by controlling for the role of the selection problem on production and adoption decisions.The findings revealed that farmers who implemented a single or full package of CSA practices had a higher crop yield per hectare than those who did not.One of the most important findings of this study is that combining CSA technologies produces more crop yield than a single practice.It was also shown that households that adopted input-based crop management practices combined with sustainable soil and water conservation practices achieved a greater yield per hectare than any other CSA, either in isolation or in combination. This means, higher crop productivity was gained by combining improved seed, chemical fertilizers, and water management practices.The model results showed that the second highest productivity was estimated when input based crop management , conservation farming , and water management practices were adopted jointly.However, it was not predicted that implementing all of the packages together result in increased crop productivity.

The following policy recommendations can be made based on the model results.Adoption of two or more CSA practices in tandem should be encouraged because all combinations result in significant increases in crop net revenue per hectare.Multiple CSA practices should be promoted because they produce more crop net revenue per hectare than single practices.Despite unobserved and observed effects, combining input-based crop management (improved drought-resistant crop varieties and efficient inorganic fertilizer applications) and water management (soil/stone bunds, infiltration ditches, and small-scale irrigation) yields the highest crop net revenue per hectare of any possible combination.The estimation also shows that farmers who used all types of CSA practices considered in this study did not have the best crop income per hectare on average. This could be due to the low effectiveness of climate risk reduction measures, which, when combined with others, have little effect.Furthermore, there are some limitations to this study. We were unable to observe the dynamics of CSA practice adaptation over time because we used cross-sectional farm-level household data.

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Authors’ contributions

The author conceptualized the study, designed it, collected data, analyzed it, and wrote the report.

Declarations

Ethics approval and statement

The local research ethics committee at the Woldia University, Ethiopia, waived ethical approval due to the survey nature of the study and the fact that all procedures performed were routine care.

Consentto participate

First, we received a letter of support from the research committee at the Woldia University. The farmers were then shown and read the letter, and if they agreed, we asked them to fill out the questionnaire.

Competing interests

The authors claim that they have no competing interests.

Missing Data Availability Statement

The datasets used in the current study are available from the author.

REFERENCES

[1]. Abebe, Y., & Bekele, A. (2014). The impact of soil and water conservation program on the income and productivity of farm households in Adama District, Ethiopia. Science, Technology and Arts Research Journal, 3(3), 198-203.

[2]. Adego, T., Simane, B., &Woldie, G. A. (2019). The impact of adaptation practices on crop productivity in northwest Ethiopia: an endogenous switching estimation. Development Studies Research, 6(1), 129-141.

[3]. Admassie, A., et al. (2008). Perceptions of stakeholders on climate change and adaptation strategies in Ethiopia, International Food Policy Research Institute.

[4]. Alemu, T., & Mengistu, A. (2019). Impacts of climate change on food security in Ethiopia: adaptation and mitigation options: a review. Climate change-resilient agriculture and agroforestry, 397-412.

[5]. Alemu, Z. G., Oosthuizen, K., & Van Schalkwyk, H. D. (2003). Contribution of agriculture in the Ethiopian economy: A time-varying parameter approach. Agrekon, 42(1), 29-48.

[6]. Alexandrova, M. (2018). A principal component analysis of project portfolio management practices. Ekonomicko-manazerskespektrum, 12(2), 96-105.

[7]. Amadu, F. O., McNamara, P. E., & Miller, D. C. (2020). Understanding the adoption of climate-smart agriculture: A farm-level typology with empirical evidence from southern Malawi. World Development, 126, 104692.

[8]. Araya, T. (2019). 3. Conservation Agriculture for Enhancement of Livelihoods and Environments in Ethiopia. Climate-Smart Agriculture, 27.

[9]. Asfaw, A., Simane, B., Bantider, A., & Hassen, A. (2019). Determinants in the adoption of climate change adaptation strategies: evidence from rainfed-dependent smallholder farmers in north-central Ethiopia (Woleka sub-basin). Environment, Development and Sustainability, 21(5), 2535-2565.

[10]. Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. Food policy, 37(3), 283-295.

[11]. Asmare, F., Teklewold, H., &Mekonnen, A. (2019). The effect of climate change adaptation strategy on farm households' welfare in the Nile basin of Ethiopia: Is there synergy or trade-offs? International Journal of Climate Change Strategies and Management.

[12]. Asrat, P., &Simane, B. (2017). Adaptation benefits of climate-smart agricultural practices in the Blue Nile Basin: empirical evidence from North-West Ethiopia. Climate Change Adaptation in Africa (pp. 45-59): Springer.

[13]. Bewket, W. (2009). Rainfall variability and crop production in Ethiopia: Case study in the Amhara region. Proceedings of the 16th International Conference of Ethiopian Studies, Norwegian University of Science and Technology Trondheim, Norway.

[14]. Beyene, A. D., Mekonnen, A., Kassie, M., Di Falco, S., &Bezabih, M. (2017). Determinants of adoption and impacts of Sustainable Land Management and Climate Smart Agricultural Practices (SLM-CSA): Panel data evidence from the Ethiopian highlands.

[15]. Bryan, E., Deressa, T. T., Gbetibouo, G. A., & Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: options and constraints. Environmental science & policy, 12(4), 413-426.

[16]. Calzadilla, A., Zhu, T., Rehdanz, K., Tol, R. S., & Ringler, C. (2013). Economywide impacts of climate change on agriculture in Sub-Saharan Africa. Ecological Economics, 93, 150-165.

[17]. Chatterjee, S., Goswami, R., &Bandopadhyay, P. (2015). Methodology of identification and characterization of farming systems in irrigated agriculture: case study in west Bengal State of India. Journal of Agricultural Science and Technology, 17(5), 1127-1140.

[18]. Cholo, T. C., Fleskens, L., Sietz, D., &Peerlings, J. (2018). Is land fragmentation facilitating or obstructing adoption of climate adaptation measures in Ethiopia? Sustainability, 10(7), 2120.

[19]. Choularton, R. J., & Krishnamurthy, P. K. (2019). How accurate is food security early warning? Evaluation of FEWS NET accuracy in Ethiopia. Food Security, 11(2), 333-344.

[20]. Conway, D. (2000). Some aspects of climate variability in the north east Ethiopian Highlands-Wollo and Tigray. Ethiopian Journal of Science, 23(2), 139-161.

[21]. Debalkie, G., & Solomon, B. (2014). Community-based, participatory integrated watershed management as an approach to climate change adaptation in HaroJila and Wurba watersheds. Adapting to climate change through land and water management in Eastern Africa, 48.

[22]. Deichert, G., Gedamu, A., &Nemomsa, B. (2017). Role of sustainable land management (SLM) in adapting to climate variability through agricultural practices—Experiences from Ethiopian highlands. In Climate change adaptation in Africa (pp. 475-492). Springer, Cham.

[23]. Deressa, T. T., & Hassan, R. M. (2009). The economic impact of climate change on crop production in Ethiopia: evidence from cross-section measures. Journal of African economies, 18(4), 529-554.

[24]. Di Falco, S., & Veronesi, M. (2013). How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. Land Economics, 89(4), 743-766.

[25]. Di Falco, S., Veronesi, M., &Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. American Journal of Agricultural Economics, 93(3), 829-846.

[26]. Di Falco, S., Yesuf, M., Kohlin, G., & Ringler, C. (2012). Estimating the impact of climate change on agriculture in low-income countries: household-level evidence from the Nile Basin, Ethiopia. Environmental and Resource Economics, 52(4), 457-478.

[27]. Ethiopian Panel on Climate Change (EPCC). (2015). First Assessment Report, Working Group II Agriculture and Food Security, Published by the Ethiopian Academy of Sciences

[28]. Etwire, P. M., Koomson, I., &Martey, E. J. C. C. (2022). Impact of climate change adaptation on farm productivity and household welfare. 170(1), 1-27.

[29]. Evangelista, P., Young, N., & Burnett, J. (2013). How will climate change spatially affect agriculture production in Ethiopia? Case studies of important cereal crops. Climatic change, 119(3), 855-873.

[30]. FAO (2017) The future of food and agriculture–Trends and challenges. FAO Rome. http://www.fao.org/3/a-i6881e.pdf

[31]. FAO. (2013). Climate-smart agriculture sourcebook. Food and Agriculture Organizations of United States, Rome Italy, 2013

[32]. Fenta, A. A., Hailu, G., &Hadush, Z. (2019). Integrating climate-smart approaches across landscapes to improve productivity, climate resilience, and ecosystem health. Climate-smart Agriculture: Enhancing resilient agricultural systems, landscapes and livelihoods in Ethiopia and beyond. World Agroforestry (ICRAF), Nairobi, Kenya, 15-23.

[33]. Fentie, A., &Beyene, A. D. (2019). Climate-smart agricultural practices and welfare of rural smallholders in Ethiopia: Does planting method matter? Land Use Policy, 85, 387-396.

[34]. Ferede, T., Ayenew, A. B., Hanjra, M. A., &Hanjra, M. (2013). Agroecology matters: Impacts of climate change on agriculture and its implications for food security in Ethiopia. Global food security: Emerging issues and economic implications, 71-112.

[35]. Gashaw, T., Mebrat, W., Hagos, D., &Nigussie, A. (2014). Climate change adaptation and mitigation measures in Ethiopia. Journal of Biology, Agriculture and Healthcare, 4(15), 148-152.

[36]. Gebreegziabher, Z., Stage, J., Mekonnen, A., & Alemu, A. (2016). Climate change and the Ethiopian economy: a CGE analysis. Environment and development economics, 21(2), 205-225.

[37]. Gebreegziabher, Z., Stage, J., Mekonnen, A., & Alemu, A. (2016). Climate change and the Ethiopian economy: a CGE analysis. Environment and development economics, 21(2), 205-225.

[38]. Gebreegziabher, Z., Stage, J., Mekonnen, A., & Alemu, A. (2016). Climate change and the Ethiopian economy: a CGE analysis. Environment and development economics, 21(2), 205-225.

[39]. Gelaw, A. (2017). Climate-Smart agriculture in Ethiopia. International Center for Tropical Agriculture, 26.

[40]. Georgisea, K., Negussieb, A., Birhanec, E., Hadgud, K. M., Bishawe, B., &Iiyamaf, M. (2019). 1. Climate-Smart Agriculture for Ethiopia and Beyond. Climate-Smart Agriculture, 1.

[41]. Gorst, A., Dehlavi, A., & Groom, B. (2018). Crop productivity and adaptation to climate change in Pakistan. Environment and development economics, 23(6), 679-701.

[42]. Habtewold, T. M. (2021). Impact of climate-smart agricultural technology on multidimensional poverty in rural Ethiopia. Journal of Integrative Agriculture, 20(4), 1021-1041.

[43]. Hadgu, K. M., Bishaw, B., Iiyama, M., Birhane, E., Negussie, A., Davis, C. M., &Bernart, B. (2019). Climate-Smart Agriculture: Enhancing Resilient Agricultural Systems, Landscapes, and Livelihoods in Ethiopia and Beyond. World Agroforestry (ICRAF), Nairobi, Kenya, 251.

[44]. Heckman, J. J. (1979). Sample selection bias as a specification error. Econometrica: Journal of the econometric society, 153-161.

[45]. Heckman, J., & Navarro-Lozano, S. (2004). Using matching, instrumental variables, and control functions to estimate economic choice models. Review of Economics and statistics, 86(1), 30-57.

[46]. Helfand, S. M., & Taylor, M. P. (2021). The inverse relationship between farm size and productivity: Refocusing the debate. Food Policy, 99, 101977.
[47]. Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. Psychometrika, 23(3), 187-200.
[48]. Kassie, M., Pender, J., Yesuf, M., Kohlin, G., Bluffstone, R., &Mulugeta, E. (2008). Estimating returns to soil conservation adoption in the northern Ethiopian highlands. Agricultural economics, 38(2), 213-232.
[49]. Kassie, M., Pender, J., Yesuf, M., Kohlin, G., Bluffstone, R., &Mulugeta, E. (2007). Impact of soil conservation on crop production in the Northern Ethiopian Highlands. Intl Food Policy Res Inst.
[50]. Kassie, M., Teklewold, H., Marenya, P. P., Moti, J., &Erenstein, O. (2014). Production Risks and Food Security under A lternative T echnology C hoices in Malawi: A pplicationofa Multinomial Endogenous Switching R egression.
[51]. Kassie, M., Teklewold, H., Marenya, P., Jaleta, M., &Erenstein, O. (2015). Production risks and food security under alternative technology choices in Malawi: Application of a multinomial endogenous switching regression. Journal of Agricultural Economics, 66(3), 640-659.
[52]. Komarek, A. M., Thurlow, J., Koo, J., & De Pinto, A. (2019). Economywide effects of climate-smart agriculture in Ethiopia. Agricultural Economics, 50(6), 765-778.
[53]. Kothari, C. R. (2004). Research methodology: Methods and techniques: New Age International.
[54]. Kulcsár, E. (2010). Principal component analysis in tourism marketing. Management & Marketing, 5(2), 151-158.
[55]. Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., . . . Henry, K. (2014). Climate-smart agriculture for food security. Nature climate change, 4(12), 1068-1072.
[56]. Lokshin, M., &Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. The Stata Journal, 4(3), 282-289.
[57]. Maddala, G. S. (1983), Limited-Dependent and Qualitative Variables in Economics, New York: Cambridge University Press, pp. 257-91.
[58]. Mideksa, T. K. (2010). Economic and distributional impacts of climate change: The case of Ethiopia. Global Environmental Change, 20(2), 278-286.
[59]. Miheretu, B. A., &Yimer, A. A. (2017). Determinants of farmers' adoption of land management practices in Gelana sub-watershed of Northern highlands of Ethiopia. Ecological processes, 6(1), 1-11.
[60]. MoEFCC/Ministry of Environment, Forest and Climate Change (2017) REDD+ MRV implementation in Ethiopia: Review of the context, framework and progress. Federal Democratic Republic of Ethiopia, Addis Ababa
[61]. Pender, J., & Gebremedhin, B. (2008). Determinants of agricultural and land management practices and impacts on crop production and household income in the highlands of Tigray, Ethiopia. Journal of African Economies, 17(3), 395-450.
[62]. Robinson, S., Strzepek, K., &Cervigni, R. (2013). The cost of adapting to climate change in Ethiopia: Sector-wise and macro-economic estimates. Ethiopia Strategy Support Program II (ESSP) working Paper, 53.
[63]. Sedebo, D. A., Li, G. C., Abebe, K. A., Etea, B. G., Ahiakpa, J. K., Ouattara, N. B., ... & Frimpong, S. (2021). Smallholder farmers' climate change adaptation practices contribute to crop production efficiency in southern Ethiopia. Agronomy Journal, 113(6), 4627-4638.
[64]. Sedebo, D. A., Li, G., Etea, B. G., Abebe, K. A., Ahiakpa, J. K., Arega, Y., &Anran, Z. (2022). Impact of smallholder farmers' climate-smart adaptation practices on wheat yield in southern Ethiopia. Climate and Development, 1-15.
[65]. Shiferaw, A. (2017). Productive capacity and economic growth in Ethiopia. United Nations, Department of Economics and Social Affairs.
[66]. Shiferaw, A., Tadesse, T., Rowe, C., & Oglesby, R. (2018). Precipitation extremes in dynamically downscaled climate scenarios over the Greater Horn of Africa. Atmosphere, 9(3), 112.

[67]. Solomon, R., Simane, B., & Zaitchik, B. F. (2021). The impact of climate change on agriculture production in ethiopia: Application of a dynamic computable general equilibrium model. American Journal of Climate Change, 10(1), 32-50.

[68]. Solomon, R., Simane, B., & Zaitchik, B. F. (2021). The impact of climate change on agriculture production in ethiopia: Application of a dynamic computable general equilibrium model. American Journal of Climate Change, 10(1), 32-50.

[69]. Tadesse, M., Simane, B., Abera, W., Tamene, L., Ambaw, G., Recha, J. W., ...& Solomon, D. (2021). The effect of climate-smart agriculture on soil fertility, crop yield, and soil carbon in southern ethiopia. Sustainability, 13(8), 4515.

[70]. Taffesse, A. S., Dorosh, P., Gemessa, S. A. J. F., Progress, a. i. E., & challenges, p. (2012). Crop production in Ethiopia: Regional patterns and trends. 53-83.

[71]. Tambo, J., &Wünscher, T. (2016). Beyond adoption: welfare effects of farmer innovation behavior in Ghana. ZEF-Discussion Papers on Development Policy, (216).

[72]. Tegegne, M. (2012). An assessment on the role of women in agriculture in Southern Nation Nationality People's Region: The case of Halaba Special Woreda, Ethiopia (Doctoral dissertation, Indira Gandhi National Open University).

[73]. Teklewold, H., Gebrehiwot, T., &Bezabih, M. (2019). Climate-smart agricultural practices and gender-differentiated nutrition outcome: Empirical evidence from Ethiopia. World Development, 122, 38-53.

[74]. Teklewold, H., Kassie, M., Shiferaw, B., &Köhlin, G. (2013). Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. Ecological Economics, 93, 85-93.

[75]. Teklewold, H., Mekonnen, A., Kohlin, G., & Di Falco, S. (2017). Does Adoption of Multiple Climate-Smart Practices Improve Farmers'climate Resilience? Empirical Evidence From The Nile Basin Of Ethiopia. Climate Change Economics, 8(01), 1750001.

[76]. Tesfaye, W., &Tirivayi, N. (2020). Crop diversity, household welfare and consumption smoothing under risk: evidence from rural Uganda. World Development, 125, 104686.

[77]. Tsige, M., Synnevåg, G., & Aune, J. B. (2020). Gendered constraints for adopting climate-smart agriculture amongst smallholder Ethiopian women farmers. Scientific African, 7, e00250.

[78]. Wekesa, B. M., Ayuya, O. I., &Lagat, J. K. (2018). Effect of climate-smart agricultural practices on household food security in smallholder production systems: micro-level evidence from Kenya. Agriculture & Food Security, 7(1), 80.

[79]. World Bank, (2021). Climate Risk Profile: Ethiopia 2021. The World Bank Group.

[80]. World Bank. (2010). the economics of adaptation to climate change: a synthesis report final consultation draft August 2010

[81]. Wubie, A. A. (2015). Review on the impact of climate change on crop production in Ethiopia. J. Biol. Agric. Healthcare, 5(13), 103-112.

[82]. Yalew, A. W., Hirte, G., Lotze-Campen, H., &Tscharaktschiew, S. (2018). Climate change, agriculture, and economic development in Ethiopia. Sustainability, 10(10), 3464.

[83]. Yesuf, M., Di Falco, S., Deressa, T., Ringler, C., &Kohlin, G. (2008). The impact of climate change and adaptation on food production in low-income countries: evidence from the Nile Basin, Ethiopia. Intl Food Policy Res Inst.

[84]. Yirgu, L., Nicol, A., & Srinivasan, S. (2013). Warming to change? climate policy and agricultural development in Ethiopia. Future Agricultures Working Paper, 71.

[85]. Zeleke, G., Teshome, M., & Ayele, L. (2022). Assessment of Land Degradation Neutrality Status in North Wello Zone, Northern Ethiopia. Ethiopian Renaissance Journal of Social Sciences and the Humanities, 9(1), 47-75.

[86]. Zeleke, T., Giorgi, F., MengistuTsidu, G., &Diro, G. T. (2013). Spatial and temporal variability of summer rainfall over Ethiopia from observations and a regional climate model experiment. Theoretical and applied climatology, 111(3), 665-681.

[87]. Zingiro, A., Okello, J. J., &Guthiga, P. M. (2014). Assessment of adoption and impact of rainwater harvesting technologies on rural farm household income: the case of rainwater harvesting ponds in Rwanda. Environment, development and sustainability, 16(6), 1281-1298.