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Research article

Determinants of adoption of climate smart agricultural practices among farmers in Bale-Eco region, Ethiopia

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ABSTRACT

Adoption of climate smart agricultural (CSA) practices has been widely recognized as a promising and successful alternative to minimize the adverse impacts of climate change. However, their adoption among smallholder farmers remains low in developing countries, including Ethiopia. This study examines factors that influence adoption and the level of adoption of multiple CSA practices, including improved agronomy, soil and water conservation, drought tolerant high yielding crop variety, small-scale irrigation, integrated disease, pest, and weed management, and integrated soil fertility management, using survey data from 404 farm households in Bale-Eco Region (BER), Ethiopia. The study applied a multivariate probit model for analyzing the simultaneous adoptions of multiple CSA practices, and ordered probit model for examining the factors influencing the level of adoption. The CSA practices are found to be complementary. Moreover, farmers' adoption of multiple CSA practices, as well as their intensity of adoption, is significantly influenced by the age of the household head, education, land size, household total asset value, frequency of extension contacts, farmer awareness of climate change, farmer experience with climatic shocks, parcel fertility, slope, and severity of soil erosion. The study's findings suggest that agricultural policy makers and implementers of CSA should recognize the complementarity among CSA practices in order to intensify their adoption among BER farmers and disseminate CSA practices in other parts of the country. Moreover, policymakers should consider household socio-economic, institutional, and parcel-specific factors that positively influence CSA adoption.

1. Introduction

Agriculture is the most vulnerable sector to climate change, yet it is also one of the most significant contributors to the climate change (Smith et al., 2008; OECD, 2016; Lewis et al., 2018; Arora, 2019). Increases in mean temperatures, rainfall variability, frequency and intensity of extreme weather events (droughts, floods, unreliable rainy seasons, hurricanes), and atmospheric carbon dioxide concentrations are all indicators of climate change that have impacted and will continue to impact the agricultural sector (OECD, 2016; NSAC, 2019). Climate change reduces the environment's ability to provide its services, as mainly evidenced by the failure to meet food demand of the world's growing population (FAO, 2019). Moreover, climate change will increase the agricultural sector's production risks, causing producers of agricultural products to make irrational decisions.

Addressing the 'lose-lose' relationship between agriculture and climate change is critical for reducing the adverse effects of climate change, especially in countries where agriculture is the main economic activity, such as Ethiopia. Ethiopia's economy is one of the most vulnerable in Sub-Saharan Africa (SSA) (Demeke et al., 2004; Kassie et al., 2013a, b; Tesfaye et al., 2016).

Climate change and associated droughts are causing damages to the country's agricultural sector. Agriculture in Ethiopia is vulnerable to climate change since it is mostly a traditional, rain-fed and practiced by smallholder farmers with low capacity to adapt to climate change and catastrophic occurrences (Skambraks, 2014; Hirpha et al., 2020). What happens to Ethiopia's agricultural sector as a result of climate change has an impact on the country's economy (Thornton et al., 2014). For instance, according to Gelaw (2017), climate change is expected to reduce Ethiopia's GDP by 8–10% by 2050, but agricultural adaptation measures could reduce climate shock-related losses by 50%. Climate change poses a significant challenge to Ethiopian smallholder farmers, causing variability in their production and income (Abebe and Bekele, 2017). As a result, the smallholder farmers are becoming increasingly exposed to

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food insecurity and poverty (Aragie, 2013; Alemu and Mengistu, 2019; Fekad and Bekalu, 2020).

Adoption of climate smart agricultural (CSA hereafter) practices has been widely recognized as a promising and successful alternative to lessen the adverse impacts of climate change (Lipper et al., 2014; FAO, 2018a, b; Mazhar et al., 2021). CSA is an integrated approach that aims to achieve three outcomes simultaneously: increased productivity and income, enhanced resilience (adaptation) and reduced emissions (FAO, 2013; FAO, 2018a, b).

Several CSA practices have been implemented in Ethiopia in order to improve livelihoods and food security (FAO, 2016; Eshete et al., 2020). Integrated watershed management, intergraded soil fertility management, sustainable land management, conservation agriculture, agroforestry, crop residue management, composting, improved livestock feed promotion, and rangeland management all are instances of CSA practices in Ethiopia (FAO, 2016; Eshete et al., 2020).

Theoretically, farmers need to maximize profits to adopt a typical or a combination of CSA practices. Farmers' adoption of CSA practices remains low in developing countries, including Ethiopia (Mazhar et al., 2021). CSA practices and technologies, such as conservation agriculture and agroforestry continue to be under adopted by Ethiopian smallholder farmers due to lack of financial resources for initial investments and existing insecure land tenure system (Gelaw, 2017).

Therefore, a better knowledge of factors that influence farmer's adoption behavior is critical for developing policies that will sustainably increase uptake of CSA practices. Empirical evidences indicate that smallholder farmers' adoption of CSA practices is greatly influenced by socio-economic, farm characteristics, institutional, access to basic infrastructure services, informational and technology awareness, social capital and climate-related factors (Tey et al., 2014; Murage et al., 2015; Tembo et al., 2017; Tran et al., 2019; Anuga et al., 2019; Kurgat et al., 2020; Lungu, 2021). Household, plot, and village factors, as well as resource constraints and climate-associated factors, all influence adoption of climate smart technology in Ethiopia (Teklewold et al., 2013, 2016; Mohammed et al., 2015; Marie et al., 2020).

Earlier studies on adoption of CSA practices in Ethiopia concentrated mainly on factors affecting a specific CSA practice. However, farmers are frequently presented with a variety of technologies that can be used in combination as complements or substitutes to mitigate and adapt to climate change. Thus, one of the current study's contributions is modeling CSA practice adoption while taking into account the interdependence between them. Besides, the farmers adopt different level of CSA practices (Usman et al., 2021). Examining the intensity/level of CSA adoption using ordered choice model is the second contribution of this paper. Another contribution is the use of farm household survey data from three agroecological zones (AEZs): highland, midland and lowland.

The rest of this paper is organized as follows. Materials and methods will be briefly described in section two. Section three will present descriptive and econometric estimation results. The conclusion and policy implications will be presented in the final section.

2. Materials and methods

2.1. Study site

This study was conducted in the Bale-Eco Region (BER), which is located in the Southeast of Ethiopia and encompasses sixteen Woredas in Bale and West-Arsi Zones (see Figure 1). The eco-region lies between 6° 29′ N to 7° 10′ N latitude and 39° 28′ E to 39° 57′ E longitude, with an altitude range of 272 amsl[1] in the South to 4,377 in the North and the BER is 38,036 square kilometres in size (WLRC & IWMI, 2017).

BER shows a wide range of temporal and spatial climate variability, as indicated by the wide altitude range. The BER covers a wide range of ecosystems and it is part of one of the world's 34 biodiversity hotspots (Chaudhary, 2021). The region is also known as a water tower since it is a source of numerous springs that drain into five major rivers namely; Genale Dawa (also called Juba), Wabe-Shebelle, Welmel, Weyb and Dumal, on which about 12 million people in downstream areas rely for their livelihoods (WLRC and IWMI, 2017). In the region, there are three main livelihoods: crop-livestock-forest production in the highland; mixed crop and livestock farming in the midland; and primarily livestock farming in the lowland (SHARE-Bale Eco-Region Project, 2018; Birhan et al., 2021). These agricultural practices cover about 333, 977 hectares of land in the region (Oromia Forest and Wildlife Enterprise (OFWE), 2016).

2.2. Sampling technique and data collection

The study drew a sample woreda from each AEZ of BER, where CSA has been implemented, to get a representative sample of farm households. The study chose three woredas[2] randomly: Berbere from the lowland, Harena Buluk from the midland, and Dodola from the highland. Furthermore, the study involved identification of kebeles[3] from each sample woreda, from which sample households were randomly selected. Deneba, Bura Adele, Sirima, Gelma, and Bekaye were chosen as CSA beneficiary kebeles, whereas Berisa, Cheketa, and Anole were chosen as non-beneficiary kebeles.

The study collected data from 404 households randomly selected from the three sample woredas. The sample size was determined using a power calculation. The minimum detectable effect of 5% was established using a significance level of 5% and a power of 80%, as well as a sample size of 404 and the baseline proportion of non-poor households in the study area. According to the baseline assessment of BER's impact, 83.3% of households in BER are non-poor (Tilahun, 2020). The overall sample size was shared equally between CSA beneficiaries and non-beneficiaries, resulting in almost 200 sample households for each group.

A structured questionnaire was implemented with the use of computer-assisted personal interview to collect data from the sample households. The data was collected on important study variables such as basic household characteristics, household ownership of land and livestock assets, household ownership of consumer durable and production assets, access to information and farming technology, agricultural input usage and harvests in different seasons, non-farm and transfers income, standards of living, household consumption expenditure, food security, climate change and shocks, household adaptive capacity, household and community resilience indicators and adoption of CSA practices.

2.3. Econometric framework

Farmer's adoptions of CSA practices are correlated (Teklewold et al., 2019; Kurgat et al., 2020; Usman et al., 2021). The correlation arises from technological complementarity or substitutability among CSA practices (Wainainaa et al., 2016; Bedeke et al., 2019). When there is such interdependence in the adoption of CSA practices, application multivariate probit (MVP) results in unbiased and efficient estimates (Wainainaa et al., 2016; Greene, 2018).

The formulation of MVP model is based on the random utility theory (RUT). Let U_0 denotes the expected benefits to a farmer from non-adoption, and U_j denotes the expected benefits from adopting j^{th} CSA practice. According to the RUT, a farmer i chooses to adopt j^{th} CSA practice if the expected benefit from adoption is greater than the benefit from non-adoption (Leonardi, 1981; Leonardi and Tadel, 1984; Kreps,

[1] amsl denotes above mean sea level.

[2] Woreda is the third -level of the administrative division of Ethiopia – after zone and regional state.

[3] Kebele is the smallest administrative unit in Ethiopia's government structure – after woreda.

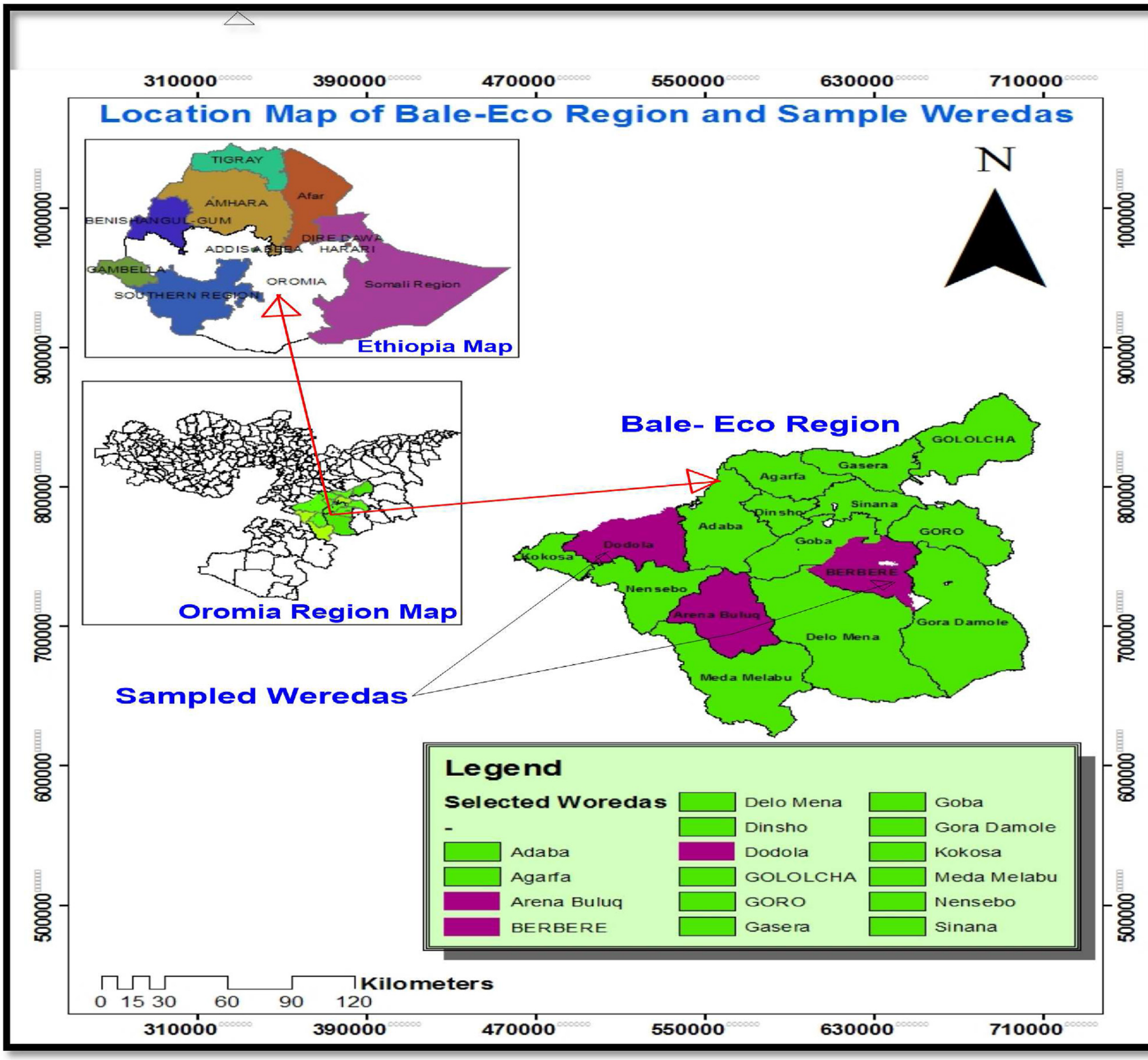

Figure 1. Location map of BER and sample woredas.

1990; Varian, 1992; Horowitz et al., 1994; Bowles, 2004; Verbeek, 2004; Newbold, 2005; Andersson and Ubøe, 2010).

Assume U_{ij}^{*} represents the expected net benefits. The farmer decides to adopt CSA practice j if the condition in Eq. (1) is satisfied:

$$U_{ij}^{*} = U_{j}^{*} - U_{0} > 0 \tag{1}$$

U_{ij}^{*} is a latent variable that is considered to be a linear function of household socio-economic characteristics, plot characteristics, institutional factors, and agroecological zone, where all of them are represented by a vector $\mathbf{X}_{ij}$, and the error term (ε_{ij}).

$$U_{ij}^{*} = \mathbf{X}_{ij}^{'}\boldsymbol{\beta}_{j} + \varepsilon_{ij} \tag{2}$$

where $j = A,\ C,\ D,\ I,\ P,\ S$

The observed binary outcome for each farmer's CSA adoption decision is given in Eq. (3) as follows:

$$U_{ij} = \begin{cases} 1 & \text{if } U_{ij}^{*} > 0 \\ 0 & \text{Otherwise} \end{cases} \tag{3}$$

If CSA practice adoptions are correlated, it is more realistic to assume that the error terms in Eq. (2) are jointly follow a multivariate normal distribution with zero conditional mean and variance normalized to unity. That is, $\varepsilon_{ij} \sim MNP\ (0,\ \Omega)$, where Ω is the symmetric covariance matrix which is given by Eq. (4).

$$\Omega = \begin{bmatrix} 1 & \rho_{AC} & \rho_{AD} & \rho_{AI} & \rho_{AP} & \rho_{AS} \\ \rho_{CA} & 1 & \rho_{CD} & \rho_{CI} & \rho_{CP} & \rho_{CS} \\ \rho_{DA} & \rho_{DC} & 1 & \rho_{DI} & \rho_{DP} & \rho_{DS} \\ \rho_{IA} & \rho_{IC} & \rho_{ID} & 1 & \rho_{IP} & \rho_{IS} \\ \rho_{PA} & \rho_{PC} & \rho_{PD} & \rho_{PI} & 1 & \rho_{PS} \\ \rho_{SA} & \rho_{SC} & \rho_{SD} & \rho_{SI} & \rho_{SP} & 1 \end{bmatrix} \tag{4}$$

If the estimated off-diagonal correlation coefficients are jointly significant, we infer that CSA practices are interdependent in adoption.

Assessing the factors that influence intensity of adoption of CSA practice is another interest of this study. The intensity/level of adoption of CSA practices is measured by the number of CSA practices adopted by farm households (Ojoko et al., 2017; Oladimeji et al., 2020; Usman et al., 2021). Farmers may choose to adopt no CSA practice, one, two, or more CSA practices. Therefore, adoption can be treated as an ordinal variable that follows categories of ordered outcomes. The adoption of CSA practice by farmers in our study takes on seven different values ($y_i = 0, 1, 2, \ldots, 7$), which are naturally ordered.

Following (Davidson and MacKinnon, 1999; Cameron and Trivendi, 2009; Verbeek, 2004; Greene, 2018), we assume that the observed ordered outcomes y_i is generated by a latent variable y_i^*, where y_i^* is specified in Eq. (5) as follows;

$$y_i^* = X_i'\beta + \varepsilon_i \tag{5}$$

ε_i is assumed to be normally distributed with normalized mean and variance zero and one, respectively.

The relationship between the latent variable and the observed outcome is shown in Eq. (6) as follows;

$$y_i = \begin{cases} 0 & \text{if } y_i^* \le 0 \\ 1 & \text{if } 0 < y_i^* \le \mu_1 \\ 2 & \text{if } \mu_1 < y_i^* \le \mu_2 \\ \vdots & \vdots \\ m & \text{if } \mu_{m-1} \le y_i^* \end{cases} \tag{6}$$

The μ 's are cut points to be estimated with **β.** For an *m*-alternative ordered categories, we generally define:

$y_i = j$ if $\mu_{j-1} < y_i^* \le \mu_j$, $j = 1, 2, \ldots,$ m where $\mu_0 = -\infty$ and $\mu_m = \infty$

According to Cameron and Trivendi (2009), the probability of observing outcome *j* is given by Eq. (7):

$$P(y_i = j) = \Phi\left(\mu_j - X_i'\beta\right) - \Phi\left(\mu_{j-1} - X_i'\beta\right) \tag{7}$$

where Φ is the cumulative normal distribution function of ε_i.

3. Results and discussion

3.1. Descriptive results

The CSA practices are treated as the dependent variables of this study. Farmers in BER have adopted different CSA practices, which mainly include improved agronomic practices, soil and water conservation (SWC) practices, drought tolerant high yielding crop variety, small-scale irrigation (SSI), integrated disease, pest and weed management (IPM) and integrated soil fertility management (ISFM). SWC practices, improved agronomic practices and IPM are adopted by about 87%, 70% and 65% of the sampled farmers in BER, respectively (see Figure 2). This is followed by drought tolerant high yielding crop variety (50%), ISFM (33%), and SSI (25%).

The adoption of a maximum combination of CSA practices, which includes improved agronomic practices, drought tolerant high yielding crop variety, integrated disease, pest and weed management, soil and water conservation, small-scale irrigation, and integrated soil fertility management, varies significantly across BER's AEZs (see Figure 3).

Figure 3 depicts that combination of more CSA practices is more likely adopted by farmers in lowland and midland AEZs as compared to those in highland AEZ. Moreover, explanatory variables that are essential in CSA adoption decision-making are presented in Table 1.

3.2. Interdependence of CSA practices

Table 2 reports the possibility of positive interdependence among the CSA practices considered in this study. The interdependence is evidenced by the correlation coefficient of error components retrieved from MVP estimate. The estimated off-diagonal correlation coefficients are jointly significant; indicating the null hypothesis that there is no correlation between error terms in different equations is rejected. As a result, the MVP model is more efficient than the probit model in explaining CSA practice adoption. Furthermore, Table 2 shows that most of the estimated correlation coefficients are significant and positive. This implies that those practices are complementary and, hence, are jointly used by the farmers. This result is consistent with the findings of Teklewold et al.,

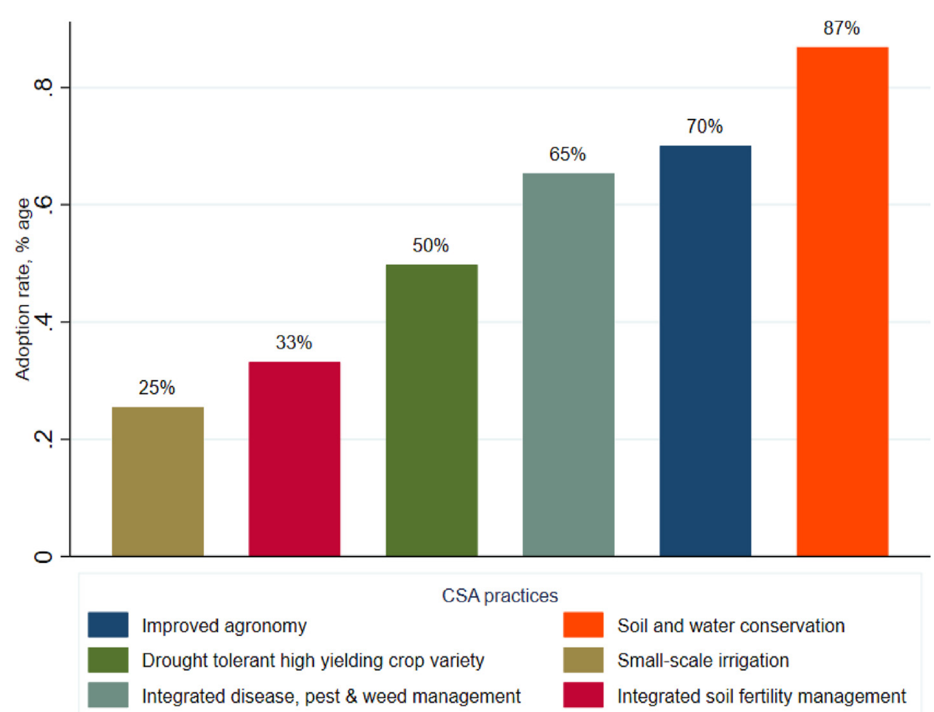

Figure 2. CSA practices and their adoption among farmers in BER.

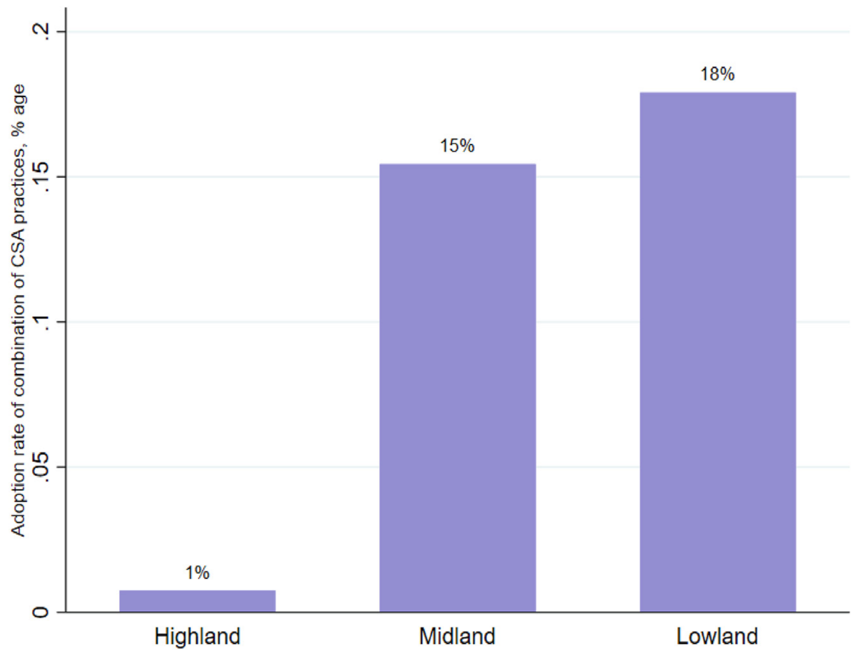

Figure 3. Adoption of a combination of CSA practices by AEZ.

Table 1. Description and descriptive statistics of explanatory variables used in the analysis.

Variables	Variable description	Mean			Mean difference	t-value	Overall SD
		Overall sample	Adopters	Non-adopters			
Socio-economic characteristics							
HHSEX	1 if the household head is male, 0 otherwise	0.88	0.89	0.87	-0.02	-0.566	-
HHSIZE	Household size (in number)	7.02	7.40	6.64	-0.76	-3.319***	2.34
HHAGE	Age of household head (in years)	42.18	41.49	42.86	1.37	1.030	13.42
EDUCHEAD	Household head's years of education	3.43	3.21	3.65	0.43	1.303	3.33
EDUCSPOUSE	Spouse's years of education	1.65	1.34	1.95	0.61	2.502**	2.48
FARMEXP	Farming experience (in years)	22.73	22.64	22.82	0.18	0.153	11.88
LANDSIZE	Total landholding size (in hectare)	1.40	1.67	1.13	-0.53	-4.817***	1.14
LIVSTOCK	Total livestock (in tropical livestock unit)	4.22	5.15	3.29	-1.86	-5.339***	3.62
TAV	Total value of assets (in '000' Birr)	75.01	96.86	53.37	-43.49	-6.246***	73.19
NONFARM	1 if the household participates in non-farm activity, 0 otherwise	0.26	0.25	0.27	0.02	0.396	-
Institutional factors							
CREDIT	1 if the household access credit, 0 otherwise	0.11	0.09	0.13	0.04	1.217	-
SAVING	1 if the household practice saving, 0 otherwise	0.54	0.60	0.47	-0.13	-2.617**	-
EXTFREQ	Frequency of extension contact (in days per year)	11.49	16.02	7.00	-9.02	-5.943***	15.89
Parcel characteristics							
FERTINDEX	Parcel average fertility index[a]	0.59	0.57	0.61	0.04	1.217	0.30
SLOPEINDEX	Parcel average terrain index[b]	0.73	0.71	0.75	0.05	1.960	0.24
EROSIOINDEX	Parcel average erosion index[c]	0.70	0.69	0.71	0.01	0.544	0.27
Climate characteristics							
BELG	1 if the household cultivates in Belg[d] season, 0 otherwise	0.62	0.62	0.62	0.00	-0.025	-
CCNOTICE	1 if the household noticed climate change during the last 10–15 years, 0 otherwise	0.61	0.73	0.49	-0.24	-5.064***	-
SHOCK	1 if the household faces shocks during the last five years, 0 otherwise	0.23	0.21	0.25	0.04	0.886	-
AEZ dummies							
HIGHLAND[e]	1 if the household lives in highland AEZ, 0 otherwise	33.17	0.33	0.33	0.01	0.141	-
MIDLAND[e]	1 if the household lives in midland AEZ, 0 otherwise	33.66	0.33	0.34	0.01	0.139	-

SD is standard deviation.
[a] Farmer ranked each parcel as "poor" (value = 1), "medium" (value = 2) and "fertile" (value = 3).
[b] Farmer ranked each parcel as "sloppy" (value = 1), "medium" (value = 2) and "flat" (value = 3).
[c] Farmer ranked each parcel as "severe" (value = 1), "moderate" (value = 2) and low (value = 3).
[d] Belg is agricultural cultivation season which is equivalent to autumn in southern hemisphere.
[e] LOWLAND is the reference category.

Table 2. Correlation coefficients of the CSA practices.

Correlation between CSA practices	Correlation coefficients
Soil & water conservation and improved agronomy (rhoCA)	0.778***
Drought tolerant high yielding crop variety and improved agronomy (rhoDA)	0.897***
Small-scale irrigation and improved agronomy (rhoIA)	0.510***
Integrated disease, pest & weed management and improved agronomy (rhoPA)	0.408***
Integrated soil fertility management and improved agronomy (rhoSA)	0.469***
Drought tolerant high yielding crop variety and soil & water conservation (rhoDC)	0.843***
Small-scale irrigation and soil & water conservation (rhoIC)	0.554***
Integrated disease, pest& weed management and soil & water conservation (rhoPC)	0.462***
Integrated soil fertility management and soil & water conservation (rhoSC)	0.532***
Small-scale irrigation and drought tolerant high yielding crop variety (rhoID)	0.616***
Integrated disease, pest & weed management and drought tolerant high yielding crop variety (rhoPD)	0.381***
Integrated soil fertility management and drought tolerant high yielding crop variety (rhoSD)	0.394***
Integrated disease, pest & weed management and small-scale irrigation (rhoPI)	-0.104
Integrated soil fertility management and small-scale irrigation (rhoSI)	0.099
Integrated soil fertility management and integrated disease, pest & weed management (rhoSP)	0.783***
Likelihood ratio test of rhoCA = rhoDA = rhoIA = rhoPA = rhoSA = rhoDC = rhoIC = rhoPC = rhoSC = rhoID = rhoPD = rhoSD = rhoPI = rhoSI = rhoSP = 0, Chi^2 (15) = 445.388, Prob > chi^2 = 0.000	

Note: A = improved agronomic practices, C = soil and water conservation practices, D = drought tolerant high yielding crop variety, I = small scale irrigation, P = integrated disease, pest & weed management and S = integrated soil fertility management.
***, **, and * indicate statistical significance at 1%, 5% and 10%, respectively.
Rho represents correlation between CSA practices.

2013; Kassie et al., 2013a, b; Kassie et al., 2015; Wainainaa et al., 2016; Mwungu et al., 2018; Teklewold et al., 2019; Zampaligré and Fuchs, 2019; Bedeke et al., 2019; Kurgat et al., 2020; Ali, 2021; Wordofa et al., 2021.

3.3. Factors influencing adoption of multiple CSA practices

Table 3 reports MVP estimate wherein six sets of parameters are estimated; one for adoption of each mutually interdependent CSA practices. The Wald test rejected the null hypothesis that all regression coefficients are simultaneously equal to zero.

The MVP estimate shows that factors that have a significant effect on CSA practice adoption differ depending on the type of CSA practice. Factors such as frequency of extension contact, awareness about climate change, and perception on the climate change impacts have a significant influence on adoption of most of CSA practices.

The frequency with which extension services are provided to the farmers has a positive influence on the adoption of all CSA practices. Many previous studies (Chowdhury et al., 2013; Alam, 2015; Atinkut and Mebrat, 2016; Onyeneke et al., 2017; Belay et al., 2017; Akrofi-Atitianti et al., 2018; Fadina and Barjolle, 2018; Nkonya et al., 2018; Waibel, 2018; Ayenew et al., 2020; Ali, 2021; Abegunde et al., 2020; 2021; Acevedo et al., 2020; Sardar et al., 2021; Wordofa et al., 2021) identified extension services as a key driver of adoption of different CSA practices. Ayenew et al. (2020) explained that extension service has a positive effect on agricultural technologies adoption through several channels. First, providing extension services to farmers improves their human capital and access to information. Second, it reinforces input distribution and access to agricultural credit. Third, it is the primary channel for transferring agricultural research and development outputs to smallholder farmers.

Farmers' awareness of climate change positively influences adoption of improved agronomic practices, SWC practices, drought tolerant high yielding crop variety practices and IPM. This result seems to be plausible and is in line with the findings of many studies (Murage et al., 2015; Justin et al., 2017; Abegunde et al., 2020; Dung, 2020; Sardar et al., 2021).

On the other hand, farmers who were affected by climate change in the past are less likely to adopt improved agronomic practices, SWC practices, drought tolerant high yielding crop variety practices, SSI and IPM. The negative sign explains the fact that the cost of adopting the mentioned CSA practices is high when farmers experience crop failure as a result of climate change. As a result, farmers may be hesitant to adopt CSA practices in the future.

The age of household head has a significant and negative effect on the adoption of improved agronomy, drought tolerant high yielding crop variety and IPM. One possible explanation for the negative relationship is that the older often prefer to stick to farming practices already exist in the community. This result is in line with the findings of (Teklewold et al., 2013; Alam, 2015; Justin et al., 2017; Ayenew et al., 2020; Faleye and Afolami, 2020).

Adoptions of improved agronomic practices, SWC and drought tolerant high yielding crop variety are negatively associated with household head education. Likewise, spouse education negatively influences adoptions of improved agronomic practices, drought tolerant high yielding crop variety, SSI and ISFM. Faleye and Afolami (2020) also found a negative influence of education on CSA adoption, justifying that educated individuals prefer white collar employment as a means of diversifying their income rather than diversifying towards CSA adoption.

Land size has a positive effect on the adoption of drought tolerant high yielding crop variety and IPM. The result is convincing because farmers with larger landholdings are more likely to produce more and, hence, have more financial resources which enable them to purchase these modern agricultural inputs. The result also agrees with the findings of many empirical studies (Alam, 2015; Atinkut and Mebrat, 2016; Belay et al., 2017; Wekesa et al., 2018; Fadina and Barjolle, 2018; Ayenew et al., 2020; Dung, 2020; Sardar et al., 2021).

Farmers' total value of assets has a significant and positive impact on the adoption of improved agronomic practices and drought tolerant high yielding crop variety. The total asset value is used as a proxy of farmer's wealth in this study. Farmers with more wealth can sell their assets at any time to purchase CSA technologies, such as drought-tolerant high-yielding crop varieties (Belay and Bewket, 2013), and hire labor, which is critical in row planting (Vandercasteelen et al., 2018).

A closer look at Table 3 reveals that adoptions of SWC practices and drought tolerant high yielding crop variety increase when the slope index of parcels increases. Farmers are increasingly vulnerable to land degradation as parcels get sloppier, which reduces their agricultural productivity (FAO, 2013). As a result, they are pushed to use SWC practices, such as bund construction and water conservation structures. However, farmers are unwilling to cultivate improved high yielding crop varieties on sloppy parcels since they are risk averse (Binici et al., 2003; Todaro and Smith, 2012; Teklewold et al., 2013). Furthermore, an increase in parcel soil fertility or severity of soil erosion leads to an increase in the adoption of SSI and ISFM.

Farmers in different AEZs do not respond to climate shocks in the same way and, hence, they do not adopt the same CSA practices to mitigate vulnerability and risks associated with climate change

Table 3. Factors driving adoption of CSA practices.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	A	C	D	I	P	S
HHSEX	0.277	0.197	0.548**	0.559	0.131	0.018
	(0.222)	(0.255)	(0.221)	(0.340)	(0.241)	(0.223)
HHSIZE	0.053	0.035	0.022	0.015	-0.050	-0.002
	(0.036)	(0.037)	(0.033)	(0.035)	(0.036)	(0.037)
HHAGE	-0.029***	-0.017	-0.029***	-0.012	-0.021**	-0.016
	(0.010)	(0.011)	(0.011)	(0.013)	(0.010)	(0.012)
EDUCHEAD	-0.070**	-0.086***	-0.060**	0.011	-0.027	-0.018
	(0.029)	(0.030)	(0.026)	(0.029)	(0.027)	(0.030)
EDUCSPOUSE	-0.060*	0.011	-0.089**	-0.088**	-0.007	-0.074**
	(0.034)	(0.038)	(0.036)	(0.041)	(0.032)	(0.037)
FARMEXP	0.016	0.006	0.009	-0.006	0.027**	0.013
	(0.013)	(0.013)	(0.012)	(0.014)	(0.011)	(0.014)
LANDSIZE	0.134	0.179	0.322***	0.071	0.240***	0.070
	(0.092)	(0.117)	(0.094)	(0.077)	(0.090)	(0.069)
LIVSTOCK	-0.167***	-0.104	-0.091	0.026	0.021	-0.038
	(0.064)	(0.082)	(0.065)	(0.064)	(0.062)	(0.058)
TAV	0.012***	0.006	0.009***	0.001	0.000	0.004
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
CREDIT	-0.544**	0.004	-0.268	-0.020	-0.326	-0.027
	(0.273)	(0.286)	(0.259)	(0.247)	(0.242)	(0.249)
SAVING	0.156	0.025	0.117	0.528***	-0.129	0.060
	(0.173)	(0.194)	(0.160)	(0.185)	(0.154)	(0.165)
NONFARM	0.033	0.013	0.041	-0.497**	-0.284	0.241
	(0.187)	(0.202)	(0.173)	(0.201)	(0.192)	(0.177)
EXTFREQ	0.019***	0.025***	0.022***	0.019***	0.011**	0.014***
	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
FERTINDEX	0.146	-0.270	-0.304	0.547*	0.268	0.709**
	(0.289)	(0.299)	(0.289)	(0.305)	(0.254)	(0.292)
SLOPEINDEX	-0.434	-1.100*	-0.718*	0.308	-0.377	0.599
	(0.504)	(0.566)	(0.404)	(0.441)	(0.438)	(0.427)
EROSIOINDEX	-0.610	-0.028	0.030	-0.771*	0.100	-0.956**
	(0.443)	(0.439)	(0.390)	(0.428)	(0.361)	(0.390)
BELG	-0.110	0.176	-0.106	-0.355	0.721***	0.549*
	(0.344)	(0.297)	(0.300)	(0.306)	(0.274)	(0.287)
SHOCK	-0.709***	-0.772***	-0.829***	-0.483**	-0.400**	-0.290
	(0.232)	(0.245)	(0.200)	(0.231)	(0.196)	(0.194)
CCNOTICE	0.357*	0.668***	0.893***	-0.026	0.482***	0.121
	(0.192)	(0.216)	(0.174)	(0.180)	(0.175)	(0.196)
MIDLAND	0.930***	-0.143	0.393*	-0.323	-0.137	0.108
	(0.245)	(0.239)	(0.213)	(0.212)	(0.192)	(0.207)
HIGHLAND	-0.106	1.112***	0.081	-1.690***	1.451***	-0.281
	(0.383)	(0.415)	(0.360)	(0.379)	(0.334)	(0.336)
Constant	1.045*	1.647***	-0.046	-0.384	-0.292	-0.859*
	(0.575)	(0.577)	(0.519)	(0.545)	(0.504)	(0.519)
Observations	404	404	404	404	404	404

Log pseudolikelihood = -892.59.
Wald $chi^2(126) = 605.09$.
Prob > $chi^2 = 0.000$.
Values in the parentheses are robust standard errors.
*, ** and *** represent statistical significance at 10%, 5% and 1%, respectively.

(Rahaman et al., 2019). Table 3 shows that farmers in midland are more likely to adopt improved agronomic practices and drought tolerant high yielding crop variety than farmers in lowland AEZ. On the other hand, farmers in highland are more likely to adopt SWC and IPM practices, but they are less likely to adopt SSI as compared to farmers in lowland AEZ.

3.4. Factors influencing intensity of CSA adoption

Table 4 reports the result of ordered probit estimates of factors influencing the intensity of CSA adoption among BER farmers. The Wald chi-squared statistic generated from the ordered probit estimate is statistically significant; implying that the model is of good fit.

The result also shows that male-headed farmers adopt more CSA practices than female-headed farmers. This could be attributed to male dominance in decision-making and ownership of productive resources in farming system, which is common among farmers in Ethiopia (Ajadi et al., 2015; Yadeta and Abashula, 2019). The finding corroborates the finding of (Usman et al., 2021), whereby female-headed households were less likely to adopt more sustainable agricultural practices. On the other hand, the age of the household has a negative effect on the intensity of CSA adoption, for the same reason explained in the MVP estimate (see Table 3). However, farming experience positively influences the CSA adoption intensity, which seems plausible. This is because as farmers accumulate experience in farming, they will be able to recognize the benefits of early-adopted CSA practices and will accept additional CSA practices. The result is consistent with (Ainembabazi and Mugisha,

Table 4. Ordered probit estimates of the factors influencing the number of CSA practices adopted.

Variables	Coefficients	Average marginal effects						
		Pr (Y = 0|X)	Pr (Y = 1|X)	Pr (Y = 2|X)	Pr (Y = 3|X)	Pr (Y = 4|X)	Pr (Y = 5|X)	Pr (Y = 6|X)
HHSEX	0.404***	-0.059**	-0.024*	-0.043**	-0.006*	0.030*	0.038**	0.063*
	(0.151)	(0.022)	(0.010)	(0.016)	(0.003)	(0.012)	(0.014)	(0.025)
HHSIZE	0.010	-0.001	-0.001	-0.001	-0.000	0.001	0.001	0.002
	(0.026)	(0.004)	(0.001)	(0.003)	(0.000)	(0.002)	(0.002)	(0.004)
HHAGE	-0.026***	0.004**	0.002**	0.003**	0.000*	-0.002**	-0.002**	-0.004**
	(0.008)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
EDUCHEAD	-0.051**	0.007*	0.003*	0.005*	0.001*	-0.004*	-0.005*	-0.008*
	(0.021)	(0.003)	(0.001)	(0.002)	(0.000)	(0.002)	(0.002)	(0.003)
EDUCSPOUSE	-0.067***	0.010**	0.004**	0.007**	0.001*	-0.005**	-0.006**	-0.010**
	(0.024)	(0.004)	(0.002)	(0.003)	(0.000)	(0.002)	(0.002)	(0.004)
FARMEXP	0.016*	-0.002	-0.001	-0.002	-0.000	0.001	0.002	0.003
	(0.009)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
LANDSIZE	0.162***	-0.024**	-0.010*	-0.017**	-0.002*	0.012*	0.015*	0.025**
	(0.060)	(0.009)	(0.004)	(0.006)	(0.001)	(0.005)	(0.006)	(0.009)
LIVSTOCK	-0.048	0.007	0.003	0.005	0.001	-0.004	-0.005	-0.008
	(0.043)	(0.006)	(0.003)	(0.005)	(0.001)	(0.003)	(0.004)	(0.007)
TAV	0.005***	-0.001**	-0.000*	-0.001**	-0.000*	0.000*	0.001**	0.001**
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CREDIT	-0.202	0.029	0.012	0.021	0.003	-0.015	-0.019	-0.032
	(0.212)	(0.031)	(0.013)	(0.023)	(0.003)	(0.016)	(0.020)	(0.033)
SAVING	0.207*	-0.030	-0.012	-0.022	-0.003	0.015	0.020	0.032
	(0.120)	(0.018)	(0.007)	(0.013)	(0.002)	(0.009)	(0.012)	(0.019)
NONFARM	-0.142	0.021	0.008	0.015	0.002	-0.011	-0.013	-0.022
	(0.133)	(0.020)	(0.008)	(0.014)	(0.002)	(0.010)	(0.013)	(0.021)
EXTFREQ	0.021***	-0.003***	-0.001***	-0.002***	-0.000**	0.002***	0.002***	0.003***
	(0.004)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
FERTINDEX	0.419*	-0.061	-0.025	-0.044	-0.006	0.031	0.040	0.066
	(0.226)	(0.033)	(0.014)	(0.024)	(0.004)	(0.017)	(0.022)	(0.036)
SLOPEINDEX	-0.230	0.034	0.014	0.024	0.003	-0.017	-0.022	-0.036
	(0.312)	(0.046)	(0.019)	(0.033)	(0.005)	(0.024)	(0.030)	(0.048)
EROSIOINDEX	-0.476*	0.070	0.028	0.050	0.007	-0.035	-0.045	-0.075
	(0.287)	(0.042)	(0.017)	(0.031)	(0.005)	(0.022)	(0.028)	(0.045)
BELG	0.238	-0.035	-0.014	-0.025	-0.004	0.018	0.023	0.037
	(0.250)	(0.037)	(0.015)	(0.027)	(0.004)	(0.019)	(0.024)	(0.039)
SHOCK	-0.644***	0.094***	0.038***	0.068***	0.010**	-0.048***	-0.061***	-0.101***
	(0.159)	(0.024)	(0.011)	(0.018)	(0.004)	(0.013)	(0.015)	(0.028)
CCNOTICE	0.391***	-0.057**	-0.023**	-0.042**	-0.006*	0.029**	0.037**	0.061**
	(0.139)	(0.022)	(0.009)	(0.015)	(0.003)	(0.011)	(0.014)	(0.022)
MIDLAND	0.085	-0.012	-0.005	-0.009	-0.001	0.006	0.008	0.013
	(0.180)	(0.026)	(0.011)	(0.019)	(0.003)	(0.014)	(0.017)	(0.028)
HIGHLAND	-0.011	0.002	0.001	0.001	0.000	-0.001	-0.001	-0.002
	(0.278)							
μ_1	-1.404***							
	(0.425)							
μ_2	-1.051**							
	(0.426)							
μ_3	-0.311							
	(0.418)							
μ_4	-0.102							

(continued on next page)

Table 4 (*continued*)

Variables	Coefficients	Average marginal effects						
		Pr (Y = 0|X)	Pr (Y = 1|X)	Pr (Y = 2|X)	Pr (Y = 3|X)	Pr (Y = 4|X)	Pr (Y = 5|X)	Pr (Y = 6|X)
	(0.418)							
μ_5	1.017**							
	(0.414)							
μ_6	1.607***							
	(0.413)							
Observations	404	404	404	404	404	404	404	404

Log pseudolikelihood = -648.080.
Wald $chi^2(21) = 162.12$.
Prob > $chi^2 = 0.000$.
Pseudo $R^2 = 0.096$.
Note: μ's represents cut points.
Values in the parentheses are robust standard errors.
***, **, and * indicate statistical significance at 1%, 5% and 10%, respectively.

2014), wherein it was indicated that farming experience is particularly important in the early stages of agricultural technology adoption. Table 4 reveals that the household head's and spouse's educational levels have a negative effect on the level of CSA adoption. This was unexpected and inconsistent with many empirical studies.

Moreover, Table 4 underlies the importance of land size and total value of tradable assets in increasing the number of CSA practices adopted among farmers in BER. Regarding the effect of land size, the finding complements those of (Aryal et al., 2020), who found that farmers with more land are relatively wealthy and are more likely to change their farming practises and, therefore, have more capacities to invest in more climate adaptation strategies. The total value of tradable assets influences the CSA adoption intensity positively since it is also an indicator of the farmer's wealth.

The frequency of extension contacts and saving practices are the institutional factors that significantly influence the intensity of CSA practices adopted by farmers in BER. The positive influence of frequency of extension contact on the intensity of CSA adoption is attributed to the same reasons explained in the MVP analysis. Farmers who practice saving have a higher CSA adoption rate than those who do not. Similar finding was also obtained by Yigezu et al. (2018), indicating that high initial investment, which requires saving and credit, enhances agricultural technology adoption.

Other important factors that influence the intensity of CSA adoption include parcel fertility, soil erosion severity, climate change awareness, and shock experience. The intensity of adopting more CSA practices increases as parcel fertility improves or severity of soil erosion increases. Interestingly, the number of CSA practices adopted rises as farmers' awareness of climate change improves. However, because of the reasons explained in the MVP analysis, the intensity of CSA adoption decreases as farmers' experience of climatic shocks increase.

4. Conclusion and policy implications

Addressing the 'lose-lose' relationship between agriculture and climate change is critical for reducing the adverse effects of climate change in countries where agriculture is the mainstay of the economy. Adoption of CSA practices has been widely recognized as a promising and successful alternative to minimize the adverse impacts of climate change. However, adoption of CSA practices among smallholder farmers remains low in Ethiopia.

This study examined factors that influence adoption of CSA practices and the intensity with which they are adopted among smallholder farmers in BER, Ethiopia. Understanding the factors that influence the adoption of CSA practices helps in the formulation of agricultural policies that can accelerate the dissemination of CSA practices. Our empirical result shows the possibility of positive interdependence (complementarity) among the CSA practices. Farmers' adoption of multiple CSA practices, as well as their intensity of adoption, is significantly influenced by the age of the household head, education, land size, household total asset value, frequency of extension contacts, farmer awareness of climate change, farmer experience with climatic shocks, parcel fertility, slope, and severity of soil erosion.

The results of this study have important policy implications for increasing CSA adoption and its intensity among BER farmers. First and foremost, as evidenced in the results, the CSA practices are complementary in terms of adoption. This suggests that the agricultural policy makers and implementers of CSA should recognize the complementarity among CSA practices in order to intensify their adoption among BER farmers and disseminate CSA technologies in other parts of the country. Second, policymakers should consider household socioeconomic, institutional, and parcel-specific factors that positively influence CSA adoption. Providing smallholder farmers with regular extension and advisory services should be prioritized, since the frequency of extension visits and services enable smallholder farmers to adopt more CSA practices. Besides, creating awareness and disseminating information about the impacts of climate change and benefits associated with adoption of CSA practices using various media outlets assists farmers in adopting CSA practices and, thus, coping with the adverse effects of climate change. Some CSA practices, for example drought tolerant high yielding crop variety, are unpopular among farmers in BER. Therefore, scaling-up of its adoption requires high incentive payments. Land is an important wealth and has intergenerational impacts on agricultural technology adoption in Ethiopia. Our result reveal that farmers with larger land are more likely to use CSA practices. As a result, agricultural policies should emphasize on regulating agricultural land rental markets, which enables efficient small farmers to acquire land. Improving the fertility of parcels is also crucial to enhance the intensity of CSA adoption.

Declarations

Author contribution statement

Mebratu Negera: Conceived and designed experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Tekie Alemu, Fitsum Hagos: Conceived and designed experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Amare Haileslassie: Conceived and designed experiments; Contributed reagents, materials, analysis tools or data.

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The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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