



The impact of climate smart agriculture practices on the technical efficiency of wheat farmers in northwestern Ethiopia

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Abstract

Wheat is one of the most important cereal crops cultivated in a wide range of agro-ecologies in Ethiopia. It is also the source of food for the majority of Ethiopian people, next to maize. However, factors such as climate change and other challenges have contributed to its consistently low productivity. Therefore, this study aimed to analyze the impact of climate-smart agriculture practices (CSAPs) (wheat row planting, crop rotation and improved wheat variety in isolation and in combination) on the technical efficiency of wheat farmers. The data were generated from 385 randomly selected wheat producers, encompassing 702 plots across three prominent wheat-producing districts in northwestern Ethiopia. A stochastic production frontier (SPF) with selection correction model and a multinomial endogenous switching regression (MNESR) model were applied to estimate the technical efficiency and the impact of CSAPs on technical efficiency, respectively. The estimated mean technical efficiency of wheat farmers was 84.5%, ranging from a minimum of 32.8% to a maximum of 99.8%. The MNESR model result showed that the adoption of CSAPs in isolation or in combination considerably improved wheat farmers' technical efficiency. The highest technical efficiency was recorded when farmers implemented all three CSAPs simultaneously within a single plot, rather than when they adopted them separately. This implies that policymakers and stakeholders should promote the adoption of a combination of CSAPs to enhance wheat productivity.

Keywords Climate smart agriculture practices · Technical efficiency · Impact · Multinomial endogenous switching regression · Ethiopia

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1 Introduction

Wheat is the second most important source of calories and protein to the Ethiopian diet after maize, contributing 13.41% of the total calorie intake and 13.82% of the total protein intake (FAO, 2022). According to CSA (2022), in 2021/22 production year, wheat covered 1.867 million hectares of land at the national level, which accounts for approximately 18.67% of the total area covered by cereal crops. The total volume of wheat production in the same year amounted to 58.078 million quintals, representing 19.97% of the total cereal crop output. The Oromia region produced the largest volume, accounting for 55% of the wheat area coverage and 59% of the production, followed by the Amhara region, which covered 36% of the area and contributed 33% of the production (CSA, 2022).

Despite the importance of wheat as a food and industrial crop, its productivity remains low. CSA (2022) and FAO (2022) indicate that the average productivity of wheat in Ethiopia is 31.11qt/ha, which is lower than average global productivity (35.47 qt/ha) and the average productivity of other African countries, such as Egypt (64.5 qt/ha) and South Africa (43.12 qt/ha) in 2021. The production and productivity of wheat in Ethiopia face significant challenges, including soil degradation, disease, insect pests, a decrease in farm size, the use of local varieties, rainfall variability, and recurrent drought/water stress due to climate change (Sewenet et al., 2021; Wato, 2021). Research by Solomon et al. (2021) indicates that wheat production is highly vulnerable to climate change, with a projected decrease of 25.5% in 2050. The low level of productivity, exacerbated by climate change, alongside the increasing demand for wheat in Ethiopia, is expected to worsen food shortages in the country (Workineh et al., 2020). Therefore, it is crucial to widely adopt yield-enhancing technologies and practices that not only improve wheat productivity but also ensure environmental sustainability, while mitigating greenhouse gas emissions (Mekonnen, 2017).

Since 2010, the Ethiopian government, in collaboration with the Food and Agricultural Organization (FAO), has introduced climate-smart agriculture practices (CSAPs). The aim is to enhance agricultural productivity in a sustainable manner, adapt and build resilience to climate change, and reduce greenhouse gas emissions (FAO, 2016). Climate-smart agriculture practices have the potential to improve soil fertility, reduce erosion, break pest life cycles, lower GHG emissions, suspend weeds, and ultimately enhance crop productivity (Bongole et al., 2020; Hallama et al., 2019). For example, crop rotation and row planting are vital practices that mitigate the risk of pest and weed infestations, enhance nitrogen fixation and organic matter formation, improve water and nutrient distribution in the soil profile, and notably reduce greenhouse gas emissions while enhancing productivity (FAO, 2016; Martey et al., 2020). The use of improved crop varieties reduces the risk of crop failure resulting from rainfall variability and enhances productivity (Martey et al., 2020; Tekelewold et al., 2019).

Several studies have been conducted in Ethiopia that have evaluated the impact of CSAPs on crop productivity and household welfare. However, previous studies have mostly considered single CSA practices (Merga et al., 2023; Mossie, 2022; Workineh et al., 2020) and their impact on crop yield and income (Adego et al., 2019; Fentie & Beyene, 2019; Mossie, 2022; Sedebo et al., 2022). Additionally, most of the previous studies measured the aggregate effects of CSAPs on yield and welfare (Adego et al., 2019; Belay et al., 2023; Sedebo et al., 2022), yet each CSAPs may not contribute equally. Thus, an independent study is required to provide detailed CSAP measures for designing specific interventions. In addition, many studies were focused on other crop than wheat (Adego et al., 2019;

Beyene, 2019; Merga et al., 2023; Shako et al., 2021). To the best of our knowledge, there is a dearth of studies on the impact of CSAPs on technical efficiency in Ethiopia, including the study area.

Furthermore, a significant portion of the studies relied on econometric models that may not adequately control for both observable and unobservable differences between users and nonusers of CSAPs, which can impact outcome variables. For instance, Abate et al. (2023), Belay et al. (2023), Fentie and Beyene (2019), Mossie (2022) and Wordofa et al. (2021) relied on the propensity score matching (PSM) model, which does not account for the unobservable characteristics of farmers. If there are unobservable characteristics that can influence adoption decisions and the outcome variable, the result from PSM is likely to be biased (Ma & Abdulai, 2016). Besides, most of the previous studies did not consider selection bias in favor of a single production frontier model to estimate technical efficiency by assuming that adopters and non-adopters have similar production characteristics. For instance, Ho and Shimada (2019) study the effects of climate-smart agriculture and climate change adaptation on the technical efficiency of rice farming, not accounting for selection bias from unobserved characteristics. Pangapanga-Phiri and Mungatana (2021) also did not consider selection bias when analyze the effect of CSAPs on the technical efficiency of maize production under extreme weather events. The reported impacts from these studies, which do not account for selection bias, are likely to be biased estimations (González-Flores et al., 2014; Greene, 2010). According to Greene (2010), a stochastic frontier model with correction for sample selection takes into account the selection bias from observed and unobserved factors by assuming that the unobserved characteristics in the selection equation are correlated with the noise in the stochastic frontier.

Hence, unlike previous studies, this study tries to control for both observed and unobserved heterogeneities to estimate production efficiency and evaluate the impact of CSAPs on technical efficiency. Accordingly, we applied the multinomial endogenous switching regression model and the recently introduced frontier model, which corrects for sample selection bias, to measure the impact of the adoption of CSAPs on the technical efficiency of wheat farmers (Greene, 2010). Hence, this study aimed to examine the individual and combined effects of wheat row planting, crop rotation, and improved wheat varieties on the technical efficiency of wheat farmers in northwestern Ethiopia. This empirical study will, therefore, be vital for designing appropriate policies and strategies that can stimulate the adoption of CSAPs to enhance the technical efficiency of wheat farmers and ultimately improve food security and overall livelihoods without harming the environment. This study will also contribute to the literature by identifying factors affecting the adoption of CSAPs and its impact on technical efficiency.

2 Methodology

2.1 Study area description

The study area, East Gojjam zone is one of the administrative zones of the Amhara National Regional State (ANRS), which is located in the northwestern part of Ethiopia (Fig. 1). East Gojjam is bordered on the south by the Oromia Region, on the west by West Gojjam, on the north by South Gondar, and on the east by South Wollo. The East Gojjam zone has sixteen districts and four urban administrations. The total land area of the zone is 14,010 km². The average annual rainfall varies from 900–1800 mm, while

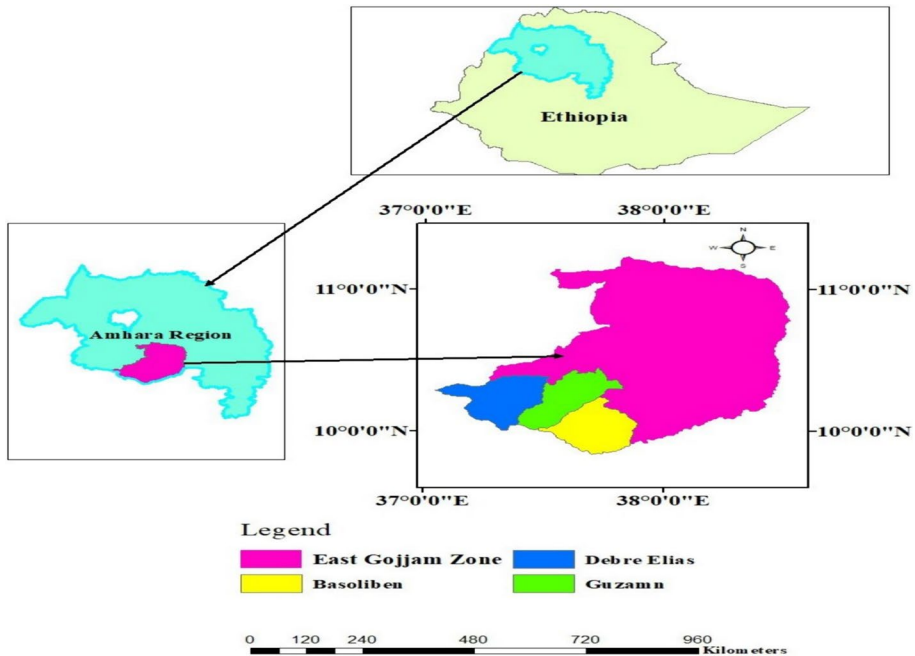


Fig. 1 Study area map

there is a short rainy season (Belg) during February and March in highland agro-ecology. The average temperature ranges from 7.5° C—27° C. The zone is generally characterized by mixed crop-livestock production. East Gojjam is among the high potential crop production areas in the Amhara National Regional State with a marketable surplus for urban markets. Food grain production is the dominant subsector in the zone (CSA, 2022).

East Gojjam stands out as the leading zone in terms of area coverage, production and productivity of wheat in the Amhara region. In 2021/22, the east Gojjam zone produced 5.3 million quintals of wheat from 166,578 hectares of land. Moreover, wheat is the first crop, followed by maize and *teff*, in terms of their contribution to total food grain production in the zone, which accounts for nearly 29%, 24% and 23%, respectively, of the total food grain production in the zone. The average productivity of wheat in the east Gojjam zone is 31.84 qt/ha, which is higher than the average productivity of Ethiopia (31.11 qt/ha) (CSA, 2022), but lower than the world average productivity (35.47 qt/ha) (FAO, 2022).

This may be because crop production systems are predominantly dependent on rain-fed farming systems, which makes the sector most vulnerable to climate change and variability. In addition, the prevalence of diseases, insect pests, soil degradation, unreliable rainfall, temperature rise and variability, and recurrent drought are major climate change related problems that undermine the productivity and sustainability of the agriculture sector in the area (Ferede et al., 2020). In response, different CSAPs have been adopted to a limited extent, such as improved crop production technology, agronomic management practices, soil and water conservation, crop rotation, and past management practices.

Table 1 Selected districts, kebeles, and their sample sizes

Sampled districts	Kebeles	Total hhs	Sample hhs
Gozamen	Enerata	1168	50
	Wonka	1142	49
	Libanos	1372	59
Debre Elias	Gofichima	1636	49
	Yemezeegn	1300	39
Basoliben	Dendegeb	2019	78
	Limchi	1558	61
Total		10,195	385

“hhs” means household heads

2.2 Sampling procedure and sample size determination

The target population for this study was smallholder wheat producer farmers in the east Gojjam zone. A combination of purposive and random sampling procedures was used to select the sample wheat producer smallholder farmers. The east Gojjam zone was chosen because it is the leading zone of wheat production in the Amhara region. Debre Elias, Gozamin, and Basoliben districts of the East Gojjam zone were chosen purposively for high level wheat production in the area and for the importance of the crop in rural livelihoods. Then, a total of seven *kebeles*¹ within the three districts were randomly selected based on the proportion of *Kebeles* found in each district. From the selected rural *Kebeles*, wheat producer households were identified, and a total of 385 wheat producer farmers were selected randomly using a probability proportional sampling method based on the numbers of wheat producer farmers in each *Kebele* (Table 1). Moreover, the data were collected at the smallholder farmers' plot level leading to 702 wheat plots cultivated in the 2021/2022 production period. The total sample size was determined using a formula that provides the maximum size to ensure the desired precision (acceptable error) using the formula given by (Kothari, 2004). Kothari is considered essentially appropriate in a situation with a large or unknown population and where the population is divided into distinct subgroups or strata. According to Cochran (1977), assume there is a large population but the variability of the proportion “*p*” is not known, *p* = 0.5 variability can be taken at 95% confidence level and ± 5% precision. This value will give a sample size sufficiently large to guarantee an accurate prediction.

$$n = \frac{Z^2 pq}{e^2} = 385$$

where, *n* is the desired sample size; *Z* is the standard cumulative distribution that corresponds to the level of confidence with the value of 1.96; *e* is the level of precision its value equals to 0.05; *p* is the estimated proportion of an attribute present in the population, with a value of 0.5 as recommended by (Cochran, 1977) to get the desired minimum sample size of households at a 95% confidence level and ± 5% precision; *q* = 1 - *p*.

¹ *Kebeles* are the lowest administrative structure where a group of *kebeles* makes up a district.

2.3 Data collection method

The study relied on data collected from primary and secondary sources. Face-to-face personal interviews using a semi-structured questionnaire were employed to collect primary data. Prior to the survey, the questionnaire underwent pretesting with 15 sample households to assess appropriateness, and necessary modifications were made to the questionnaire. The questionnaire was intended to generate information related to demographic, socioeconomic, institutional, and farm plot characteristics of the sample households, while it was also used to provide information related to different kinds of CSAPs adopted in the study area. Primary data were supplemented with secondary data collected from the zone and district offices of agriculture and rural development.

2.4 Method of data analysis

2.4.1 Estimation of technical efficiency

Technical Efficiency (TE) refers to the ability of a decision-making unit to produce the maximum feasible output from a given bundle of inputs (Chen et al., 2005; Farrell, 1957). Technical efficiency measures how well the inputs are combined to produce maximum output in the production process (FAO, 2017). Any deviation from this maximal output is considered inefficient (Coelli et al., 2005). Production efficiency is measured using either Parametric or nonparametric methods. Nonparametric production efficiency techniques, such as data envelopment analysis, assume that the decision-making unit has complete control over the production process and that any deviations from the frontier are considered inefficient (Coelli, 1995; Kumbhakar & Lovell, 2000). However, in agriculture, the prevalence of factors outside of farmers' control, thus it is difficult to accept that any departure from the frontier is inefficient (Bauman et al., 2019). Hence, the parametric production efficiency technique was employed. The technical efficiency of wheat production was measured by the Stochastic Production Frontier (SPF) correcting for sample selection bias, which was developed by (Greene, 2010). This model was used by (Ahmed et al., 2017; Dagneu et al., 2024) to analyze the impact of improved seed and contract farming on productivity.

The stochastic production frontier approach requires a prior specification test of the functional form of the production function, and a log-likelihood ratio (LR) test was used to choose from Cobb–Douglas and translog production functions, which are the most commonly used to measure technical efficiency. The Cobb–Douglas production functional equation can be expressed as follows:

$$\ln y_i = \beta_0 + \sum \beta_i \ln X_i + v_i - u_i \quad (1)$$

where, \ln denotes the natural logarithm; y_i is the observed wheat production of the i th farmer, x_i is the inputs used by the i th farmer (land, labor, DAP, urea, oxen, and wheat seed), β_0 and β_i are unknown parameters, v_i is a random variable beyond the farmers control, u_i is a nonnegative random variable assumed to account for production inefficiency.

Given the level of input, the technical efficiency of the i th wheat farmers is the ratio of the observed output to the maximum potential output (frontier output):

$$TE_i = \frac{\text{actualoutput}}{\text{potentialoutput}} = \frac{f(x_i; \beta) \exp(v_i - \mu_i)}{f(x_i; \beta) \exp(v_i)} = \exp(-\mu_i) \quad (2)$$

A stochastic production frontier model correcting for sample selection bias assumes that the unobserved characteristics in the selection equation are correlated with the noise in the stochastic frontier model. Then, the selected approach for the SPF analysis equations can be formulated as:

Selection equation:

$$A_{im} = 1[\alpha Z_{im} + \omega_{im} > 0], \quad \omega_{im} \sim N(0, 1) \quad (3)$$

SPF:

$$y_{im} = \beta X_{im} + \varepsilon_{im}, \quad \varepsilon_{im} \sim N(0, \sigma_2); \quad (y_{im}, X_{im}) \text{ are observed only when } A_{im} = 1 \quad (4)$$

The error structure is specified as follows: $\varepsilon_{im} = v_{im} - u_{im}$,

$$u_{im} = |\sigma_\mu u_{im}| = \sigma_\mu |u_{im}| \text{ where, } u_{im} \sim N(0, 1) \quad (5)$$

$$v_{im} = \sigma_\nu v_{im} \text{ where, } v_{im} \sim N(0, 1)$$

$$(v_{im}, \omega_{im}) \sim N(0, 1), \quad (1, \rho\sigma_\nu, \sigma_\nu^2)$$

where, A_{im} is a binary variable equal to 1 for adopters of different combinations of CSAPs and 0 for non-adopters; y_{im} is the amount of wheat produced by the i th farmer; z_{im} is an explanatory variables included in the sample selection equation; x_{im} is a vector of inputs used in the production frontier; α and β are parameters to be estimated; v_{im} is the stochastic effect beyond the farmer's control, measurement errors and other statistical noise; and u_{im} is a nonnegative random variable assumed to account for technical inefficiency in production. It is useful to underscore that the parameter ρ captures the presence or absence of selectivity bias.

2.4.2 Impact of climate smart agriculture practices on technical efficiency

To determine the accurate impact of CSAPs on technical efficiency, it is important to take into account both observable and unobservable characteristics of wheat farmers. The farmers' decision to adopt CSAPs does not fully depend on the observed factors. It also depends on unobserved factors such as managerial ability, skills, and motivation, which in turn affect the outcome variables that cause endogeneity problems. Failure to capture this endogeneity may result in inconsistent and biased estimates (Greene, 2008). To control for unobserved and observed heterogeneity and self-selection bias, this study used the MNESR model. This framework has the advantage of evaluating both individual and alternative combinations of CSAPs while capturing self-selection bias (Teklewold et al., 2013).

The two-stage MNESR model was developed by (Deb & Trivedi, 2006). The first stage is farmers' decision on the adoption of CSAP combinations, which was estimated using an MNL selection model. In the second stage, the impact of each combination of CSAP on technical efficiency was evaluated. Economic theory suggests that farmers adopt a single or a combination of CSAPs that can maximize their utility. This means that adoption occurs when the expected utility of the chosen CSAP is greater than that of the other alternative

CSAPs. However, because the utility obtained from adopting CSAPs is not observed but only its choice of CSAPs observed, one can assume an expected utility model that states conditional probability choice given a farmer's choice. To formalize this, consider the following latent variable:

$$A^*_{im} = \beta_m X_i + \mu_{im} \quad (6)$$

where, A^*_{im} is a latent variable that captures the i th farmer's expected utility in adopting alternative combinations of CSAPs m with respect to another alternative K . X_i is a vector of observed independent variables (household characteristics, socioeconomic factors, institutional factors, and farm plot characteristics), and μ_{im} are unobserved characteristics that are relevant to the farm household's decision maker but are unknown to the researcher, such as expectations, skills, perceptions, and motivations.

Thus, the farmer chose a combination of CSAP "m" over any other CSAP combination k , if it provides greater expected utility than any other alternative k , $k \neq m$.

$$A_{im} = \begin{cases} 1 \text{ if } A^*_{i1} > \max_{k \neq 1} A^*_{ik} \text{ or } \eta_{i1} < 0 \\ 2 \text{ if } A^*_{i2} > \max_{k \neq 2} A^*_{ik} \text{ or } \eta_{i2} < 0 \\ \dots \\ m \text{ if } A^*_{im} > \max_{k \neq m} A^*_{ik} \text{ or } \eta_{im} < 0 \\ \eta_{im} = \max_{k \neq m} (A^*_{ik} - A^*_{im}) < 0 \end{cases} \quad (7)$$

where, A_{im} indicates the farmer's observed choice of a combination of CSAPs; and η_{im} is the expected utility difference between alternative combination m and any other alternative k . Assuming that μ_{im} are independent and identically distributed, that is under the independence of irrelevant alternatives (IIA) hypothesis. The probability of choosing an alternative package of m can be computed as:

$$p_{im} = \text{pr}(\eta_{im} < 0 | X_i) = \frac{\exp(\beta_m X_i)}{\sum_{k=1}^m \exp(\beta_k X_i)} \quad (8)$$

Selecting a valid instrumental variable is a difficult task; following several other studies, this study used sources of information (development agents and cooperatives) as instrumental variables for the household decision to adopt CSAPs (Sileshi et al., 2019). A valid instrumental variable should influence the adoption decision of CSAPs but should not influence the outcome variable (technical efficiency of wheat farmers). Thus, the validity of the instrument variables was tested using a falsification test. In the second stage, we apply the selection bias correction model to examine the impact of each alternative CSAP choice on the outcome variables. The outcome equation for each possible regime (m) can then be expressed as:

$$\begin{cases} \text{Regime 1; } Y_{i1} = \beta_1 X_i + v_{i1} \text{ if } A_{i1} = 1; \\ \text{Regime 2; } Y_{i1} = \beta_2 X_i + v_{i2} \text{ if } A_{i2} = 1 \\ \dots \\ \text{Regime } m; Y_{im} = \beta_m X_i + v_{im} \text{ if } A_{im} = m \end{cases} \quad (9)$$

where, Y_{im} indicates the TE of wheat farmers, X_i are exogenous variables that affect the outcome variable; and v_{im} denotes error terms that capture the uncertainty faced by farmers and are unobserved and satisfy zero mean and constant variance. To obtain consistent

estimates, one can take into account the correlation between the error terms μ_{im} from the multinomial logit model estimated in the first stage and the error term v_{im} from the outcome equation.

$$\begin{cases} \text{Regime1}; Y_{i1} = \beta_1 X_i + \sigma_1 \lambda_{i1} + \omega_{i1} \text{if } A_{i1} = 1; \\ \text{Regime2}; Y_{i1} = \beta_2 X_i + \sigma_2 \lambda_{i2} + \omega_{i2} \text{if } A_{i2} = 2 \\ \dots \\ \text{Regimem}; Y_{im} = \beta_m X_i + \sigma_m \lambda_{im} + \omega_{im} \text{if } A_{im} = m \end{cases} \tag{10}$$

where, σ_m is the covariance between μ_{im} and v_{im} , ω_{im} is the error term with an expected value of zero, and λ_{im} is the inverse Mills ratio computed as;

$$\lambda_{im} = \sum_{k \neq m}^m \rho_m \left[\frac{p_{ik} \ln(p_{ik})}{1 - p_{ik}} + \ln(p_{im}) \right] \tag{11}$$

where, ρ_m in the above equation represents the correlation coefficient between μ_{im} and v_{im}

At this point, a counterfactual analysis will be performed to examine average treatment effects (ATT) by comparing the expected outcomes of adopters with and without adoption of a particular CSA strategy following (Di Falco & Veronesi, 2014). The ATT in the actual and counterfactual scenarios will be determined as follows:

Adopters with adoption (actual adoption observed in the sample):

$$E(Y_{im} | A_{im} = m) = \beta_m X_{im} + \sigma_m \lambda_{im} \tag{12}$$

Non-adopters with non-adoption (observed in sample):

$$E(Y_{i1} | A_{i1} = 1) = \beta_1 X_{i1} + \sigma_1 \lambda_{i1} \tag{13}$$

The counterfactual case in which adopters did not adopt is also stated as follow:

$$E(Y_{i1} | A_{im} = m) = \beta_1 X_{im} + \sigma_1 \lambda_{im} \tag{14}$$

Non-adopters with adoption (counterfactual):

$$E(Y_{im} | A_{i1} = 1) = \beta_m X_{i1} + \sigma_m \lambda_{i1} \tag{15}$$

Equations (12) and (13) model the actual expected outcomes for CSA adopters and non-adopters, respectively, which are observed in the data. In contrast, Eqs. (14) and (15) represent the counterfactual outcomes; that is, the outcomes that adopters would achieve without adoption and non-adopters would achieve with adoption. Thus, the difference between Eq. (12) and (14), that is, adopters with adoption and counterfactual adopters who did not adopt was the ATT, which is calculated as follows:

$$\begin{aligned} ATT &= E(Y_{im} | A_{im} = m) - E(Y_{i1} | A_{im} = m) \\ &= \beta_m X_{im} + \sigma_m \lambda_{im} - (\beta_1 X_{im} + \sigma_1 \lambda_{im}) \\ &= X_{im} (\beta_m - \beta_1) + \lambda_{im} (\sigma_m - \sigma_1) \end{aligned} \tag{16}$$

The first term on the right-hand side of Eq. (16) represents the expected change in the mean outcomes (TE) of the CSA adopters, assuming that the adopters had the same

characteristics as non-adopters. The second term (λ_{im}) is the selection term that captures all potential differences between adopters and non-adopters that arise due to unobserved variables.

Similarly, the average treatment effect on the untreated (ATU) is the difference between Eqs. (13) and (15). This indicates the counterfactual impact of CSAPs on non-adopting farmers if they had adopted the practices and can be specified as:

$$\begin{aligned}
 ATU &= (Y_{im}|A_{i1} = 1) - \epsilon (Y_{i1}|A_{i1} = 1) \\
 ATU &= \beta_m X_{i1} + \sigma_m \lambda_{i1} - (\beta_1 X_{i1} + \sigma_1 \lambda_{i1}) \\
 ATU &= X_{i1}(\beta_m - \beta_1) + \lambda_{i1}(\sigma_m - \sigma_{m1}) \quad (17)
 \end{aligned}$$

The first term of Eq. (17) shows the expected change in non-adopter TE if they had decided to adopt alternative CSAPs given that adopters had the same characteristics as non-adopters.

3 Result and discussion

3.1 Characteristics of sample household

Table 2 summarizes the characteristics of the sampled farm households. The majority of the sampled household heads (88.89%) were male. The average household size, measured in adult equivalents, was 5. The average age of the sampled households was 45 years. The average education level of the sampled household heads was grade 3. Most of the sampled households practiced integrated farming systems (a mix of crop production and livestock rearing). The mean number of livestock owned by the sampled farmers, measured in the TLU, was 8.426. Agriculture was the only activity and income source for most of the sampled households. Only 27.07% of the sampled farmers engaged in off-farm activities such as petty trade, handcraft, and daily labor, the remaining 72.93% participated in agricultural activities such as crop production and livestock rearing.

Among the sample respondents, only 37.32% had access to credit. This indicates that more than half of the respondents lacked access to credit. The average distance from the household residence to the input supplier institution was 30 min. The descriptive statistics in Table 2 show that approximately 45.87% of the sample respondents had access to training on climate change and CSAPs to adapt to climate change effects. Concerning information access, 55.13% and 47.29% of the sample households have information from development agents and cooperatives about the effect of climate change on production and its adaptation strategy, respectively.

In this study various plot specific characteristics including the average walking distance to the plot (plot distance), slope of the plot, soil fertility status of the plot, and plot size were considered. The average time that the farmers spent to reaching their wheat plots was 25 min. The average wheat plot size for the sampled households was 0.54 hectares. Table 2 shows that 68.09% of the wheat plots had flat slopes, with 7.55%, 64.96% and 27.49% of the sampled wheat plots had fertile, moderately fertile and less fertile soil fertility, respectively.

Table 2 Characteristics of the household

Continuous variables	Mean	Std. dev
Age of the household (year)	44.96	11.649
Education level of the household (year of schooling/grade)	2.83	3.22
Family size (adult equivalence)	4.886	1.715
Livestock holding (tropical livestock unit)	8.426	4.26
Wheat plot area (hectare)	0.539	0.256
Plot distance (human walking minute)	25.443	15.377
Input distance(human walking minute)	30.786	19.334
Discrete variables		Percentage
Sex of the household (Male = 1)		88.89
Credit access (Yes = 1)		37.32
Training access (Yes = 1)		45.87
Access to information from cooperatives (Yes = 1)		47.29
Access to information from development agents (Yes = 1)		55.13
Participation in off-farm activities (Yes = 1)		27.07
Wheat plot slope (Flat = 1)		68.09
Soil fertility status of the plot		
-Fertile		7.55
-Medium fertile		64.96
-Low fertile		27.49

Source: Own survey

3.2 Adoption of climate smart agriculture practices

Different CSAPs were implemented by wheat producer smallholder farmers in the study area. The most commonly implemented CSAPs were wheat row planting, crop rotation and improved wheat variety. Smallholder farmers used these CSAPs either solely or simultaneously in their wheat plots. Table 3 illustrates the various combinations of CSAPs implemented in 702 smallholder farmers' wheat plots. Out of 8 possible combinations of CSAPs, 7 were implemented in the study area. The combined use of crop rotation with improved wheat varieties ($R_0C_1IV_1$) was not implemented during the study period. Smallholder wheat farmers mostly implemented the three CSAPs together in their plots, followed by wheat row planting, which was performed independently. In contrast, a small proportion of wheat farmers (6.13%) adopted crop rotation ($R_0C_1IV_0$), while approximately 7.26% of the framers did not use CSAPs.

3.3 Estimation of stochastic production frontier and measurement of technical efficiency

3.3.1 Model test

Before the estimation of the SPF, various tests were conducted, and the results were reported in Table 4. First hypothesis tests were conducted to determine the correct

Table 3 CSAP adoption status of the plots of sampled households

Adoption of CSAPs	Freq	Percent	Cum
Non-adopter($R_0C_0IV_0$)	51	7.26	7.26
Row planting($R_1C_0IV_0$)	171	24.36	31.62
Crop rotation($R_0C_1IV_0$)	43	6.13	37.75
Improved wheat variety($R_0C_0IV_1$)	59	8.40	46.15
Row planting and crop rotation($R_1C_1IV_0$)	95	13.53	59.69
Row planting and improved wheat variety($R_1C_0IV_1$)	105	14.96	74.64
Crop rotation and improved wheat variety ($R_0C_1IV_1$)	0	0	74.64
Row planting, improved wheat variety and crop rotation($R_1C_1IV_1$)	178	25.36	100.00

R refers wheat row planting, C refers crop rotation, IV refers improved wheat variety, subscript ‘‘1’’ indicates adopter, whereas ‘‘0’’ indicates non-adopter

Source: Own survey

Table 4 The generalized likelihood ratio hypothesis test

Null hypothesis	Calculated LR value	Critical value	Decision
Ho: Production function is Cobb–Douglas	25.277	32.671	Fail to reject Ho
Inefficiency test; Ho: $\gamma = 0$	9.365	3.84	Reject Ho
Ho: $\delta_1, \delta_2 \dots \delta_{11} = 0$	86.2496	19.67	Reject Ho

Source: Own survey

functional form, i.e., the choice between Cobb–Douglas vs. translog functional forms. To determine the best functional form, the generalized likelihood ratio (LR) test computed as $LR = -2[\ln(H_0) - \ln(H_1)]$ was used. where, $\ln(H_0)$ and $\ln(H_1)$ are the log-likelihood values of the Cobb–Douglas (null hypothesis) and translog functional (alternative hypothesis) functions, respectively. The results of the LR test showed that we cannot reject the null hypothesis that Cobb–Douglas is more appropriate than the less restrictive translog functional form in this study. The critical value was greater than the computed LR value and statistically significant at a 5% significant level.

The second hypothesis test was the existence of the inefficiency component of the composed error term of the SPF model. This finding indicates that wheat producing farmers were efficient and had no room for efficiency improvement (null hypothesis of $\gamma = 0$). The alternative hypothesis states that there is inefficiency in the production of wheat in the study area ($\gamma \neq 0$). This was used to decide whether the traditional average production function (OLS) best fit the data set compared to the SPF model. The hypothesis test was conducted based on the generalized likelihood ratio (LR) test as expressed in the above paragraph. The test results showed that the calculated LR value is 9.365, which is greater than the critical value of 3.84 at 1 degree of freedom and a 5% significant level. Thus, the alternative hypothesis was accepted, proving the presence of inefficiency in wheat production in the study area.

To determine whether the inefficiency effect model has an effect on the inefficiency of wheat producer farmers in the study area, the likelihood ratio (LR) for the inefficiency

effect was computed. The computed LR value (86.25) was greater than the 5% critical value (19.67) at 11 degrees of freedom, indicating that the null hypothesis (H_0) that all the explanatory variables are equal to zero was rejected.

3.3.2 Estimation of the stochastic production frontier model with corrected selectivity bias

In Table 5, the results of the maximum likelihood estimate of the SPF model corrected for selectivity bias estimated by NLOGIT 5 software were presented. The coefficient of ρ , which indicates the presence of selection bias, was significant for both non-adopters and adopters of the three CSAPs simultaneously. This suggests the presence of selection bias, which supports the use of a sample selection framework to estimate separate SPFs for adopters of each CSAP combination. The results revealed that the output of wheat increased with the wheat plot area in all the SPF model specification at a 1% significant level.

In the pooled SPF model, the amount of wheat seeds and the amount of urea used had a positive and significant impact on wheat production efficiency. The amount of wheat seed had a positive significant effect on the production of wheat crops for non-adopter farmers ($R_0C_0IV_0$), who adopted the $R_1C_0IV_0$, and $R_0C_1IV_0$ SPF selection correction models. Endalew et al. (2023) also reported that wheat farm size, amount of urea, and amount of seeds used had significant positive effects on wheat production efficiency.

Oxen labor was also positively and significantly related to wheat productivity in the adoption of $R_1C_0IV_0$ SPF selection correction model at a 5% significance level. However, oxen labor was negatively and significantly relation to wheat output in the adoption of $R_0C_1IV_0$ and $R_0C_0IV_0$ SPF selection bias correction model at the 5% and 10% significance levels, respectively. The amount of urea used also increased wheat output in the SPF selection bias correction model specifications of adoption of $R_0C_1IV_0$, $R_1C_1IV_1$, and $R_0C_0IV_0$. The amount of human labor used and the amount of urea used had a negative and significant impact on wheat output in the SPF correction for selectivity bias model specification of $R_0C_0IV_0$ at a 1% significance level. The production of wheat was significantly and negatively related to the amount of DAP fertilizer used for the pooled and $R_0C_1IV_0$ SPF selection correction models at the 1% and 5% significance levels. This negative sign suggests the excessive use of DAP fertilizer in the production of wheat in the study area.

The coefficient related to the input variables measures the elasticity of output with respect to inputs. The sum of all partial production elasticities of inputs, i.e., return to scale (RTS), for all frontier models except for the non-adopters of CSAPs and the adopters of crop rotation only are consistently greater than one. This result shows that there is potential for wheat producers to expand their production; hence, farmers are in the stage I production area. Thus, a unit increase in all inputs proportionally would increase wheat output by more than a unit amount. Getachew et al. (2020) also found that wheat production in the north Shewa Zone of Ethiopia had an increasing return to scale. In contrast, Endalew et al. (2023) revealed that wheat production in northwestern Ethiopia follows decreasing returns to scale.

3.3.3 Technical efficiency of wheat farmers

After estimating the SPF corrected for both observed and unobserved heterogeneities, the technical efficiency score of each sample of wheat farmers was predicted and presented

Table 5 Cobb–Douglas SPF with correction for selectivity bias model estimation results

Variable	Pooled	$R_0C_0IV_0$	$R_1C_0IV_0$	$R_0C_1IV_0$	$R_0C_0IV_1$	$R_1C_1IV_0$	$R_1C_0IV_1$	$R_1C_1IV_1$
Constant	7.675*** (0.382)	10.644*** (0.710)	6.314*** (0.813)	10.002*** (2.175)	5.592*** (2.272)	7.687*** (1.559)	8.742*** (1.806)	8.763*** (1.039)
Plot area	1.092*** (0.047)	1.365*** (0.079)	0.912*** (0.108)	1.108*** (0.211)	0.916*** (0.244)	1.140*** (0.173)	1.201*** (0.248)	1.177*** (0.108)
Seed	0.193*** (0.042)	0.221** (0.088)	0.231** (0.098)	0.474* (0.283)	0.361 (0.218)	0.062 (0.174)	0.112 (0.239)	0.096 (0.124)
DAP	-0.136*** (0.028)	0.062 (0.070)	-0.117 (0.071)	-0.545** (0.220)	-0.039 (0.248)	-0.055 (0.136)	-0.029 (0.120)	-0.101 (0.070)
Urea	0.066** (0.024)	-0.109*** (0.039)	-0.044 (0.054)	0.246* (0.148)	0.072 (0.091)	0.090 (0.086)	0.036 (0.126)	0.119* (0.061)
Labor	0.037 (0.047)	-0.434*** (0.089)	0.117 (0.108)	-0.039 (0.225)	0.135 (0.208)	0.024 (0.191)	-0.154 (0.231)	-0.113 (0.162)
Oxen	-0.045 (0.079)	-0.367** (0.148)	0.279 (0.147)*	-0.682* (0.393)	-0.036 (0.631)	0.006 (0.393)	-0.112 (0.382)	-0.108 (0.207)
Sigma	1.237 (0.107)***							
Lambda	0.359 (0.000)***							
Sigma(μ)		0.332 (0.023)***	0.199 (0.095)**	0.260 (0.065)***	0.288 (0.193)	0.175 (0.393)	0.223 (0.277)	0.188 (0.154)
Sigma(ν)		0.168 (0.038)***	0.206 (0.043)***	0.099 (0.090)	0.226** (0.109)	0.252*** (0.095)	0.280*** (0.091)	0.327*** (0.067)
Rho		-1.000 (0.000)***	-0.329 (0.403)	0.413 (1.649)	0.448 (0.885)	-0.221 (0.647)	-0.092 (0.661)	-0.628*** (0.212)
RTS	1.201	0.74	1.378	0.562	1.409	1.267	1.054	1.07

The value in parenthesis are standard errors (SE). ***, **, and * represent significance at the 1%, 5%, and 10% significant levels, respectively
 Source: Own survey

Table 6 The mean technical efficiency score estimated after bias correction for each CSAP

Variable	Obs	Mean	Std.Dev	Min	Max
Non-adopter($R_0C_0IV_0$)	51	0.789	0.169	0.329	0.999
Row planting($R_1C_0IV_0$)	171	0.856	0.052	0.589	0.935
Crop rotation($R_0C_1IV_0$)	43	0.819	0.11	0.484	0.958
Improved wheat variety($R_0C_0IV_1$)	59	0.804	0.087	0.413	0.929
Row planting and crop rotation($R_1C_1IV_0$)	95	0.871	0.038	0.737	0.938
Row planting and improved wheat variety($R_1C_0IV_1$)	105	0.838	0.05	0.651	0.93
Row planting, improved wheat variety and crop rotation($R_1C_1IV_1$)	178	0.861	0.04	0.685	0.949
Overall sample mean technical efficiency	702	0.845	0.075	0.329	0.999

Source: Own survey

in Table 6. Accordingly, the overall average technical efficiency of the wheat farmers was 84.5%, with a range between 32.8% and 99.8%. This implies that wheat farmers could increase production by 15.5% by improving their technical efficiency. Specifically, the mean technical efficiency of non-adopter ($R_0C_0IV_0$) wheat farmers was 78.9%, whereas for the adopter of $R_1C_0IV_0$, the mean technical efficiency was 85.6%. The mean technical efficiency of the adopter of $R_0C_1IV_0$ was estimated to be 81.9%, implying that 18.1% of the production was lost due to technical inefficiency alone. The mean technical efficiency of the adopter of $R_0C_0IV_1$ was estimated to be 80.4%. This shows that wheat farmers could increase production by 19.6% by improving their technical efficiency. When looking at the combined adoption of CSAPs including, $R_1C_1IV_0$, $R_1C_0IV_1$, and $R_1C_1IV_1$, the mean technical value was estimated to be 87.1%, 83.8% and 86.1%, respectively.

3.4 Determinants of adoption of climate smart agriculture practices

The first stage of the MNESR model for each adoption choice estimation result is presented in Table 7. The base category or reference was non-adopters of any of the alternative CSAPs ($R_0C_0IV_0$). The model fits the data reasonably well. The Wald test in which all regression coefficients are jointly equal to zero was rejected ($X^2=207.365$; $p=0.000$). The results show that the estimation coefficients differ substantially across the alternative packages.

The demographic characteristics of the household such as the sex of the household head and family size were significantly associated with the adoption of $R_0C_0IV_1$ and $R_1C_1IV_0$. Male-headed households are more likely to adopt $R_0C_0IV_1$ than female headed households. A study conducted by Beyene et al. (2017) reported that male-headed households were more likely to adopt CSAP packages than to female-headed households. This might be because women are resource and time constrained. Family size positively and significantly affected the adoption of $R_0C_0IV_1$ and $R_1C_1IV_0$. This may be due to the availability of labor at the household level to utilize different CSAPs at the same time. Similarly, Erekaló and Yadda (2023) and Alemu et al. (2023) reported that availability of labor could be deployed to accomplish additional tasks that are associated with implementing adaptation and mitigation strategies that minimize the cost that farmers pay for other daily labor workers.

Household head education level had a positive and significant effect on the adoption of $R_0C_1IV_0$ and $R_1C_1IV_1$. This might be because better education is associated with

Table 7 First stage of MNESR model estimation results

Adoption practices	$R_1C_0IV_0$	$R_0C_1IV_0$	$R_0C_0IV_1$	$R_1C_1IV_0$	$R_1C_0IV_1$	$R_1C_1IV_1$
Variables	Coef. (St.Err.)	Coef. (St.Err.)	Coef. (St.Err.)	Coef. (St.Err.)	Coef. (St.Err.)	Coef. (St.Err.)
Sex of the hh	0.448(0.497)	0.103(0.613)	1.222(0.69)*	0.44(0.566)	0.291(0.535)	0.245(0.497)
Age	-0.026(0.016)	0.01(0.019)	-0.003(0.02)	-0.03(0.019)	-0.003(0.017)	-0.017(0.017)
Education	-0.005(0.066)	0.127(0.076)*	0.112(0.073)	0.068(0.07)	0.1(0.068)	0.133(0.064)**
Family size	0.039(0.105)	-0.207(0.137)	0.226(0.126)*	0.341(0.116)***	0.001(0.113)	0.118(0.106)
Livestock	0.034(0.046)	-0.019(0.06)	-0.001(0.054)	0.013(0.05)	0.111(0.047)**	0.045(0.045)
Off-farm	-0.427(0.39)	0.874(0.575)	0.829(0.512)	0.017(0.429)	-0.142(0.42)	0.376(0.406)
Plot area	-0.462(0.677)	0.208(0.843)	0.524(0.758)	-0.446(0.741)	-0.696(0.742)	-0.023(0.675)
Plot slope	-0.883(0.418)**	-0.654(0.54)	0.062(0.484)	-0.895(0.454)**	-0.859(0.452)*	-0.471(0.415)
Plot distance	-0.017(0.011)	-0.008(0.014)	-0.017(0.014)	-0.009(0.012)	-0.004(0.012)	-0.02(0.011)*
<i>Soil fertility status</i>						
_Medium fertile	0.594(0.594)	0.261(0.745)	0.146(0.686)	1.694(0.887)*	0.107(0.602)	0.857(0.612)
_Less fertile	1.133(0.699)	0.975(0.871)	0.25(0.81)	2.274(0.972)**	0.324(0.73)	1.195(0.717)*
Credit	0.351(0.385)	-0.041(0.507)	0.205(0.454)	0.663(0.412)	0.812(0.404)**	0.747(0.384)*
Training	0.915(0.37)**	0.251(0.48)	1.211(0.429)***	0.865(0.399)**	0.966(0.394)**	0.865(0.374)**
<i>Source of information</i>						
_From DA	1.405(0.449)***	0.986(0.572)*	0.669(0.521)	1.498(0.486)***	1.781(0.486)***	2.004(0.456)***
_From cooperatives	0.877(0.435)**	0.463(0.56)	0.149(0.514)	1.065(0.475)**	1.21(0.471)**	1.162(0.442)***
Input distance	-0.002(0.009)	-0.007(0.011)	-0.023(0.011)**	-0.021(0.01)**	-0.004(0.009)	-0.018(0.009)**
Constant	0.785(1.295)	-1.214(1.637)	-3.019(1.631)*	-2.395(1.587)	-1.772(1.405)	-1.44(1.332)
Pseudo r-squared		0.081	Number of obs		702	
Chi-square		207.365	Prob > chi2		0.000	

The value in parenthesis are standard errors (SE); ***, **, and * represent significance at the 1%, 5%, and 10% significant levels, respectively

Source: Own survey

greater access to information and awareness about climate change-related problems, CSAPs, and their benefits, which motivate them to adopt. In addition, education makes farmers more open, rational, and able to analyze the benefits of new technology. This finding is in line with the finding of Beyan et al. (2023), who reported that education enhances farmers' ability to acquire and analyze new ideas, thereby facilitating the adoption of CSAPs.

The adoption of alternative combinations of CSAPs was also affected by wheat plot specific characteristics, including plot slope, soil fertility status of the plot and plot distance. If the plot is flat, then the probability of adoption of $R_1C_0IV_0$, $R_1C_1IV_0$, and $R_1C_0IV_1$ decreases. This suggests that households with steep or hilly lands are more inclined to adopt CSAPs, likely due to their increased vulnerability to climate change impacts such as floods and erosion. Similar results were reported in a previous study (Beyene et al., 2017). Plot distance is the other variable that negatively affects the probability of adoption of $R_1C_1IV_1$. This implies that for farmers whose wheat plots are far from their home residence, the likelihood of the adoption of this practices decrease. In line with this result, Alemu et al. (2023) found that a longer walking distance between plots and household homesteads had a negative and significant correlation with the continuous adoption of CSAPs. The soil fertility status of a plot is another factor that determines the adoption decision of CSAPs. By taking the fertile plot as a reference, soil fertility had a positive and significant effect on the adoption of $R_1C_1IV_0$ and $R_1C_1IV_1$. The study results revealed that farmers are more likely to adopt $R_1C_1IV_0$ on medium and less fertile plots than on fertile plots. Similarly, farmers are more likely to adopt $R_1C_1IV_1$ on less fertile plots than on fertile plots. This result is consistent with the findings of (Beyene et al., 2017; Tilahun et al., 2023).

Institutional factors such as credit access, access to training, source of information and distance to the input supplier institution center determined the adoption of different combinations of CSAPs. The result in Table 7 show that access to credit had a positive and significant relation with the adoption of $R_1C_0IV_1$ and $R_1C_1IV_1$. This shows that the probability of adoption of $R_1C_0IV_1$ and $R_1C_1IV_1$ increases as small-holder farmers gain access to credit. Beyan et al. (2023) also found that access to credit positively affects the adoption of medium level CSAPs.

The other institutional variable that affects the probability of adoption of CSAPs is access to training. Access to training had a positive and significant impact on the adoption of all alternative CSAPs except the adoption of $R_0C_0IV_1$. This finding is consistent with the findings of (Beyan et al., 2023). Additionally, obtaining information from development agents and cooperatives about climate change and its effect on crop production, different climate change adaptation strategies, and the importance of adaptation strategies for production and productivity will enable farmers to adopt different CSAPs. Zegeye et al. (2022) found that extension agents provide information about the application and benefit of agricultural technologies, thus, in turn, increasing the likelihood of adoption of agricultural technology packages. In addition, distance to the input supplier institution significantly and negatively affects the adoption of $R_0C_0IV_1$, $R_1C_1IV_0$, and $R_1C_1IV_1$. This could be mainly due to the increase in agricultural input transportation costs as farmers are far away from input supply institutions. In addition, distance to the input supply institution could also be taken as a proxy for distance to obtain information about the use and availability of agricultural inputs, technology and practices. This finding is congruent with the finding of (Tilahun et al., 2023).

3.5 The impact of climate smart agriculture practice on technical efficiency

The average effects of the adoption of a combination of CSAPs on the technical efficiency of wheat farmers are presented in Table 8. To estimate the average treatment effects on the treated (ATT), the technical efficiency of wheat farmers who adopted CSAPs (actual) was compared with the technical efficiency of wheat farmers if they had not adopted (counterfactual). The ATT result indicates that the technical efficiency of adopters of any alternative CSAPs would significantly decrease if households chose not to adopt these practices.

When looking at the impact of various CSAPs independently, wheat row planting ($R_1C_0IV_0$) had the greatest impact on technical efficiency, followed by crop rotation ($R_0C_1IV_0$). As shown in Table 8, households who adopt $R_1C_0IV_0$ might shift to not adopt this practice, the mean technical efficiency would be significantly reduced by 7.2%. Similarly, if $R_0C_1IV_0$ adopters decide not to adopt this practice, the average technical efficiency would significantly decrease by 7%. The mean technical efficiency of wheat farmers could be reduced by 4.9%, if farmers adopting improved wheat varieties ($R_0C_0IV_1$) decide not to adopt them, which has the lowest impact of all alternative practices. However, when these practices are implemented in combination the returns are even greater. In particular, the adoption of $R_1C_1IV_0$ and $R_1C_1IV_1$ has the greatest impact, decreasing the technical efficiency by 10.1% and 10.3%, respectively, if wheat farmers decide not to adopt these practices. The adoption of $R_1C_0IV_1$ have the lowest impact, which decrease in technical efficiency by 7.2%, even compared to $R_1C_1IV_0$ and $R_1C_1IV_1$. However, $R_1C_0IV_1$ had the greatest impact compared to the separate use of CSAPs.

To estimate the average treatment effects on untreated (TTU), the technical efficiency of non-adopters is compared with the technical efficiency of wheat farmers if they had adopted alternative CSAPs (counterfactual). Accordingly, wheat farmers who did not adopt CSAPs would have gained more if they had adopted CSAPs in isolation or in combination except for the use of improved wheat varieties. If non-adopter wheat farmers choose to implement wheat row planting ($R_1C_0IV_0$), the mean technical efficiency would significantly increase by 5%. Similarly, if non-adopter wheat farmers choose to implement crop rotation ($R_0C_1IV_0$), the mean technical efficiency would significantly increase by 4.5%. Households that have not adopted CSAPs would experience greater improvements in technical efficiency if they choose to implement these practices collectively rather than individually. If a combination of CSAPs ($R_1C_1IV_0$, $R_1C_0IV_1$, and $R_1C_1IV_1$) is implemented by non-adopter wheat farmers, the mean technical efficiency could be increased by 7.6%, 5.6% and 7%, respectively.

Moreover, the result shows that the adoption of any of CSAPs in isolation or in combination provide higher average technical efficiency as compared to the non-adopters. In addition, the adoption of a combination of CSAPs provides more technical efficiency than does the adoption of each CSAP implemented in isolation. The result reveals that, from the combination of CSAPs, the highest technical efficiency is obtained when farmers adopt the three CSAPs ($R_1C_1IV_1$) simultaneously in the same plot. Thus, adopting multiple CSAPs simultaneously guarantees the maximum return.

In line with this finding, Ahmed et al. (2017) reported that improved maize varieties resulted in a 4.42% increase in technical efficiency compared to their non-adopter counterparts. Similarly, Ho and Shimada (2019) studied the effects of climate-smart agriculture and climate change adaptation on the technical efficiency of rice farming

Table 8 The impact of climate smart agriculture practices on technical efficiency

Alternative CSAPs	Decision stage		Treatment effect for treated		Decision stage		Treatment effect for untreated	
	TE actual for adopter		TE counterfactual		TE counterfactual		TE actual for non-adopter	
	TE actual for adopter	TE counterfactual	TE counterfactual	TE actual for treated	TE counterfactual	TE actual for non-adopter	Treatment effect for untreated	
R ₁ C ₀ IV ₀	0.856(0.002)	0.784(0.013)	0.784(0.013)	0.072(0.013)***	0.839(0.005)	0.789(0.017)	0.050(0.018)***	
R ₀ C ₁ IV ₀	0.819(0.013)	0.749(0.026)	0.749(0.026)	0.070(0.029)**	0.834(0.011)	0.789(0.017)	0.045(0.020)**	
R ₀ C ₀ IV ₁	0.804(0.007)	0.755(0.027)	0.755(0.027)	0.049(0.028)*	0.758(0.016)	0.789(0.017)	-0.032(0.023)	
R ₁ C ₁ IV ₀	0.871(0.001)	0.769(0.016)	0.769(0.016)	0.101(0.016)***	0.865(0.002)	0.789(0.017)	0.076(0.017)***	
R ₁ C ₀ IV ₁	0.838(0.003)	0.766(0.014)	0.766(0.014)	0.072(0.015)***	0.845(0.004)	0.789(0.017)	0.056(0.018)***	
R ₁ C ₁ IV ₁	0.861(0.001)	0.758(0.013)	0.758(0.013)	0.103(0.013)***	0.859(0.002)	0.789(0.017)	0.070(0.017)***	

Source: Own survey

in Vietnam. Their finding shows that climate-smart agriculture and climate change adaptation play crucial roles in improving the technical efficiency of rice production by increasing 13–14% compared to no adaptation response. Besides, the adoption of soil and water conservation, maize improved variety, and adopting organic manure and inorganic fertilizers in combination significantly improves maize technical efficiency by 9%, 15%, and 18%, respectively (Pangapanga-Phiri & Mungatana, 2021).

4 Conclusion

This study was conducted in northwestern Ethiopia with the aim to examine the impact of CSAPs on the technical efficiency of wheat farmers. In this study, various climate smart agriculture practices were considered, including crop rotation, wheat row planting, the use of improved wheat varieties, and alternative combinations of these practices. The study used primary data collected from 385 smallholder farmers (702 wheat plots) selected by using purposive and two-stage sampling methods. The stochastic production frontier with a selection correction model was used to estimate the technical efficiency, and the MNESR mode was applied to analyze the impact of CSAPs on the technical efficiency of the wheat farmers.

The result of the first stage of the MNESR model shows that, sex of the household head, education level, family size, slope of the plot, plot distance, soil fertility status of the plot, credit access, training access, access to information from development agents and cooperatives and distance to the input supplier institution are the major factors that determine the adoption of alternative combinations of CSAPs in the study area. The second stage of the MNESR result revealed that, the adoption of wheat row planting, crop rotation, and improved wheat variety in isolation as well as in combination had significant contribution to improve technical efficiency of wheat farmers. Thus, the government and stakeholders should prioritize scaling up the adoption of multiple CSAPs to enhance technical efficiency. This can be achieved by improving farmers' skills through providing technical and practical training about CSAPs; strengthening the contact of development agents with farmers, and facilitating and reinforcing the existing input supply market centers and credit supply institutions.

Although this study is informative, it relies on cross-sectional data, which limits the investigation of the dynamics of CSAPs intervention over time. Additionally, this study focused on only three CSAPs. This narrow scope may not fully capture the diverse range of CSAPs available and their varying impacts on agricultural productivity and sustainability. Therefore, future studies should use panel data collected from both participants and non-participants before and after the intervention to evaluate the long-term effects and dynamic nature of CSAPs.

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Data availability Data will be made available on reasonable request.

Declarations

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

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