https://doi.org/10.17221/74/2024-AGRICECON

# The effect of climate-smart agriculture on productivity and cost efficiency: Insights from smallholder wheat producers in Pakistan

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**Citation:** Mustafa P.G., Wang S., Mwalupaso G.E., Yu Y., Li Z. (2024): The effect of climate-smart agriculture on productivity and cost efficiency: Insights from smallholder wheat producers in Pakistan. Agric. Econ. – Czech, 70: 334–348.

**Abstract:** Unique challenges have been elicited by climate change, demanding the utilisation of effective adaptation strategies that are both environmentally and economically sustainable. Regrettably, the agricultural sector has not been spared from the effects of climate change, but it is among the largest employers and the primary source of food security globally. The situation is worse in Pakistan, where poverty, hunger, and malnutrition are reported to be prevalent. The complexity of risks posed by climate change has called for climate-smart agriculture (CSA) technologies, which potentially could augment cost efficiency and yield in wheat production. Surprisingly, previous studies have largely overlooked this crucial aspect. Therefore, our research seeks to address two fundamental questions: What is the comparative cost efficiency between adopters and non-adopters of CSA practices in wheat production? And what are the yield effects associated with CSA adoption, particularly compared to non-adopters? To this end, a multi-stage sampling technique was employed to randomly select 400 farm households in a climate risk hotspot province in Pakistan, on which the stochastic frontier analysis (SFA) and endogenous switching regression (ESR) were applied. The results revealed that CSA adoption was associated with improved cost efficiency and yield. Interestingly, if non-adopters decided to adopt CSA, they would increase their wheat yield by about 20%. Given the importance of wheat for food security, this would contribute to poverty and hunger eradication. Therefore, our study conforms to the aspirations of the 2030 agenda by promoting rethinking food production through possible improvement in cost efficiency and yield in the face of a changing climate.

**Keywords:** adaptation strategies; climate change; climate risk hotspot; sustainable agriculture; wheat productivity

The world is at risk of losing its natural richness to climate change. The impacts of climate change extend to employment and food production, disrupting trade, productivity, and production (Ray et al. 2019). This widespread effect has prompted policymakers, practitioners, and scientists to search for comprehensive and robust solutions, recognising that food security is under severe threat due to reduced agricultural productivity and increased production costs (Smit et al. 1996). Porter et al. (2014) further support this concern by documenting how climate change has drastically affected cereal crop yields, with rice and wheat experienc-

Supported by the Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD).

https://doi.org/10.17221/74/2024-AGRICECON

ing global losses of about 60%. Consequently, adapting to climate change is considered a key strategy to mitigate its impacts on agriculture and food production.

However, formulating effective policies remains a significant challenge due to limited scientific evidence on how climate change influences the knowledge, practices, and vulnerabilities of smallholder farmers (IPCC 2014). There is an increasing demand for scientists and practitioners to elucidate the real-world efficacy of technologies such as climate-smart agriculture (CSA) to enhance the scientific validity of these approaches.

While the literature on CSA is mature and extensive, understanding the benefits for farmers, particularly in terms of productivity gains and cost efficiency in production, remains inconclusive for climate risk hotspots. Recent studies by Amadu et al. (2020) and Akter et al. (2022) indicate positive yield effects of CSA adoption in drylands and flood-prone areas, respectively. However, empirical evidence is lacking for regions that face both drought and flood risks. Additionally, the cost efficiency of adopting *versus* non-adopting cereal-producing farmers has not been thoroughly analysed. To address these knowledge gaps, this study has two main objectives: first, to evaluate whether CSA adoption influences farmers' cost efficiency, and second, to examine whether CSA adoption affects yields in a climate risk hotspot that is both drought and flood-prone.

The contribution of this study is two-fold. First, it addresses the often-overlooked aspect of cost efficiency in agricultural production and technology adoption studies, providing essential insights for policymakers on effective policy support measures. Given that farmers adopt various adaptation practices to counter the adverse impacts of climate change, as noted by Ali and Erenstein (2017), understanding cost efficiency in production is crucial for agricultural sustainability. Second, in alignment with the Sustainable Development Goals, this study contributes to poverty alleviation and enhanced food security. Salik et al. (2015) emphasise that coastal communities are highly sensitive to climate change-driven threats, and insights on yield effects from adaptation strategies can significantly contribute to goals such as zero hunger, poverty reduction, and climate action.

## Literature review and context analysis

***Climate-smart agriculture: An overview and critical analysis.*** Climate-smart agriculture (CSA), an approach coined by the FAO in 2010, aims to enhance national food security and development goals, mitigate greenhouse gas emissions, and increase productivity resilience sustainably (FAO 2015). Rather than introducing a new set of agricultural practices, CSA is an overarching methodology contributing to climate change adaptation and mitigation while promoting sustainability and productivity in agricultural communities (Brandt et al. 2017). CSA does not follow a one-size-fits-all approach; its integration into agriculture is influenced by geography, institutional factors, capacity, technological innovations, and temporal scales (Chandra et al. 2017). The key to CSA's success lies in adequately educating agricultural communities and making climate information widely available. CSA is both an investment and a tool for achieving favourable agricultural outcomes. For detailed information on the approach, evolution, perspectives, and framings of CSA, refer to Chandra et al. (2018), Lipper and Zilberman (2018), and Matteoli et al. (2020).

For CSA to be effective, broader comprehension, sound policy, secure funding, and robust institutions at global, national, local, and community levels are necessary (Leviston and Walker 2012). Beyond transforming agricultural production, CSA demands a conscious effort to adopt practices that combat climate change and support the agricultural sector's success. Awareness among farmers is crucial as CSA advocates for sustainable and productive agricultural practices while managing the environment correctly (Nantui et al. 2012). Despite scientific support, some stakeholders criticise CSA, leading to a divide regarding its approach. Critiques include the lack of smallholder-specific considerations, weak nutrition recognition, absence of performance criteria to differentiate CSA from unsustainable models, lack of governance accountability, and equity and justice issues (Anderson and Feder 2004; Ewbank 2015).

Moreover, CSA's ability to address complex interactions between climate, food production, and social factors at the community level remains unclear, necessitating further research to integrate mitigation and adaptation in food production practices. The lack of empirical evidence regarding cost implications and yield effects has contributed to lower-than-expected adoption rates, particularly in climate risk hotspots (Scherr et al. 2012; Harvey et al. 2014; Lipper et al. 2014).

***Country context.*** Like many developing countries, agriculture is the backbone of Pakistan's economy, employing about 43% of the workforce and contributing 20% of the total Gross Domestic Product (GDP). Since most of the population resides in rural areas, their livelihoods are closely tied to agriculture and related activities. Wheat, cotton, rice, fruit, sugarcane, maise, and

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vegetables account for more than 75% of the total value of crop output. Therefore, agriculture plays a crucial role in ensuring food security and reducing poverty. However, weather variability and climate change pose significant threats to the success of agriculture. Rising temperatures severely impact agriculture by increasing evapotranspiration (heat stress on crops) and irrigation requirements. Studies have shown that wheat is particularly vulnerable to heat stress and temperature rises; a 1°C increase can lead to yield declines of 5–7% (Aggarwal and Sivakumar 2010) or 6–9% in arid, semi-arid, and sub-humid regions (Sultana and Ali 2006). Other climatic factors affecting agriculture in Pakistan include reduced rainfall, increased evapotranspiration, and drought. Currently, Pakistan ranks among the top 10 countries most severely affected by climate change globally, with Sindh province being one of the hardest-hit regions (Eckstein et al. 2019).

Wheat is a priority cereal crop promoted by the Government of Pakistan to eradicate poverty, achieve food security, and increase both farmers' and national income. Improving wheat productivity is a critical issue that attracts the attention of development practitioners, policymakers, and researchers (Ahmad et al. 1991; Gelaw and Bezabih 2004; Galiakpar 2011; Hagos and Hadush 2016; Kakraliya et al. 2018). Enhancing productivity is essential for ensuring food security, reducing poverty, and eradicating hunger. Sindh, a major producer of wheat, experiences four distinct seasons: a cool, dry winter (December through February); a hot, dry spring (March through May); a summer rainy season (June through September); and the retreating monsoon period (October and November).

Despite the reliance on agriculture for livelihoods, the sector is highly vulnerable to climate change and variability (Azam and Shafique 2017; Fahad and Wang 2020). Climate change has introduced diverse uncertainties and impacts, such as severe and frequent extreme weather events, shifting precipitation patterns, increasing temperatures, and loss of ecosystems and biodiversity. These outcomes undermine food and agricultural production systems (Smith and Gregory 2013; Ray et al. 2019). Poverty and hunger are widespread, further exacerbating the situation (Hameed et al. 2021). Consequently, households' capacity to adapt to climate change remains uncertain (Adger and Vincent 2005; Wood et al. 2014).

There is growing confidence, though not yet supported by robust empirical evidence, that climate-smart agriculture (CSA) can advance agriculture in the face of climate change. However, many stakeholders lack a proper understanding of CSA in policy formulation and application (Fahad and Wang 2020), often viewing it as a one-size-fits-all solution. This represents a significant practice gap because adaptation strategies, particularly CSA, are context-specific and evolve over time, across different areas, and even within particular societies (Smit and Wandel 2006; Malone 2009).

***CSA programme.*** CSA is seen as a dual solution to contemporary society's prevalent agricultural challenges – environmental change and food security. However, inadequate income diversification, lack of access to basic facilities, and low education levels are believed to negatively impact the adaptive capacity of the local population as a whole. Therefore, the CSA program has two primary objectives: to provide training on effective implementation of CSA practices and to assist with limited resources and inputs to facilitate the adoption of CSA practices. Mass media and extension services are utilised to inform and educate farmers about the CSA programme, ensuring equal opportunities for participation for all farmers.

Given that different areas of the country are prone to various climate risks, this study focuses on five common practices: crop rotation with legumes, which improves soil fertility (Hossain et al. 2016), reduces the incidence of weeds and pests, and minimises disease risk, minimum tillage, which reduces soil disturbances and soil erosion and improves soil fertility and carbon emissions due to reduced tractor power (Delgado et al. 2011), stress-tolerant varieties, which enhance adaptation to climate threats such as drought, floods, heat, salinity, and temperature stress (Jagadish et al. 2012), intercropping with legumes, which increases nitrogen availability and improves soil quality, and furrow irrigated bed planting, which enhances nutrient management (Limon-Ortega et al. 2000). The training programs are arranged through village leadership and developed in consultation with farmer groups in the area. There is an emphasis on multiple adoption and continuous learning for participants, where lead farmers are paired with groups to train the farmers.

## MATERIAL AND METHODS

### Data

The study was conducted in Sindh Province of Pakistan (Figure 1). Cross-sectional data collected from a household survey conducted from March to June 2020 is used in this study. The data were collected using a multi-stage sampling technique. Initially, the province was conveniently selected, and then four districts

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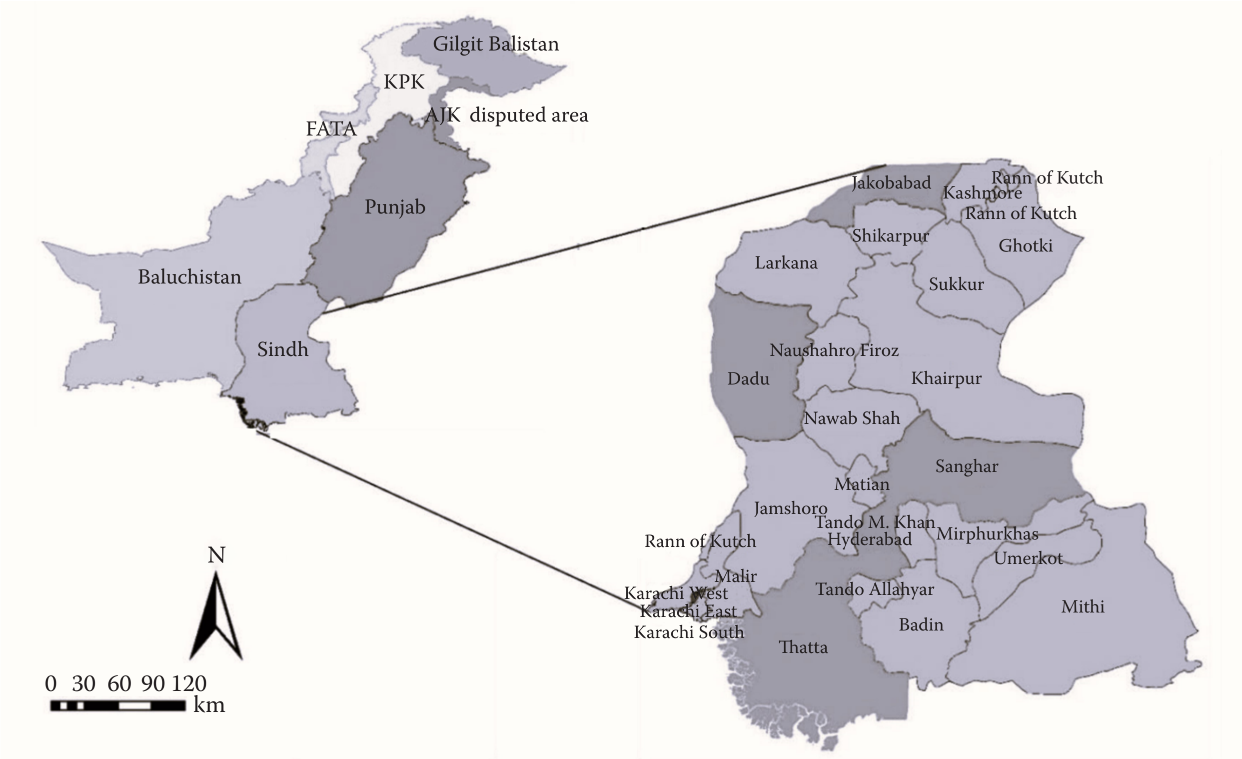


Figure 1. Study areas Sindh, Pakistan

FATA – Federally Administered Tribal Areas; KPK – Khyber Pakhtunkhwa; AJK – Azad Jammu and Kashmir
Source: Ahmad et al. (2020)

were randomly chosen. Subsequently, a list of farmers obtained from the Ministry of Agriculture was used to randomly select 400 wheat farmers (100 from each district). Fortunately, all selected farmers consented to participate in the study, and ethical clearance was obtained from local authorities in each district.

The primary data collection tool was a structured questionnaire administered by well-trained and experienced enumerators. The instrument was pretested to ensure uniformity and adequacy for the intended purpose. The questionnaire included questions on CSA (adoption, importance, types of technologies), as well as farm characteristics (wheat output, farm size, off-farm activities) and demographic information (age, education, and gender).

Table 1 presents the summary statistics of the sampled households, revealing notable differences in characteristics between adopters and non-adopters that could introduce bias in subsequent estimations if not appropriately controlled. For instance, adopters tend to have higher output compared to non-adopters. Moreover, a majority of adopters are trained in CSA and perceive it as important, whereas non-adopters have attained a higher level of basic education compared to their counterparts. Such differences in characteristics can introduce bias in estimations if a naive estimator is employed, as these characteristics are not comparable. Therefore, estimations must address bias stemming from observed variables.

Interestingly, it was noted that although education facilitates the adoption of agricultural innovations and skills, as endorsed by Alene and Manyong (2007) and Adamsone-Fiskovica et al. (2021), the majority of educated farmers in this area are non-adopters.

**Conceptual framework**

Given that climate change can disrupt food availability, reduce access to food, and affect food quality, CSA adoption is programmed in such a way that some farmers provide agricultural resources and inputs following the agreed criteria. In addition, regular training by well-experienced extension officers and farmers is administered on how to deal with the projected increases in temperatures, changes in precipitation patterns and extreme weather events, and reductions in water availability. Consequently, we posit that these efforts are likely to boost agricultural productivity and improve the cost efficiency in wheat production, as shown in Figure 2. Notably, the impact of the program is likely to be direct

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Table 1. Summary statistics of the study variables

| Variable category | Description | Units | Pooled ($N$ = 400) | Adopter ($N$ = 257) | Non-adopter ($N$ = 143) | Difference (SE) |
|---|---|---|---|---|---|---|
| Wheat output | output of wheat produced | kg | 4 566.75 | 4 923.35 | 3 925.87 | 997.47*** (347.02) |
| **Inputs prices** | | | | | | |
| Fertilizer | price of fertilizer | USD | 0.930 | 0.934 | 0.923 | 0.010*** (0.001) |
| Seed | price of seed | USD | 0.793 | 0.801 | 0.779 | 0.022*** (0.004) |
| Labour | price of labour | USD | 0.150 | 0.154 | 0.142 | 0.012*** (0.003) |
| **Explanatory variable** | | | | | | |
| CSA training | CSA training attendance | 1 = trained, 0 otherwise | 0.32 | 0.49 | 0.02 | 0.47*** (0.04) |
| CSA rating | self-reported CSA rating | 1 = important, 0 otherwise | 0.47 | 0.61 | 0.21 | 0.40*** (0.05) |
| Education | household head attained basic education | 1 = attained basic education, 0 otherwise | 0.63 | 0.58 | 0.73 | –0.15*** (0.05) |
| Marital status | marital status of household head | 1 = married, 0 otherwise | 0.72 | 0.76 | 0.83 | –0.12*** (0.04) |
| Farmer experience | experience in wheat production | years | 20.59 | 19.91 | 21.82 | –1.90 (1.22) |
| Cooperative membership | membership to cooperative | 1 = member, 0 otherwise | 0.91 | 0.88 | 0.95 | –0.07** (0.03) |
| Age | age of the household head | years | 40.64 | 38.69 | 44.13 | –5.43*** (1.31) |
| Market distance | distance from home to the market | km | 8.28 | 8.22 | 8.41 | –0.18 (0.37) |
| Cultivated land | size of the cultivated land for wheat production | acres | 1.69 | 1.76 | 1.57 | 0.19 (0.13) |
| Household size | people in a household | count | 6.02 | 5.51 | 6.94 | –1.42*** (0.33) |
| Gender | gender of the household head | 1 = male, 0 otherwise | 0.85 | 0.84 | 0.86 | –0.02 (0.04) |

*, **, *** statistical significance at 10%, 5%, and 1% levels, respectively; numbers in parentheses are standard errors of the mean difference (diff); CSA – climate-smart agriculture

Source: Author's compilation

and indirect (through cost efficiency) on augmenting crop productivity (Mwalupaso et al. 2020).

**Measurement of key variables**

The primary explanatory variable in this study was the adoption of Climate-Smart Agriculture (CSA). A household was classified as an adopter if it had implemented at least one of the five CSA practices continuously for a minimum of three years, including the survey year. Adoption status was represented as a dummy variable, where 1 indicated adoption, and 0 indicated non-adoption.

Regarding the outcome variables, yield was measured in kilograms per acre, while cost efficiency was

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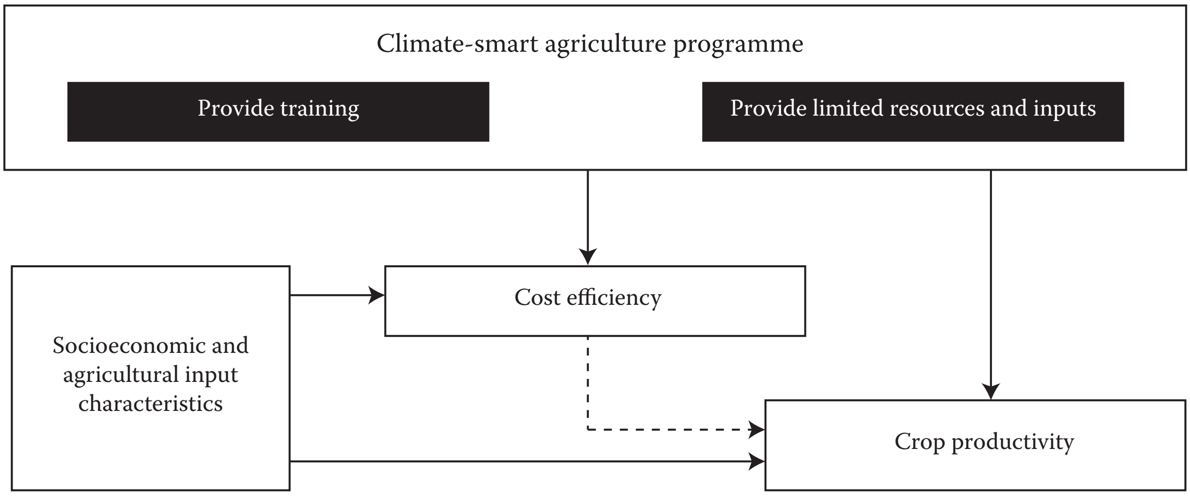


Figure 2. Conceptual framework

Source: Author's construction

derived from the output of the cost function using the Translog production function. Further details are provided in the following section.

**Analytical framework and empirical strategy**

To achieve the objectives of the study, the translog cost function, known for its flexibility as a second-order approximation of any production technology, and endogenous switching regression (ESR) were applied. The study was underpinned by three theories: production theory, induced innovation theory, and utility theory. Detailed explanations of these theories can be found in Amadu et al. (2020) and Akter et al. (2022).

***Translog cost function.*** For details about cost efficiency and how to ensure the model is linearly homogeneous, refer to Mwalupaso et al. (2020), where the price of land was divided accordingly. The translog cost function was employed in this study, based on the ratio likelihood results, was is expressed as follows:

$$\begin{aligned} \ln c_i = {} & \beta_0 + \beta_y \ln Y_i + \Sigma \beta_n \ln W_{ni} + \\ & + ½\, \Sigma_m \Sigma_j \beta_{mj} \ln Y_{mi} \ln Y_{ji} + \\ & + ½\, \Sigma_n \Sigma_k \beta_{nk} \ln W_{ni} \ln W_{ki} + \\ & + \Sigma_n \Sigma_m \beta_{nm} \ln W_{ni} \ln y_{mi} + \upsilon_i + u_i \end{aligned} \tag{1}$$

$$U_i = \beta_0 + \beta_1 CSA_i + \beta_i X_i + y_i \tag{2}$$

where: $C_i$ – total production expenditure incurred to produce; $Y_i$ – output of wheat; $W_{ni}$ – vector of the three classical input prices (fertiliser, seeds, labor) of each ith household divided by the price of land; $\beta_0$, $\beta_y$, $\beta_n$ – parameters to be estimated; $u_i$ – non-negative inefficiency component that follows a truncated-normal distribution; $\upsilon_i$ – random error following a normal distribution; $X_i$, $z_i$ – vectors of explanatory variables and the error term in the cost inefficiency model.

To ensure robust estimates, bias from observed variables was addressed by applying propensity score matching (PSM) before estimating cost efficiency (Bravo-Ureta et al. 2012).

***ESR.*** ESR was implemented using a two-stage treatment. In the first stage, a dichotomous choice criterion function was modelled and estimated using a probit model. In the second stage, two regime equations were specified to explain the relationship between the outcome variables (yield) and technology adoption (CSA adoption), based on the results of the estimated criterion function. However, we adopted a simultaneous estimation procedure, which was an efficient method developed by Lokshin and Sajaia (2004) that used the full information maximum likelihood (FIML) method.

The probit model can be written in simplified form as:

$$I^* = G'\alpha + \varepsilon_v \text{ with } T = \begin{cases} 1 \text{ if } I^* > 0 \\ 0 \text{ otherwise} \end{cases} \tag{3}$$

where: $I^*$ – not observable, but we observe a binary indicator variable ($I$) which is CSA adoption or not; $G$ – includes a range of household and farm characteristics and also farmers' attitude towards CSA; $\alpha$ – vector of parameters to be estimated; $\varepsilon_\upsilon$ – random error term with mean zero and variance $\sigma^2$.

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Specification for each regime is as follows:

$$\text{Regime 1: } Y_{\text{Adopter}} = X'\beta_{\text{Adopter}} + \varepsilon_u \quad (4A)$$

$$\text{Regime 2: } Y_{\text{Non-adopter}} = X'\beta_{\text{Non-dopter}} + \varepsilon_n \quad (4B)$$

where: $X'$ – vector of covariates; β – vector of parameters to be estimated.

Variables in $G'$ and $X'$ are allowed to overlap, and to achieve proper identification, at least one variable in $G'$ must not appear in $G'$. According to Fuglie and Bosch (1995) the error terms are assumed to follow a tri-variate normal distribution with zero mean and a non-singular covariance matrix specified as:

$$Cov(\varepsilon_a, \varepsilon_n, \varepsilon_v)\begin{bmatrix} \sigma_u^2 & \sigma_{un} & \sigma_{uv} \\ \sigma_{un} & \sigma_n^2 & \sigma_{nv} \\ \sigma_{uv} & \sigma_{nv} & \sigma_v^2 \end{bmatrix} \quad (5)$$

where: $\sigma^2_u$, $\sigma^2_n$, $\sigma^2_v$ – variances, assumed to be one (Greene 2003), of the error terms $\varepsilon_u$, $\varepsilon_n$, and $\varepsilon_v$, respectively; $\sigma_{un}$ – covariance of $\varepsilon_u$ and $\varepsilon_n$; $\sigma_{uv}$ – covariance of $\varepsilon_u$ and $\varepsilon_v$; $\sigma_{nv}$ – covariance of $\varepsilon_n$ and $\varepsilon_v$.

Under these assumptions, the truncated error terms $(\varepsilon_\alpha \mid I = 1)$ and $E(\varepsilon_n \mid I = 0)$ are:

$$\begin{aligned} E(\varepsilon_\alpha | I = 1) &= E(\varepsilon_u | \varepsilon > -G'\alpha) \\ &= \sigma_{uv} \frac{\phi \frac{M'\alpha}{\sigma}}{\Phi \frac{M'\alpha}{\sigma}} = \sigma_{uv}\lambda_a \\ E(\varepsilon_n | I = 0) &= E(\varepsilon_n | \varepsilon \leq -G'\alpha) = \\ &= \sigma_{nv} \frac{\phi \frac{M'\alpha}{\sigma}}{\Phi \frac{M'\alpha}{\sigma}} = \sigma_{nv}\lambda_n \end{aligned} \quad (6)$$

where: $\lambda_a$, $\lambda_n$ – inverse Mills ratios (IMRs) evaluated at $G'\alpha$; φ, Φ – probability density and cumulative distribution functions of the standard normal distribution, respectively.

To calculate the average treatment effect on the treated (*ATT*) and untreated (*ATU*), the expected outcome values of the adopters and non-adopters in real and hypothetical scenarios can be calculated and compared. The ESR framework allows for the computation of the expected values in the actual and counterfactual scenarios (Lokshin and Sajaia 2004) defined as follows:

Adopters with CSA adoption (observed):

$$E\,(Y_{\text{Adopter}} \mid I = 1; X) = X'\beta_{\text{Adopter}} + \sigma_{uv}\lambda_a \quad (7A)$$

Adopters had they not used CSA (counterfactual):

$$E\,(Y_{\text{Non-adopter}} \mid I = 1; X) = X'\beta_{\text{Non-adopter}} + \sigma_{nv}\lambda_a \quad (7B)$$

Non-adopters had they used CSA (counterfactual):

$$E\,(Y_{\text{Adopter}} \mid I = 0; X) = X'\beta_{\text{Adopter}} + \sigma_{uv}\lambda_n \quad (7C)$$

Non-adopters without CSA adoption (observed):

$$E\,(Y_{\text{Non-adopter}} \mid I = 0; X) = X'\beta_{\text{Non-adopter}} + \sigma_{nv}\lambda_n \quad (7D)$$

Thus, *ATT* and *ATU* are computed as follows:

$$ATT = E\,(Y_{\text{Adopter}} \mid I = 1; X) - E\,(Y_{\text{Non-adopter}} \mid I = 1; X) \quad (8)$$

$$ATU = E\,(Y_{\text{Adopter}} \mid I = 0; X) - E\,(Y_{\text{Non-adopter}} \mid I = 0; X) \quad (9)$$

## RESULTS AND DISCUSSION

**CSA adoption intensity.** We found that 64% of households have adopted at least one of the five CSA practices. Surprisingly, none of the categories reported in Table 2 have achieved 50% adoption or more. Given the incidence of climate change in the country and the resources allocated to the program, it could be expected that more than 50% of adopters have implemented at least one practice. A plausible explanation could be the lack of specific associated benefits of adoption in promotional messages, or that farmers are incorrectly implementing the practices and are not experiencing any benefits (Lopez-Ridaura et al. 2018; Sardar et al. 2021; Akter et al. 2022).

Table 2. Adoption intensity category for the CSA adoption

| Adoption intensity | Description | Frequency | % |
|---|---|---|---|
| Low | farmers who adopted 1 practice | 126 | 49 |
| Medium | farmers who adopted 2–3 practices | 91 | 35 |
| High | farmers who adopted 4–5 practices | 40 | 16 |

CSA – climate-smart agriculture
Source: Author's compilation

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**Association of CSA adoption and cost efficiency.** The estimations of the translog cost functions are presented in Table 3, with two models shown – one before and one after correcting for endogeneity, ensuring the robustness of the findings. Given the significant differences between the two groups, there was a risk of bias in the estimations because households self-select for CSA adoption. As the characteristics of the groups were not comparable, estimations may have either overestimated or underestimated the effects. Therefore, following the recommendation by Bravo-Ureta et al. (2012), we first matched the sample using 'one-to-one nearest neighbor matching without replacement' in PSM. This procedure was also utilised by Baglan et al. (2020), Mwalupaso et al. (2020), and Rasheed et al. (2020). Additionally, the substantial difference in means between the two models further confirmed that bias originating from observed variables compromised the accuracy of the estimation.

Table 3. SFA cost efficiency estimations

| Variables | SFA | |
|---|---|---|
| | before correcting for endogeneity | after correcting for endogeneity |
| $\ln Y$ | 1.637** (0.698) | −2.560*** (0.712) |
| $\ln F$ | −7.091 (10.028) | −16.410 (10.403) |
| $\ln S$ | −4.177 (9.074) | −9.397 (9.471) |
| $\ln L$ | 14.588*** (3.165) | 10.007*** (3.416) |
| $\ln Y \times \ln Y$ | −0.090*** (0.032) | 0.140*** (0.034) |
| $\ln Y \times \ln F$ | −0.996** (0.472) | −0.985** (0.495) |
| $\ln F \times \ln F$ | 2.644 (5.410) | −11.759** (4.976) |
| $\ln Y \times \ln S$ | 0.510 (0.454) | 0.629 (0.448) |
| $\ln F \times \ln S$ | −10.086 (8.007) | 3.717 (6.738) |
| $\ln S \times \ln S$ | −1.063 (3.574) | −4.342 (3.512) |
| $\ln Y \times \ln L$ | 0.081 (0.136) | −0.236** (0.119) |
| $\ln F \times \ln L$ | −2.540 (1.972) | −0.247 (1.758) |
| $\ln S \times \ln L$ | 4.881*** (1.862) | 1.120 (1.776) |
| $\ln L \times \ln L$ | 1.684*** (0.465) | 0.987* (0.522) |
| Constant | 10.501 (11.742) | 9.399 (11.318) |
| **Inefficiency model** | | |
| CSA adoption | 0.101*** (0.031) | −0.092* (0.056) |
| Education | 0.058* (0.034) | 0.094** (0.044) |
| Marital Status | 0.067* (0.036) | −0.140** (0.059) |
| Farmer experience | −0.002 (0.002) | −0.005** (0.003) |
| Cooperative membership | −0.005 (0.062) | 0.331*** (0.075) |
| Age | 0.034 (0.035) | 0.048 (0.037) |
| Market distance | 0.017*** (0.005) | −0.001 (0.005) |
| Cultivated land | 0.109*** (0.027) | −0.209*** (0.039) |
| Household size | 0.071*** (0.008) | 0.093*** (0.011) |
| Constant | 0.113 (0.303) | −0.460*** (0.135) |
| **Model diagnostic** | | |
| Log–likelihood | −41.847 | 8.763 |
| Wald $\chi^2$ | 357.46*** | 824.27*** |
| Mean | 0.414 | 0.877 |
| Observations | 400 | 282 |

*, **, *** statistical significance at 10%, 5%, and 1% levels, respectively; numbers in parentheses are standard errors of the coefficient; SFA – stochastic frontier analysis; $\ln Y$ – natural logarithm of yield; $\ln F$ – natural logarithm of fertiliser; $\ln S$ – natural logarithm of seed; $\ln L$ – natural logarithm of labour (their interaction terms are also reported in the same manner); CSA – climate-smart agriculture

Source: Author's compilation

Regarding the inefficiency model, CSA adoption, education, marital status, farming experience, cooperative membership, cultivated land size, and household size significantly influenced cost efficiency. For instance, basic education did not improve farmers' cost efficiency, which seems contradictory. However, farming is primarily learned through practice. Therefore, a farmer may have education but lack cost efficiency if they adopt CSA practices without the required skills to make it cost-effective (Freeman and Azadi 1983; Alene and Manyong 2007). Conversely, experienced farmers are more cost-efficient because they have mastered wheat production techniques. This suggests that experienced farmers have adopted more cost-effective technologies (Doss 2001; Tey and Brindal 2012; Mwalupaso et al. 2019a). Similarly, larger cultivated land areas for wheat production improved cost efficiency due to proportional savings in costs from increased production levels. Marriage also enhanced cost efficiency because it improves farm management (Peng and Wen 2016; Liu et al. 2019). Thus, even if males seek off-farm employment, their partners can effectively manage farming activities.

After correcting for endogeneity, we observed a positive association between CSA adoption and cost efficiency, with adopters exhibiting a 7% (0.912–0.842) higher cost efficiency compared to their counterparts. Despite the changing climate and limited opportunities for agricultural expansion onto additional lands, CSA addresses the challenge of meeting the growing demand for food. It also influences the trajectory of agricultural investments and supports agricultural institutions (Scherr et al. 2012; Steenwerth et al. 2014). Given that farmers have made significant investments to cope with climate change – the 'new normal' – their cost efficiency after these investments was relatively better than that of non-adopters (Table 4).

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Table 4. Cost efficiency distribution

| Cost efficiency category | Non-adopters | Adopters | Pooled |
|---|---|---|---|
| Less than 0.50 | 3.55 | 4.26 | 3.90 |
| 0.5–0.59 | 4.96 | 1.42 | 3.19 |
| 0.6–0.69 | 6.38 | 2.13 | 4.26 |
| 0.7–0.79 | 21.28 | 5.67 | 13.48 |
| 0.8–0.89 | 23.40 | 17.73 | 20.57 |
| Above 0.9 | 40.43 | 68.79 | 54.61 |
| Mean | 0.842 | 0.912 | 0.877 |

Source: Author's compilation

**Impact of CSA adoption on wheat productivity.** We analysed the effects of CSA adoption on wheat yield using endogenous switching regression (ESR). In this framework, the criterion function, which determines the regime into which each observation falls, was jointly estimated with regime equations. To achieve proper identification (Lokshin and Sajaia 2004), the criterion function included all variables from the regime equations plus two instruments – CSA training and CSA rating. While these instruments were correlated with individual adoption behaviour, they were not correlated with wheat yield. The results are presented in Table 5, with the criterion function in the first column. The lower part of Table 5 shows the estimated covariance terms along with the results from a Wald test of the joint independence of the criterion and regime equations. The statistics confirmed heterogeneity, which would cause bias if not controlled for. Therefore, the use of ESR was justified.

The most important factors positively influencing CSA adoption were education, marital status, cooperative membership, CSA training, and CSA rating. Education facilitates the adoption of technology and acquisition of skills, a well-supported view in the literature (Lockheed et al. 1980; Freeman and Azadi 1983; Asfaw and Admassie 2004; Kenis and Mathijs 2012; Ahmed et al. 2013; Zamasiya et al. 2017). Similarly, training, which falls under informal education, promotes the adoption of agricultural technologies (Lechner 1999; Hashemi et al. 2009; Boothby et al. 2010; Muhammad et al. 2014). CSA rating reflects attitudes toward climate change adaptation, which was found to be a positive determinant (Zamasiya et al. 2017). Cooperative membership influenced adoption because cooperatives provide valuable information to farmers, as noted by Aker (2010) and Mwalupaso et al. (2019b), who highlight the information dependence of modern farmers. Lastly, being married influenced CSA adoption due to easier

Table 5. Endogenous switching regression results for wheat yield

| Variable | Criterion | Adopter | Non–adopter |
|---|---|---|---|
| Gender | 0.04 (0.34) | 325.16** (158.41) | 13.37 (175.99) |
| Education | 0.40* (0.22) | –570.08*** (103.11) | –234.57** (116.72) |
| Marital status | 0.03** (0.01) | –481.09*** (149.05) | 39.99 (175.28) |
| Farmer experience | 0.03 (0.03) | 11.47 (7.23) | –1.72 (5.67) |
| Cooperative membership | 0.40*** (0.09) | –357.32*** (143.18) | 69.34 (220.49) |
| Age | –0.23*** (0.05) | 69.99 (98.36) | 333.39*** (92.37) |
| Market distance | 0.13 (0.32) | –30.35** (13.81) | –4.05 (14.01) |
| Cultivated land | 0.24 (0.35) | –201.07*** (49.80) | –214.09*** (54.95) |
| Household size | –0.45** (0.20) | –2.54 (21.14) | 11.42 (25.67) |
| CSA training | 2.35*** (0.32) | – | – |
| CSA rating | 0.25*** (0.07) | – | – |
| Constant | –0.28 (0.59) | 3 964.04*** (251.21) | 1 731.13*** (309.52) |
| **Model diagnostic** | | | |
| ln*s*1 / ln*s*2 | – | 6.54*** (0.05) | 6.42*** (0.08) |
| *r*1 / *r*2 | – | –0.46** (0.19) | –1.32*** (0.26) |
| *N* | 400 | 257 | 143 |
| LR test of independent equations: $\chi^2$ | – | – | 15.15*** |

*, **, *** statistical significance at 10%, 5%, and 1% levels, respectively; numbers in parentheses are standard errors of the coefficient; CSA – climate-smart agriculture; *s* – sigma; *r* – rho; LR – likelihood ratio

Source: Author's compilation

https://doi.org/10.17221/74/2024-AGRICECON

Table 6. Yield effects

| CSA Status | *N* | With CSA adoption | Without CSA adoption | Treatment effect | % change |
|---|---|---|---|---|---|
| Adopter | 257 | 2 932.91 | 2 011.66 | *ATT*: 921.24*** (38.63) | 45.8 |
| Non-adopter | 143 | 3 118.39 | 2 606.85 | *ATU*: 511.53*** (43.35) | 19.6 |

*** statistical significance at 1% level; numbers in parentheses are standard errors of the mean; CSA – climate-smart agriculture; *ATT* – average treatment effect on the treated; *ATU* – average treatment effect on the untreated
Source: Author's compilation

farm management, as previously explained. On the contrary, household age negatively influenced adoption because older farmers were less willing to adopt new technologies (Mwalupaso et al. 2019a).

The two regime equations are shown in the second and third columns of Table 5, revealing notable differences between the coefficients of adopters and non-adopters, confirming that ESR was more appropriate than pooling data into one model. For instance, male-headed households had higher yields than female-headed ones among adopters, consistent with the finding that males were more productive, likely due to the labour-intensive nature of wheat production. Other coefficient estimates suggested that larger land sizes reduced yield, indicating potential inefficiencies in land use and farm management (Jaime and Salazar 2011). This underscores the need to examine participation in off-farm activities and determine optimal land sizes for each household.

We estimated the average treatment effects on the treated (*ATT*) and average treatment effects on the untreated (*ATU*) to assess the net impacts of CSA adoption, controlling for confounding factors. Interestingly, households would have significantly lower yields if they had not adopted CSA as shown in Table 6. This is reasonable because climate change (increased temperatures, changes in precipitation patterns, extreme weather events, and reduced water availability) may reduce agricultural productivity, disrupt food availability, limit access to food, and affect food quality.

CSA technologies such as crop rotation with legumes, which improves soil fertility (Hossain et al. 2016), reduces weed and pest incidence, and minimises disease risk; minimum tillage, which reduces soil disturbances and erosion and improves soil fertility due to reduced traction power and soil carbon emissions (Delgado et al. 2011); stress-tolerant varieties, which improves adaptation to climate threats such as drought, floods, heat, salinity, and temperature stress (Jagadish et al. 2012); intercropping with legumes, which increases nitrogen availability and improves soil quality; and furrow irrigated bed planting, which improves nutrient

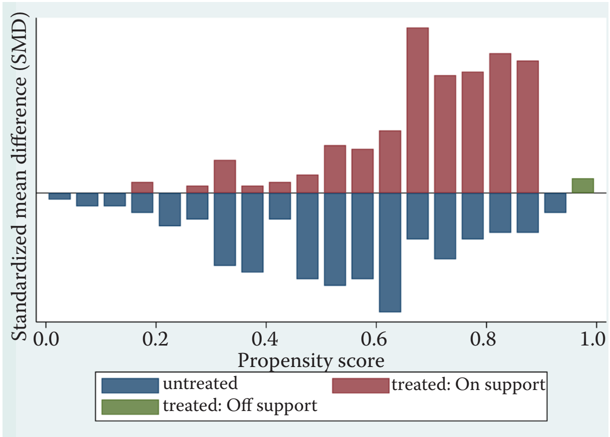


Figure 3. Balancing of covariates with 4 observations off support

Source: Authors' own processing

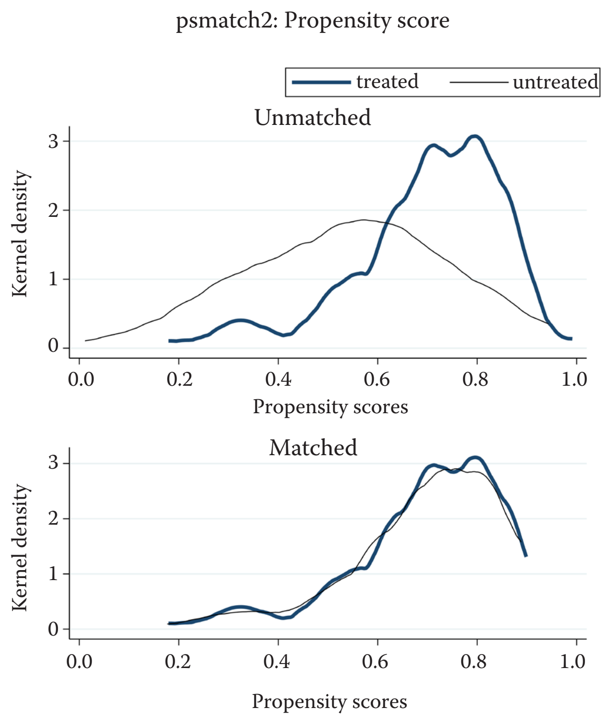


Figure 4. Bias reduction after matching-comparable observable characteristics

Source: Authors' own processing

https://doi.org/10.17221/74/2024-AGRICECON

Table 7. Propensity score matching (PSM) estimates of the yield effect

| Matching type | Wheat yield | | *ATT* | SE | % change |
|---|---|---|---|---|---|
| | with CSA adoption | with CSA adoption | | | |
| Nearest neighbor (1) | 2 961.069 | 2 658.514 | 302.555*** | 118.159 | 11.38 |
| Kernel | 2 961.069 | 2 561.096 | 399.973*** | 88.516 | 15.62 |
| Radius | 2 961.069 | 2 596.230 | 364.839*** | 54.941 | 14.05 |

CSA – climate-smart agriculture; *ATT* – average treatment effect on the treated
Source: Authors' own processing

management (Limon-Ortega et al. 2000) are expected to result in higher yields for adopters.

Interestingly, non-adopters could increase their yield by about 20% if they were to adopt CSA practices. These results are specific to Sindh province in Pakistan and should not be generalised, as the large difference between ATU and ATT underscores heterogeneity in impacts due to various socioeconomic and agroecological factors.

We also conducted robustness checks using Propensity Score Matching (PSM). Despite the disadvantage of PSM in losing some observations (Amadu et al. 2020), scholars agree on the criteria for a good match: balancing covariates with minimal observations off support and reducing bias by making the two groups comparable. We successfully achieved this, as illustrated in Figures 3 and 4, where only 4 out of 400 observations were off support, and the observable characteristics after matching were largely comparable.

The *ATT* obtained from three matching algorithms – propensity score matching (PSM) using nearest neighbour (1), kernel, and radius matching – all confirm that CSA adoption fosters yield effects consistent with the endogenous switching regression. However, it's noteworthy that the *ATT* in PSM appears notably understated compared to the other algorithms, albeit with the same level of significance at 99%. This discrepancy can be attributed to the fact that, unlike the Endogenous Switching Regression (ESR), PSM fails to account for unobserved characteristics. Therefore, this outcome underscores that the lack of control for observable characteristics in PSM did not alter the conclusions drawn in our primary model (Table 7).

## CONCLUSION

**Conclusion and policy recommendations.** Agricultural productivity is predominantly influenced by climate, which has been undergoing significant changes in recent years, prompting extensive research on its impact on agriculture. While many previous studies focus on adaptation, which is crucial for developing climate change policies and vulnerability assessments, few studies are specific in their approach, particularly concerning climate-smart agriculture in climate risk hotspots. According to rational choice theory, households are unlikely to adopt practices if no benefits are derived from adoption. This forms the basis for promoting CSA adoption through extension services in areas with similar characteristics. Therefore, this study evaluated the association of CSA adoption with cost efficiency and yield, an area where little comparative analysis exists despite the widespread belief that CSA adoption increases production costs.

The results reveal that CSA adoption is associated with improved cost efficiency and yield. This suggests potential cost savings in production that could be redirected to wheat production to improve output, as suggested by Mwalupaso et al. (2020). The policy implication of CSA adoption, given these findings, is that it promotes food security and could contribute to poverty and hunger eradication. Wheat is a critical staple crop not only for Pakistan but also globally, with Pakistan being one of the major producers. Therefore, CSA adoption is particularly important as the country's agriculture faces the challenges posed by climate change. Importantly, the results suggest that by not adopting CSA, households and the country could lose about 20% in productivity. Considering the population of wheat farmers in Pakistan, this loss is significant. Thus, we recommend policies aimed at promoting CSA adoption, including increasing CSA training, improving education levels, and encouraging membership in cooperatives. Additionally, farmers are encouraged to actively access information on climate change and CSA practices, and to consider adopting multiple CSA practices.

However, this study has its limitations. First, the use of cross-sectional data does not allow for the assessment of effects over time. Second, due to COVID-19

https://doi.org/10.17221/74/2024-AGRICECON

and low adoption rates for some CSA technologies, the determinants of each CSA practice could not be fully explored. Nevertheless, to the best of the researchers' knowledge, this is the first study to examine the association between CSA adoption and cost efficiency. This is crucial because while farmers aim to maximise profits, they also seek to adopt technologies that minimise costs. Additionally, the study contributes significantly to the literature by presenting counterfactual yields. Consequently, this will aid in formulating effective policies and disseminating beneficial information based on empirical evidence. Given that one of the greatest global challenges today is sustainably feeding nine to ten billion people by 2050 while reducing environmental impact, future studies could utilise panel data and plot-level observations to assess environmental degradation due to CSA adoption.

**Acknowledgment:** The authors are very grateful to the two anonymous reviewers for their valuable feedback. Panhwar Ghulam Mustafa, who is a joint first author with Shangao Wang, expresses immense gratitude to the Chinese Scholarship Council (CSC) for their financial support, which covered tuition fees and provided a stipend during his Ph.D. study in China, thereby facilitating the research and the subsequent publication of this paper. **CReDit Roles:** Panhwar Ghulam Mustafa and Shangao Wang as joint first authors contributed equally to methodology, software, data curation, writing – original draft preparation, and visualization. Gershom Endelani Mwalupaso: conceptualization, validation, formal analysis, writing – review and editing. Yi Yu: validation, writing – review and editing. Zhou Li: supervision, project administration, funding.

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Received: February 25, 2024
Accepted: June 19, 2024
Published online: July 25, 2024