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Assessment of Factors and Barriers Influencing the Likelihood of Adoption of Climate Smart Agriculture in Climate-Vulnerable Regions

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Research Article

Keywords: Climate smart agriculture, MESR, Barriers, Climate change, Adoption, Agriculture

Posted Date: June 24th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10106174/v1

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Additional Declarations:
The authors declare no competing interests.

Tables are available in the Supplementary Files section.

Ethics Approval Statement: This study was reviewed and approved by the Institutional Review Board (IRB)/Ethics Committee of University of Agriculture, Faisalabad Pakistan. All study procedures involving human participants were conducted in accordance with the ethical standards of the institutional research committee and the principles of the Declaration of Helsinki. Participant Consent Statement: Informed consent was obtained from all participants prior to their inclusion in the study. Participants were informed about the purpose of the research, and their voluntary participation was ensured. All data were collected and reported in a manner that maintained participant confidentiality and anonymity. These statements have been incorporated into the manuscript accordingly.

Assessment of Factors and Barriers Influencing the Likelihood of Adoption of Climate Smart Agriculture in Climate-Vulnerable Regions

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Abstract

Climate change poses significant threats to agricultural systems, especially in vulnerable areas, where farmers face rising exposure to extreme climate events, erratic rainfall, droughts, seawater intrusion, water shortages, rising temperatures, and coastal and riverine flooding. Climate-smart agriculture (CSA) has developed as a strategic approach to increase productivity, resilience, and environmental sustainability; however, its adoption remains unexplored across climate-vulnerable regions. Furthermore, this study investigates the key factors and barriers influencing the likelihood of CSA adoption via farm-level data from climate-affected areas. The multinomial endogenous switching regression model (MESRM) and constraint confrontation index (CCI) are employed to estimate the factors of adoption decisions. The results reveal that age, education, access to credit, farmers' contact with local groups, farm size, and access to extension services significantly increase the probability of adopting CSA. Conversely, knowledge and communication gaps, as well as institutional, technological, environmental, credit, social and cultural barriers act as key constraints. The outcomes further highlight that spatially deprived and financially constrained regions present significantly lower adoption rates due to multiple structural, organizational, and communicational barriers. The analysis also revealed that the adoption of individual or combined CSA practices increased the rice yield by 452 and 687 kg/ha, respectively, compared with that of nonadopters. Finally, this study reveals the need for climate-oriented policy interventions, innovative extension services, climate smart agriculture expert and capacity-building strategies to facilitate the transition toward CSA. Further, the CSA expert strengthening organizational coordination and ensuring efficient technical support can significantly increase adaptive capacity, reduce barriers, and promote agricultural sustainability and resilience in vulnerable areas.

Keywords Climate smart agriculture, MESR, Barriers, Climate change, Adoption, Agriculture

Introduction

Climate change poses a critical issue for global food production systems, with long-term negative consequences for livelihood welfare. (Nadeem et al., 2024). Key climate-induced pressures- such as extreme heat events, inconsistent rainfall, prolonged droughts, salinity, and frequent floods, increase the instability of agricultural systems. These circumstances negatively affect crop growth and are linked with decreasing agricultural production (Olowoyeye et al., 2024). Salinity, rising temperatures and prolonged droughts can decrease production by 21% to 70% in key staple crops including rice, corn, wheat and beans (Bakhsh & Kamran 2019; Fu et al., 2022; Lesk et al., 2016).

In addition to its direct effects on crop production, climate change also has wider social and economic consequences for farming communities. Moreover, recent research (Khan et al., 2026; IPCC, 2023) highlights that these climatic tremors are decreasing agricultural incomes and undermining sustainability in developing countries, where adoption levels are constrained. Climate shocks also affect crop development, contribute to land degradation, and limit water accessibility while altering pest features (Arif et al., 2025), thereby threatening

farming communities and increasing food insecurity (Arshad, 2025a). The effects of climate change vary across environmental (Lipper et al., 2014) and sociocultural dimensions, yet they are broadly recognized as a substantial threat to sustainable agriculture (IPCC, 2023).

The extensive effects of climate change on agricultural production are prevalent in the 21st century, with climate change being the primary cause (Shahzaman et al., 2021). Major agricultural regions worldwide have recognized a decline in the output of main crops such as rice, wheat, oilseeds, and maize (Shahzaman et al., 2021; Ullah et al., 2023; Khan et al., 2021). The increasing occurrence of extreme heat waves is expected to place additional stress on agricultural systems, potentially decreasing crop productivity and posing greater risks to global food security by 2040 (Iyakaremye et al., 2022; Cradock-Henry et al., 2020). This climatic shock has resulted in uncertainty in the growth of the main crops in the world (Ullah et al., 2023). The adaptation techniques are stimulated not only by the financial context but also by administrative, ecological, social, and economic features. The few prevalent adaptation techniques utilized include modifying the planting time, zero tillage, the use of certified crop types, modern irrigation, alternate cropping, and tree planting (Masud et al., 2017). However, small farmers in remote regions have very low adaptive ability and are vulnerable due to their very poor economic and social situation (Wood et al., 2014). In addition, farmers are still more vulnerable to increasing climatic risk due to their very low perception of climatic issues (Siwar et al., 2009). Without suitable adoption of climate-smart adaptation measures, global agricultural production is expected to decline by approximately 20% by the end of the century (Riaz et al., 2025). According to Adger & Vincent (2005) and Nazari et al. (2015), the majority of farmers possess very low climate-resilient capabilities that impact their agricultural output and welfare. Therefore, economic losses, malnutrition, and food insecurity are prevalent.

Farmers in developing countries utilize diverse resilience and adaptive techniques in response to climate change (Aniah et al., 2019; Shaffril et al., 2018). Previous studies indicate that coping mechanisms vary across regions, with African farmers integrating asset liquidation, household migration, and modified dietary practices (Aniah et al., 2019; Habtemariam et al., 2016; Mertz et al., 2009), whereas Asian farmers adopt water management techniques (Tripathi & Mishra, 2017; Kabir et al., 2017), crop diversification (Shaffril et al., 2018), tree planting (Keshavarz et al., 2014), and nonfarm income-generating activities to overcome financial constraints (Ashraf et al., 2014; Rahman & Aslam, 2016). Moreover, farmers in India, Pakistan, Thailand, and Bangladesh adopt mixed cropping as an adaptation measure to prolonged droughts, rising temperatures, and erratic rainfall, thereby decreasing the risks of income and production losses (Ashraf et al., 2014; Rahman & Aslam, 2016). Recent studies (Arshad & Abdulai, 2025b; Bibi, 2025; Fares et al., 2025; Shahid et al., 2021; Shahbaz et al., 2022b) have shown that Pakistani farmers commonly depend on a limited set of coping mechanisms, such as changing sowing and planting dates and increasing the application of inorganic fertilizers, to mitigate the negative impact of climate change on agricultural productivity. While these adaptation techniques are extensively adopted, especially in settings restricted by poor organizational support and constrained access to resources, they remain narrow in scope (Rao et al., 2025). Therefore, continued dependence on only one or two coping measures is principally inadequate to address the multidimensional and increasing effects of climate change in extremely vulnerable regions, emphasizing the

need for more holistic, wide-ranging, and systemic coping measures. Similarly, while CSA practices such as climate-resilient seed varieties, water-resilient irrigation, conservation agriculture, and agroforestry are recognized to provide significant advantages, their adoption among farmers in Sindh, Pakistan, remains low.

Pakistan is increasingly facing complex and intensifying challenges posed by climate change (Eckstein et al., 2021). Agricultural livelihoods in Pakistan, especially in rural areas, are highly vulnerable owing to the sector's significant contribution to agricultural production and its pronounced sensitivity to climate variability (Pakistan Bureau of Statistics, 2022). Sindh provinces have already faced devastating climate change impacts, and these adversities are projected to continue, including recurrent flooding and the intrusion of seawater into coastal areas. Moreover, these adversities have instigated losses of billions of dollars in the agricultural sector, which indicates extreme climate vulnerabilities in the country (Syed et al., 2022). The extreme flood in 2022 damaged 57% of the agricultural land of Sindh Province, indicating the highest production losses of the main crops, such as rice, cotton, and sugarcane, at 80%, 88%, and 61%, respectively, which indicates a prominent prerequisite for proactive climate-smart adaptation techniques (Ahmed A. et al., 2026). Similarly, in coastal regions of the Indus Delta, seawater invasion is increasingly moving inland, leading to soil salinization and a consequent decrease in cultivable land (IPCC, 2023). Furthermore, water scarcity is increasing owing to prolonged droughts, decreased river streamflow, and intensified erratic rainfall, thereby preventing growers from adequately irrigating their crops (Bakhsh & Kamran, 2019; Asian Development Bank, 2021). Moreover, the increasing frequency and intensity of heat spells, along with heat-induced pressure, pose severe risks to agricultural productivity. Recurring floods further exacerbate these adversities by increasing uncertainty and causing pervasive damage to crops, infrastructure, and sources of livelihood (Ahmed et al., 2026; Pakistan Meteorological Department, 2022; World Bank, 2022b; NDMA 2022).

CSA has been broadly identified as a significant technique for promoting sustainable agricultural development and addressing both climate change adaptation and mitigation (IPCC, 2019; FAO, 2017). This phenomenon stresses on increasing production, increasing resilience, and decreasing environmental effects through climate-resilient agricultural practices. Climate-smart agriculture supports reduce greenhouse gas emissions while enhancing farmers ability to adapt to increasingly variable climatic situations and strengthening food security (Tesfaye et al., 2023). Recent studies (Khumalo et al., 2025; Bedasa et al., 2025; Mora et al., 2020; Borrelli et al., 2020) emphasize that CSA techniques not only increase agricultural production but also promote the efficient use of land and support the resilience of farming systems remain resilient under climate pressure. Even the adoption of one CSA approach can significantly increase production, with reported increases ranging from 29% to 126% (Pangapanga et al., 2023). In general, CSA contributes to better farm efficiency, improved livelihoods and decreased land degradation (Khumalo et al., 2025; Pompeu et al., 2023). However, the adoption of CSA remains inadequate across the regions by a range of institutional, economic, socio-cultural, and environmental barriers. Understanding these barriers is essential for developing effective and widely applicable adaptation policies for climate-vulnerable agrarian systems (Niazi et al., 2021). Consequently, many growers continue to rely on traditional agricultural practices learned through peer networks, despite their limited effectiveness under current climatic situations. The challenge

is further intensified by constrained access to advanced technologies and climate-resilient inputs, which hinder growers' ability to implement adaptation measures effectively and safeguard their livelihoods (FAO, 2019). As a result, the adoption of CSA practices remains below the expected level, highlighting the pressing need for context-specific techniques to increase adoption and promote climate-resilient agricultural development.

Over the last decade, research on Climate-Smart Agriculture (CSA) has expanded substantially, indicating its potential to increase agricultural productivity, reinforce climate resilience, and promote sustainable agricultural systems (Lipper et al., 2014). Despite this growing body of literature, important gaps remain in understanding small-scale farmers' capacity to adapt to climate change through CSA practices. First, research evidence remains limited, as most studies have focused on the determinants and barriers to CSA adoption within specific contexts and selected countries in Africa and South Asia (Lee et al., 2022; Chisadza et al., 2025; Billah et al., 2025; Arshad & Abdulai, 2025b; Mobeen et al., 2025). Comparatively less attention has been given to highly climate-vulnerable agricultural regions, particularly rice-dependent agricultural systems. These regions face unique climate-induced challenges, including water scarcity, rising temperatures, erratic rainfall, recurrent flooding, seawater intrusion, and increasing climatic variability. Such circumstances differ greatly from those in other agroecological zones, limiting the generalizability of findings across regions (Shahzad et al., 2021). Therefore, robust empirical evidence on CSA adoption and its outcomes in highly climate-sensitive agricultural systems remains scarce.

Second, the existing literature is constrained by methodological limitations. Many studies rely on traditional econometric approaches, such as binary choice models (probit and logit) and propensity score matching techniques, which may not adequately address selection bias and unobserved heterogeneity influencing farmers' adoption decisions. As a result, evidence generated through advanced counterfactual impact evaluation methods remains limited. In particular, the application of the Multinomial Endogenous Switching Regression Model (MESRM), which can estimate the heterogeneous impacts associated with alternative CSA adoption strategies while accounting for endogeneity, remains relatively underexplored.

Third, previous studies have predominantly examined the influence of socioeconomic, financial, and institutional factors on CSA adoption decisions (Lee et al., 2022; Chisadza et al., 2025; Billah et al., 2025; Arshad & Abdulai, 2025b; Mobeen et al., 2025; Rao et al., 2025). However, limited attention has been paid to the integrated role of institutional support systems, infrastructural and information-sharing networks that facilitate access to climate-relevant knowledge among stakeholders. These systems include agricultural extension services, market actors, meteorological agencies, digital advisory platforms, and other information providers that are essential for informed decision-making by farmers (Aslam et al., 2023; Sher et al., 2025). Furthermore, there remains insufficient evidence regarding which combinations of CSA practices generate the greatest improvements in agricultural productivity and climate resilience. This knowledge gap weakens the evidence base required for designing targeted and context-specific climate adaptation strategies.

To address these gaps, this study provides a comprehensive assessment of the barriers to and determinants of CSA adoption among farmers in the study area. The study employs advanced econometric techniques, including the Multinomial Endogenous Switching Regression (MESR) model, Average Treatment Effects

(ATEs), and a Constraint Confrontation Index (CCI), to evaluate the factors influencing adoption decisions and the impacts of different CSA adoption strategies. By generating evidence from an understudied and climate-vulnerable agricultural context, the study contributes to the broader CSA literature and offers policy-relevant insights for strengthening institutional support, improving extension and advisory services, enhancing climate adaptation capacity, and promoting sustainable agricultural development and food security in climate-prone farming systems. The study intends to achieve the following objectives: 1) To investigate the key drivers influencing CSA practices among farmers in precision agriculture. 2) To identify the barriers to CSA adoption in the study area. 3) To determine the effect of CSA on rice production under climate resilience.

Methods and Materials

Research Approach

Recent studies have shown that the mixed methods technique is the most suitable approach (Billah et al., 2025; Chisadza et al., 2025). Therefore, this study utilizes a mixed method (quantitative and qualitative) approach to estimate the outcomes of barriers and factors hindering CSA practices.

Site description

This research was carried out in Sindh Province, Pakistan (23°30′-28°30′N, 66°00′-71°30′E). Four districts were selected because they face acute climate-induced threats. Two districts were chosen from the Indus delta agroecological zone, namely, Badin (24°12′N, 69°20′E) and Thatta (25°26′N, 68°45′E), which depend upon the cotton-wheat and mixed zones (rice-sugars) (FAO 2017). Both districts (Thatta and Badin) are among the most vulnerable regions, facing diverse pressures, including seawater intrusion, coastal flooding, rising temperatures, limited water availability, and salinity (World Bank, 2022a; Fatima, 2023). The remaining two districts were selected from the southern irrigated plain (Fig. 1), namely, Larkana (27°33′N, 65°16′E) and Kamber-Shahdadkot (28°02′N, 68°20′E), both of which are reliant upon the rice-wheat zone (FAO, 2017). Moreover, evidence shows that more than 70% of both districts fall into highly vulnerable regions, owing to frequent floods, rising temperatures and water shortages (Khoso et al., 2025). These climatic threats significantly decrease farmers' adoption ability, ultimately increasing their overall vulnerability and hindering the adoption of CSA practices (Akram et al., 2025).

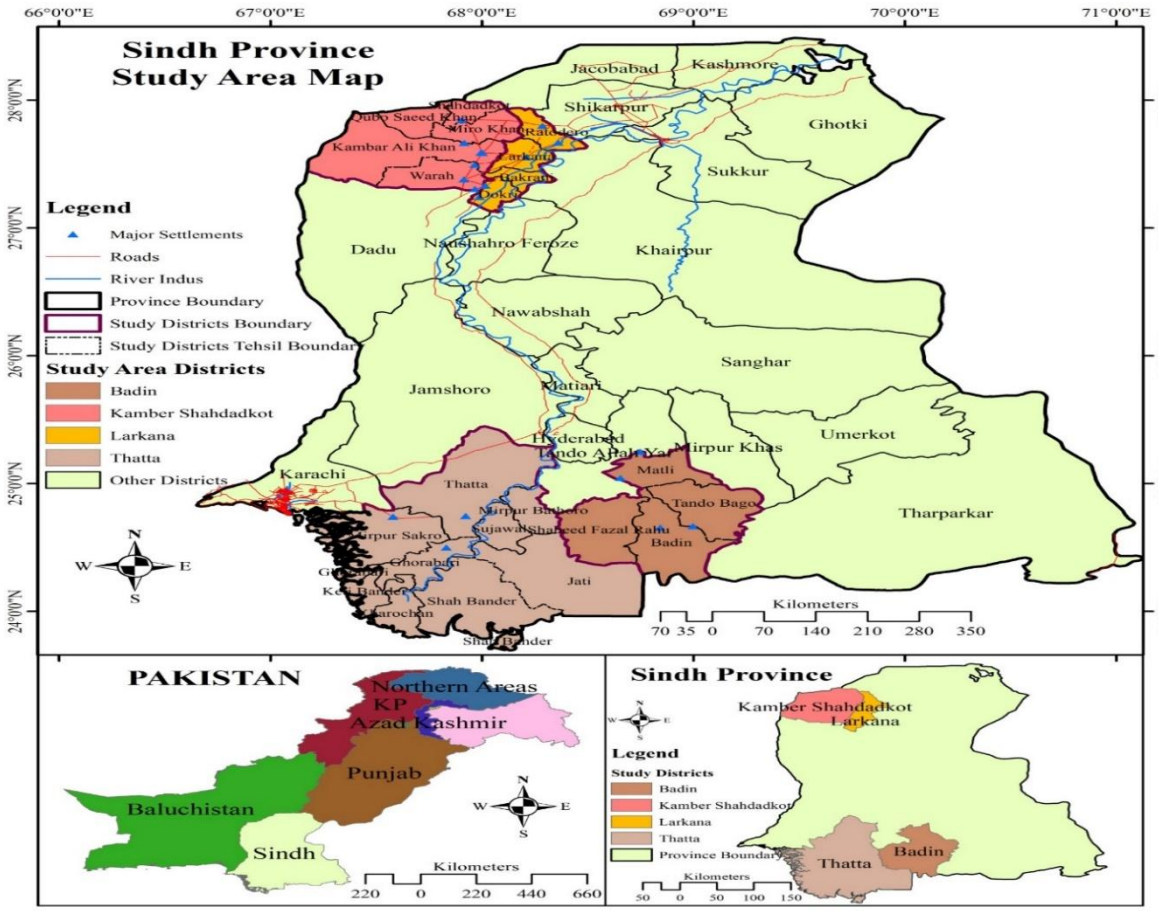


Figure 1. Map of study area
Source: Author modification.

Sampling

Data were collected via a multistage sampling technique. The method includes (1) rice-growing zones, (2) the Indus Delta, and (3) the southern irrigated plain, and is composed of five stages. (1) In the first stage, two districts, namely Thatta and Badin, were chosen from the Indus Delta. (2) In the second stage, two rice-growing districts, Larkana and Kamber-Shahdadkot, were chosen from the southern irrigated plain of Sindh province (Fig. 2). (3) In the third stage, rice-growing subdivisions (tehsils) were selected from the four districts. (4) In the fourth stage, rice-growing union councils (UCs) were selected from each subdivision. Finally, 254 farm households were randomly selected from study area according to the sample population. The Cochran statistical technique was utilized to identify a suitable sample size for the research study (Cochran, 1977).

$$n = \frac{n_o}{1 + \frac{(n_o - 1)}{N}} \quad \text{---------1}$$

$$n_o = \frac{Z^2 xy}{u^2} \quad \text{---------2}$$

N represents the total number of respondents

n_o indicates the sample size required, if the number of respondents is greater than 10,000

n explains the sample size if the respondents are fewer than 10,000

Z is the 95% confidence limit, i.e., 1.96.

x explains 0.5% (the percentage of the respondents consists of the sample size, i.e., 50%)

y = 1−0.5, i.e., (0.5)

u shows the magnitude of the error or level of accuracy needed (0.5)

The sample size was determined as follows: under no= $((1.96)^2*(0.5)*(0.5)/(0.0615)^2 = 254$

$$ni = \frac{n^{*}Ni}{N} \quad -------3$$

While ni represents the sample size for each subdivision, Ni represents the total number of households from each subdivision, N represents the total number of households for the four districts that were selected, and n represents the total sample size for the districts that were selected for the study. In total, 254 farm households were selected for the research study through proportional sampling. This sampling technique was selected because it confirms that each member of the population has an equal opportunity for participation.

Data collection

This research utilized a cross-sectional method to collect primary data from 254 rice growers residing in rice-producing districts of Sindh Province, Pakistan, namely Thatta, Badin, Larkana, and Kamber-Shahdadkot. To confirm the clarity and understanding of the primary data, prior studies (Artino et al., 2014; Cox, 1996) were followed to design a well-ordered survey questionnaire. Furthermore, the questionnaire was designed in line with research study objectives, considering key segments such as socioeconomic, demographic, agroeconomic, and growers' opinions regarding climate change and multiple constraints in the adoption of climate-smart techniques and institutional support in CSA adaptation. The study used both open-ended and close-ended techniques for effective and comprehensive perceptions from growers. To evaluate the effectiveness of the CSA, a Likert scale was employed. Furthermore, research ethics were followed to retain participant privacy and anonymity; the survey questionnaire excluded identity credentials. In conclusion, the information from individual interviews was gathered from selected research areas from November 2025 to December 2025 via a well-structured questionnaire.

Estimation Strategy

Constraint Analysis (Constraint Confrontation Index) (CCI)

To further complement the analysis, this study employs the CCI to methodically identify and rank the severity of barriers to CSA adoption. The CCI is mostly effective in capturing the multidimensional and latent nature of constraints faced by farmers, including the environmental, institutional, social, financial, technological and cultural dimensions. Prominently, it integrates both the incidence and perceived severity of constraints, thereby providing more inclusive and policy-oriented measures of adoption bottlenecks. Following Billah et al. (2025), this study finds a broad spectrum of constraints encountered by growers in adopting CSA techniques. Overall, 53 constraints were identified into seven major domains: credit, institutional, technological, social, cultural, knowledge and

communication, and environmental/infrastructural constraints. Farmers estimated each constraint via a five-point Likert scoring scale ranging from 1 (not a constraint) to 5 (extremely severe constraint), capturing a gradation in perceived intensity. Overall, the CCI delivers a robust and structural framework for measuring the relative importance of constraints, providing valuable insights into key systemic barriers shaping CSA adoption choices in climate-effected agricultural systems. The following equation is employed to analyze the severity of the constraints in the study area.

$$CCI = P_1 \times 5 + P_2 \times 4 + P_3 \times 3 + P_4 \times 2 + P_5 \times 1 \text{ -------(4)}$$

where P1 represents the number of respondents who confronted no constraint, P2 represents minor constraints, P3 represents average constraints, P4 represents extreme constraints, and P5 represents extremely serious constraints. To obtain the exact percentage of the CCI, we used the formula of Billah et al. (2023).

$$CCI = \frac{Reported\ constraints\ ranking\ score}{Viable\ greatest\ constraints\ percieved\ score} \times 100 \text{ ------(5)}$$

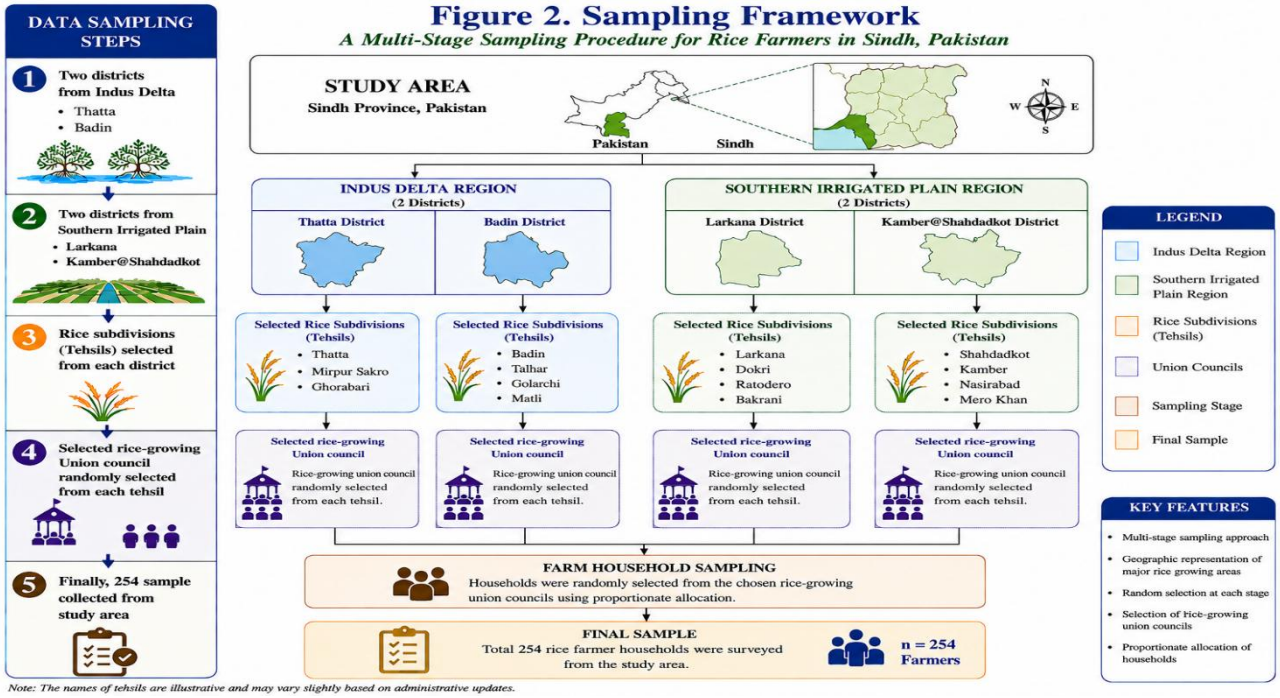


Figure 2. Sampling Framework
Source: Author modification.

Multinomial endogenous switching regression model (MESR)

A recent empirical study (Khumalo et al., 2025; Bedasa et al., 2025) revealed that the MESR is mostly suitable for determining the impacts of CSA adoption. The framework of this empirical model is fit because CSA adoption is multinomial in nature, involving multiple jointly limited adoption decisions, such as nonadoption, partial and

combined or full adoption of CSA practices.

Contrasting with multinomial logit and binary models, the MESRM reports the issue of selection bias and unobserved heterogeneity, which may arise from growers' self-selection into various adoption practices depending upon observable and unobservable features. The robustness of the MESRM lies in its ability to correct for endogeneity arising from nonrandom adoption behavior. Growers' choices to adopt CSA techniques are affected not only by observers' socioeconomic and institutional drivers but also by unobservable drivers such as risk aversion behavior, climate risk perception, and managerial skills. Therefore, this study employs the MESRM to estimate the factors affecting the adoption of CSA in climate-vulnerable regions while avoiding biased and inconsistent results. The model also addresses this limitation by mutually evaluating the selection and outcome equation, confirming the consistent evaluation of treatment effects across the various adoption decisions.

The adapter $(\beta_0\ CST_0)$ of the CSA technique is indicated by i=0. The other groups are depicted by i= 1,2,3,4, and 5. Therefore, we demonstrate each function order as indicated below:

$$\begin{cases} function\ 1: Y_{i0} = Z_i\ \propto_0 + \epsilon_{i0}\ if\ I = 0 \\ function\ J: Y_{ij} = Z_i\ \propto_j + \epsilon_{ij}\ if\ I = J \end{cases} \quad ---------(6)$$

where Y_{i0} indicates the target variable for the i^{th} rice grower who adopted CSA j; Z_i signifies a vector of descriptive variables; $\propto_1$ and $\propto_j$ are coefficients to be measured; and ϵ_{i1} and ϵ_{ij} indicate error terms. As discussed in the function above, Z_i relates to the examined selection bias issue. Despite this, the error factors of the function above are linked when rice growers select to utilize CSA, and the target variables at the same time are affected by other implicit features. Sample selection bias issues emerge if the correlation indices of the error terms are significantly dissimilar from zero. Distorted and unreliable results might be due to from the lack of consideration of this issue. Thus, to remove the implicit selection bias, the preference features produced from investigating the following function adequately fit in the MESR. With the addition of preference selection factors, the function can be revised as follows:

$$\begin{cases} function\ 1: Y_{i0} = Z_i\ \propto_0 + \delta_0\rho_0 + \mu_{i1}\ if\ I = 0 \\ function\ J: Y_{ij} = Z_i\ \propto_j + \delta_j\rho_j + \mu_{ij}\ if\ I = J \end{cases} \quad --------(7)$$

where δ_1 and δ_2 indicate the preference terms, while ρ_1 and ρ_j are the covariances among the error terms. Furthermore, J-1 preference terms are authorized by multiple choice theory, in which any single term relates to each viable group of CSA adopters.

Descriptive statistics of the variables employed in the multinomial endogenous switching regression model

This study uses a robust empirical technique, multinomial endogenous switching regression, to estimate the factors that influence the adoption of CSA. According to recent studies (Khumalo et al., 2025), MESRM is suitable for controlling the issue of selection bias in evaluating the treatment effects of CSA adoption on two outcome variables: climate-smart agriculture practice adopters and non-adopters. The MESRM model consists of a selection equation and an outcome equation for the adoption of CSA in each regime. Two additional strategies

indicate a function of independent variables, including the demographic, institutional, and social characteristics of southern and northern farmers affecting climate-smart technique adoption choices. Table 1 explains the descriptive statistics of the variables utilized in the multinomial endogenous switching regression model and their assessment and predicted outcomes.

Table 1. Paste Here

Average Treatment Effects (ATT)

Examining the predicted results of adopters and nonadopters of CSA enables the for calculation of the average treatment effect on the analyzed (ATT) in the next phase. The MESR empirical method enables the calculation of potential outcomes or the benefits of CSA practices after adoption if they are not used properly, which encourages the calculation of ATT. The function is designed for calculating of ATT investigations for the exact and potential result conditions.

Adopter of CSA with proper adoption (real adoption examined)

$$\begin{cases} E\left(Y_{i2}|I=2|\right) = Z_i \propto_2 + \delta_2\rho_2 \\ E\left(Y_{ij}|I=j|\right) = Z_i \propto_j + \delta_j\rho_j \end{cases} \quad ----------(8)$$

Grower's decision regarding not adopting CSA (different outcomes)

$$\begin{cases} E\left(Y_{i0}|I=2|\right) = Z_i \propto_0 + \delta_1\rho_0 \\ E\left(Y_{ij}|I=j|\right) = Z_i \propto_0 + \delta_j\rho_0 \end{cases} \quad ----------(9)$$

To obtain the exact outcome subtracting Eq. 8 from Eq. 9, provides the ATT mentioned below:

$$ATT = E[(Y_{i2}|I=2) - (Y_{i0}|I=2)] = Z_i(\propto_2 - \propto_0) + \delta_2(\rho_2 - \rho_0) \quad (10)$$

Results and Discussion

Barriers to climate-smart agriculture adoption

The constraint confrontation index indicates that farmers in rural areas observe multidimensional restrictions. Knowledge and communication barriers (CCI mean = 231.01) ranked as extremely serious problems; subsequently, institutional barriers (mean = 224.07), technological barriers (216.22), and infrastructural barriers (214.74) ranked as the top four barriers, indicating extremely serious problems. Nevertheless, credit barriers (mean =190.51) ranked fifth. Social barriers (mean =189.46) followed in sixth, whereas cultural barriers (152.44) were the lowest barriers (Fig. 3). The significant barriers confronted by growers are institutional barriers, which require timely information, good understanding, and training programs related to modern climate technology practices. Farmers mostly have constrained access to extension, which creates more obstacles in adoption and decreases the adoptive capacity of the farming community. This result is in line with those of (Mobeen et al., 2025; Chisadza et al., 2025; Billah et al., 2025; Abid et al., 2018), which highlighted that limited information, lack of funding, and

training significantly decrease the adoption of CSA in Pakistan.

Moreover, the highest CCI value indicates the multiple problems associated with inadequate institutional policies, such as unstable agricultural price policy, poor access to credit, a lack of extension services, a lack of climate financing, a lack of climate practice training, a lack of climate-resilient information, a lack of water, increasing poverty, and a low-level of agricultural education, which are recognized as extremely serious barriers for the farming community. Furthermore, these findings indicate that growers are trapped under multidimensional constraints in the adoption of climate-smart agriculture. The outcome is in line with (Wakweya, 2023; Billah et al., 2025; Long et al., 2016; Teklewold, 2013) who reported institutional, social, political, and economic constraints are significant obstacles. Correspondingly, constrained resources, limited land, sophisticated land ownership, and poor knowledge of climate-smart technologies decrease investment; welfare, and unstable frameworks, and inadequate climate-resilient practices have been identified as dominant barriers to the sustainability of agriculture (Zerssa et al., 2021).

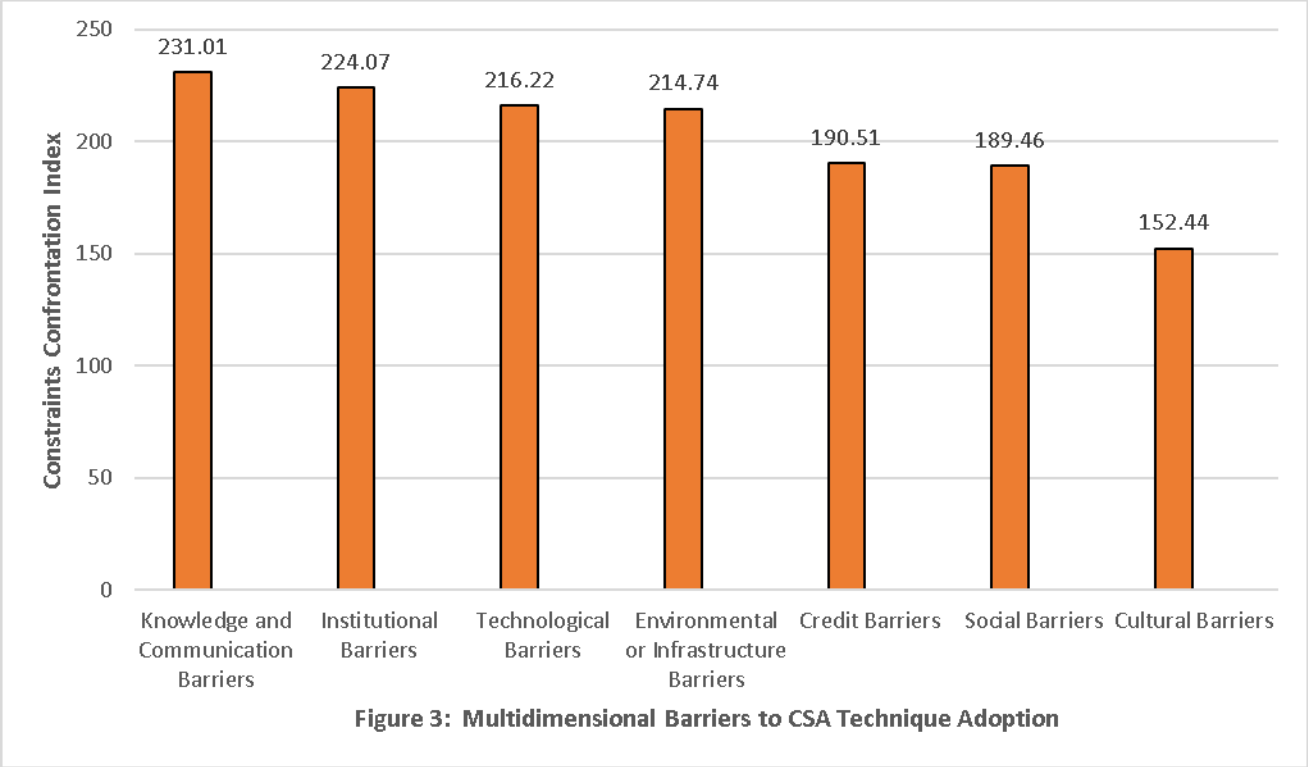


Figure 3. Multidimensional barriers to CSA Techniques adoption in the study area
Source: Author field survey December 2025.

Dimensions and scale of climate-smart agriculture adoption

Table 2 lists the farmers who adopted climate-smart agriculture. The CSA is categorized into three types of climate-smart techniques; 1. productivity-increasing (PInT), 2. climate-resilient (CRT), and 3. climate-risk management (CRMT) techniques. The majority of the farmers adopted productivity-increasing techniques, which were classified into different types, such as climate-resilient seed varieties (63.78%), land laser levelling (60.23%), efficient use of

inorganic fertilizer (46.45%), and farm manure application (10.23%). The second-highest percentage of farmers adopted climate-resilient techniques, which include water-resilient techniques (52.36%) and modifying dates of sowing and planting (28.74%). Finally, climate risk management techniques include integrated farm management (26.37%), climate information (11.41%), crop rotation (5.90%) and diversification (7.87%), which were the least adopted techniques in the study area (Table 2).

Moreover, the majority of farmers adopted PInT (45.17%), 40.55% adopted CRT and the fewest farmers adopted CRMT (12.88%). This indicates that the majority of farmers are not aware of the vulnerabilities of climate change, possibly due to inadequate access to agricultural extension services. The majority of the CSA farmers belonging to southern districts of Sindh Province Badin 63 and Thatta 57, followed by farmers from Larkana and Kamber-Shahdadkot 45 and 49, respectively. Farmers from the southern part of Sindh adopted more CSA than did northern farmers. However, southern and northern farmers frequently depend on PInT (63 and 57, respectively) (Fig. 4). The agriculture advisory and extension service sector should implement various approaches for wide-ranging adoption of climate-smart agriculture to increase the sustainability in the agriculture sector. The outcome is in accordance with Shahzad et al. (2021); Abid et al. (2016); Khatri-Chhetri et al. (2018); World Bank, (2018) and FAO, (2014). Research has emphasized that climate-resilient seed varieties, the efficient use of inorganic fertilizer, the modification of sowing and planting dates, water-smart techniques, climate information, and integrated farm management are the significant pillars for decreasing the effects of climate change.

Table 2. Paste Here

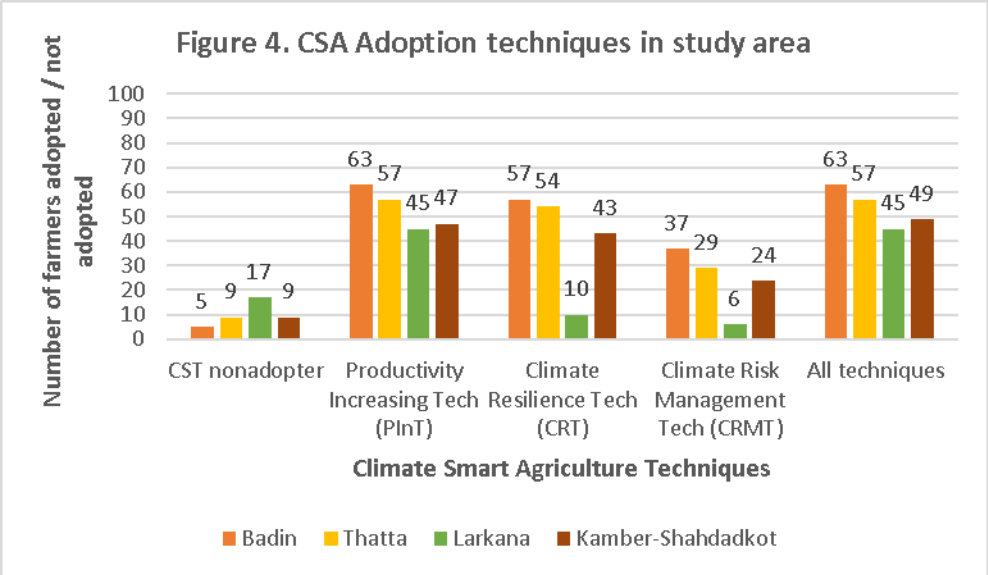


Figure 4. CSA techniques adoption in study area
Source: Author field survey December 2025.

Drivers of climate-smart agriculture adoption

A multinomial endogenous switching regression model was used to identify the drivers influencing farmers' adoption of climate-smart agriculture. The CSA measured in this research comprises various techniques intended to increase agricultural production, increase climate resilience, and improve climate risk management. These techniques involve increasing productivity, climate resilience, and climate risk management techniques. A number of these techniques have been deliberately adopted as significant parameters of CSA, such as climate-resilient seed varieties, land laser levelling, efficient use of inorganic fertilizer, water-resilient techniques, modifying dates of planting and sowing, climate information, integrated farm management, crop rotation, and crop diversification specially developed to mitigate the effects of climate change and ensure efficient management of resources. The MESRM is an advanced econometric technique that estimates multinomial categories of climate adoption. This model is preferred for estimating factors affecting CSA adoption capacity because the outcomes measured for this model are reliable and effective.

Using a sample of 254 participants, the model reveals significant results for the drivers of CSA adoption. The proof by Wald $x^2(245.3)$ and a highly significant Prob > chi2 = 0.000 explain that the model is a good fit and that the parameters jointly indicate CSA adoption effectively. The value of Pseudo R-squared (0.176) suggests that the model indicates a significant proportion of variance in CSA adoption (Table 4). A robustness test for variance (VIF) was executed among the descriptive variables utilized in the analysis. The mean VIF (1.66) is well below the predictable value of 10, indicating that there are no multicollinearity problems (Table 3). This finding indicates that the fundamental impacts are decent and statistically significant.

Table 3. Paste Here

Furthermore, the results revealed that the age of the farmers in nonadoption analysis was negative and significant for PInT and combined techniques adoption at the rates of 0.1 and 0.05, respectively. This finding indicates that young farmers have focused mostly on increasing production therefore, they only use only PInT. The negative impact of age on the adoption of PInT due to the multiple uses of techniques might reveal the younger growers' risk-averse behavior or short-term decisions for greater productivity. The outcome of age is in accordance with the study of Deressa et al. (2009). Similarly, in the adoption analysis, it is positive and significant in the CRT at the rate of 0.1. This significant effect explains why older farmers are more exposed to climate risks, which might motivate them to utilize climate risk techniques to protect crop production. Similar results were produced by Abdulai and Huffman, (2014); Adeagbo et al. (2021); Abid et al. (2018); Teklewold, (2013), who revealed that growers' age influences CSA practices in Pakistan. Furthermore, they suggested that risk experience and increased knowledge of climate shocks increase the willingness of farmers to adopt CSA approaches for sustainable production. The educational level of farmers is divided into three segments: primary, secondary, and college. The primary level of education was found to be significant in the CRMT and combined techniques at 0.1 and 0.05 in the nonadoption regime, whereas in the adoption regime, it was found to be significant in the PInT (0.1), CRT (0.05), and combined techniques (0.05). This result may indicate that less educated farmers have experience risk and therefore adopt only CRMT to gain advantages from CSA practices. The secondary level is positive and

significant in PInT, CRMT, and combined CSA at levels of 0.05 and 0.01, whereas in the adoption regime, it was significant at the level of 0.01 in most regimes. However, the college/university level of education was positive and significant in the adoption of combined CSA in both adopters and nonadopters; furthermore, this finding indicates that an increase in schooling may increase the likelihood of CSA adoption in the study area. Moreover, these findings might indicate that an increase in education significantly encourages the adoption of climate-smart agriculture. Highly educated farmers had more information, expertise, the ability to understand climate variability and good managerial skills. Furthermore, a high level of education helps them to estimate the financial and ecological advantages of advanced CSA and encourages farmers to adopt new technologies. Additionally, a high education level enhances the grower's ability to increase contact with agricultural extensions and other climate information advisories. This outcome is in line with Shahbaz et al. (2022a); Teklewold et al. (2013) and Abid et al. (2018). Furthermore, their results revealed that an increase in the level of education might increase the likelihood of CSA adoption, adoptive ability and motivate farmers to adapt to climate practices.

Access to extension is positive and significant in the adoption regime in combined CSA practices at the rate of 0.05%. However, in the nonadopter regime, access to extension is significant in the PInT, CRMT, and combined techniques at the rates of 0.1% and 0.05%, respectively. This finding indicates that farmers who have access to extension are more likely to adopt CSA than nonadopter farmers are. Extension services play a significant role in the implementation of advanced and sustainable agricultural practices. Furthermore, frequent contact with extension services may increase the skills and abilities of farmers and improve their climate adoption capacity. The outcome is in accordance with prior studies Ogundeji (2022), Shahbaz et al. (2022b), Abid et al. (2018) and Teklewold et al. (2013). Their study reported that the regular contact of farmers with extension services increases the likelihood and understanding of CSA adoption. However, irregular extension interactions are recognized as a key barrier and effective extension facilities are significant for sustainable climate adoption practices in Pakistan (Shahbaz et al. 2022b). Farmer contact with local groups is significant in both nonadopter and adopter regimes at a rate of 0.05% for both PInT and CRMT, and 0.01% for combined practices. This indicates that contact with local groups may be due to inadequate information sharing, and improper use restrains significant results. Similarly, farm size is significant in both adopter and nonadopter regimes at the rates of 0.05%, 0.1%, and 0.01% in PInT, CRMT, and combine practices, respectively. This may indicate that large-scale farmers have high adaptive capacity and are more likely to adopt CSA to increase their agricultural production. This result is in accordance with Lee et al. (2024). Farmers' location is insignificant in nonadopters. The adopter's regime is negative and significant only for CRMT, perhaps reflecting a weak agroecological situation in the area. These findings are in agreement with those of Marenya and Barrett (2007).

Table 4. Paste Here

Access to credit positively and significantly affects the adoption of CSA. This indicates a significant effect in adopters at the 0.05% threshold. The 0.1% and 0.01% levels of the PInT, CRT and combined practices are significant, whereas the 0.01%, 0.05%, 0.05% and 0.01% levels of the three CSA and combined practices are significant. This may explain why expensive resilient seeds and other inputs have high production costs and need

early investment for the adoption of CSA to protect agricultural production from climatic risks. Some farmers in the study area reported that "due to a high inflationary period they are not adopting CSA because it requires more capital to adopt CSA for the purchase of climate-resilient seed varieties as well as other climate-resilient techniques, such as preparing land and water-smart techniques in a scarcity of water to reduce the impact of climate vulnerabilities". Furthermore, funds are needed for advanced climate-smart technologies, such as land laser levelling, advanced irrigation, climate-resilient seed varieties and inorganic fertilizer. Therefore, those growers who obtain loans from credit organizations easily adopt CSA technologies without difficulty. These results are in accordance with those of Shahbaz et al. (2022b). Their study reported that access to credit increases the more possibility of adopting climate-smart agriculture and decreases the impact of climate change.

Table 5. Paste Here

This study utilized the robust instrumental variables, distance to extension, climate-resilient information and the perceived impact of climate change. These instrumental variables have been broadly adopted by recent studies that addresses both the significance and omission limitations that are necessary for instrument variables, as they impact adoption choices and do not influence outcomes, excluding CSA implementation (Mkuna, 2026). Distance to extension is a broadly recognized instrument in CSA research studies, as it enhances growers' contact with agricultural institutions, which positively impacts the execution of CSA practices. The instrumental variable distance to extension is highly significant, indicating that a closer distance to extension services increases the likelihood of more facilities such as advanced training, climate data and technical help. However, a long distance between farmers and extension offices may limit access to extension services and hinder growers from implementing of advanced practices. A recent study by Billah et al. (2025) verified that proximity to extension services enhances the probability of CSA adoption through advanced training, advisory facilities and agrarian systematic information. Similarly, a recent study by Biswas (2026) recognized extension facilities as a significant tool for CSA adoption in emerging nations.

The instrument variable climate-resilient information is highly significant for most types of CSA. These findings indicate that those growers with good knowledge of the climate, good access to weather departments and regular weather forecasts are adopting improved agricultural practices to protect their production from the effects of climate change. Furthermore, climate-resilient information enhances growers' decision-making ability and increases risk behavior for efficient farm management. It is a rational instrument showing information irregularity and communication barriers. The studies (Ewulo et al., 2025; Hagos et al., 2025; Mertz et al., 2009) confirmed that climate-resilient information further increases the likelihood of CSA adoption, increases adoption ability and enhances adoption decisions under climate vulnerability. Furthermore, a lack of climate-resilient information is known as a key barrier in adoption studies (Billah et al., 2025); it helps growers to modify sowing dates, utilize climate-resilient seed varieties, and adopt advanced irrigation techniques.

The perceived impact of CC is a significant instrument. The variable perceived impact of CC significantly affects

the climate-smart adoption. These findings indicate that those growers who perceive the effect of climate change as a critical risk to agricultural production are more likely to adopt the climate-smart practices. Furthermore, these findings suggest that growers who identify the detrimental effects of climate change are more likely to adopt advanced climate practices to decrease the risks and enhance agricultural resilience. This outcome is in accordance with the findings of Baffour et al. (2024). Furthermore, growers who have access to climate information make rational farm decisions, and climate information motivates them to adopt climate-smart practices. Additionally, recent studies (Savari and Khaleghi, 2026; Ewulo et al., 2025 and Feng et al., 2025) have shown that the perceived impact of climate change improves growers' risk perception and behavioral inspiration. Furthermore, it strongly enhances the possibilities and dominates the social motivations for CSA adoption. All instrumental variables are jointly significant ($\chi 2$ (9) = 38.2), showing that greater distance to extension leads to a decrease in adoption, whereas accurate climate information and knowledge enhance adoption (Tables 4 & 5).

Average treatment effect

Average treatment effects are employed to obtain the exact outcome of yield. The mean difference between the projected potential results of each adoption and nonadoption regime utilizes the coefficients of categorical yield equations. The results revealed that the adoption of productivity-increasing techniques (PInT) alone increases yield by approximately 452 kg/ha. Moreover, it shows that the combination of all CSAs had the greatest yield benefits, at approximately 687 kg/ha (Table 6). The highest outcome is obtained from various CSA adoptions. The ATE outcome is in line with those of Kassie et al. (2011) and Stewart et al. (2014). However, the outcome of two techniques (CRT and CRMT) is insignificant but positive at predictable levels, probably due to the low adoption rate in the sampled groups. The exact evaluation is more probable and is in accordance with the meta-analysis of the impact of climate adoption (Stewart et al. 2014).

Table 6. Paste Here

Conclusion

This research estimates the barriers and factors in the adoption of CSA among rice farmers. The growers perceived a significant understanding of CSA adoption. Climate-resilient seed varieties (63.78%), land laser levelling (60.23%), efficient use of inorganic fertilizers (46.45%), and water-resilient techniques were adopted as paramount CSAs in the study area. Among various barriers, knowledge and communication constraints (CCI=231.01), institutional barriers (CCI=224.07), technological barriers (CCI=216.22), environmental or infrastructural barriers (CCI=214.74) and credit barriers (CCI=190.51) were the most extreme and alarming. As a result of awareness, inadequate access to credit, a low level of agricultural knowledge, a lack of climate-resilient information, poverty, a lack of knowledge of climate-smart agriculture practices, a lack of extension services, and unstable agricultural price policies were identified as the most severe barriers. Furthermore, the results indicate that proper execution of production-increasing techniques would increase the rice yield by approximately 452 kg/ha. Moreover, the adoption of combined climate-smart agricultural practices would increase the rice yield by 687 kg/ha. Furthermore, the MESRM estimation indicates that age, education, access to extension, farmers' contact with local

groups, farm size, and access to credit are the most significant drivers affecting farmers in CSA adoption.

The findings indicate that the majority of the barriers are related to institutional parameters, which implies that institutions need to design effective policies for the successful implementation of climate-smart farming systems. Agriculture institutions should launch climate-smart training and awareness programs for sustainable and precision agriculture practices in the study area. Moreover, policymakers should formulate effective agricultural commodity pricing policies and support technological transformation initiatives in climate-vulnerable regions. Agricultural extension agencies and related institutions should strengthen the dissemination of climate-smart technologies through targeted advisory services, regular field monitoring, and seasonal capacity-building programs. These interventions can advance farmers' technical knowledge and adaptive capacity, thereby enabling the extensive adoption and effective implementation of Climate-Smart Agriculture (CSA) practices. Furthermore, to overcome these challenges confronted by growers and promote climate-smart agriculture, concerned authorities and policymakers should design the most feasible plans, considering growers' economic, educational, and agronomic conditions within the policy framework. Additionally, there is a need to improve the adaptive capacity of growers and the diffusion of climate-smart technology for agricultural sustainability.

Policy Implications

Furthermore, this study contributes to existing literature by indicating how climate-smart agriculture increases resilience, sustainability, and adaptive potential. Additionally, this study revealed that fewer growers have adopted climate-smart agriculture and that the majority of growers who do not adopt such agriculture properly have faced additional challenges and increased climate threats to agriculture amid the rising impacts of climate change. To overcome the various barriers to CSA adoption and improve the uptake and effectiveness of CSA practices, agricultural extension departments should appoint trained CSA experts in climate-affected districts. This is particularly important in areas where farmers face more constraints and continue to show low levels of CSA adoption. These experts can provide technical guidance, advisory services, and practical support to help farmers implement climate-smart practices more effectively. However, the results indicate that the adoption of climate-resilient farming practices is impeded by various interrelated barriers, including limited extension support, inadequate knowledge of climate-smart practices, insufficient training, poor access to climate information and climate-smart technologies, restricted access to credit, low levels of agricultural knowledge, and continued reliance on traditional farming practices. These limitations collectively limit farmers’ capacity to adopt climate-resilient agricultural practices.

The placement of climate-smart agriculture experts under agriculture extension services would strengthen management practices, organizational efficiency, and integration with existing advisory facilities. CSA experts will increase exposure and improve the services of the extension department through training programs, provide climate-specific technical support and demonstrations and encourage the adoption of climate-smart practices in climate-vulnerable areas of the province. Additionally, they can enable the interlinking of information sources into regional advisory systems, support district-level planning, and report the prevailing barriers to adoption.

Moreover, farmers can obtain rapid technical support and effective training through CSA experts. Strengthening climate-smart knowledge integration with the extension departments might improve the management of the existing system, increasing institutional services in spatially backward areas and strengthening the transition pathway toward climate resilience, while supporting farmers in adopting sustainable agricultural agriculture more efficiently.

Data availability

The data are not publicly available at this stage due to ongoing project activities and associated confidentiality considerations; however, they may be made available from the corresponding author upon reasonable request, subject to project approval.

Author contributions AC and MAK: conceptualization, Data curation, Methodology, data analysis, Writing original draft, Software, SAC: data curation and resources. RAU, KH and ABL Data curation, editing & editing.

Compliance with ethical standards

Conflict of interest The authors declare no competing interest

Funding declaration

This research was funded by the Sindh Higher Education Commission (SHEC), Government of Sindh, under the National Postdoctoral Fellowship Program-II (Grant No. AD/(QA)/SHEC/Postdoc-Fellowship/2025/130).

Acknowledgments

This project was implemented by the University of Agriculture, Faisalabad, Punjab, in collaboration with Shah Abdul Latif University, Khairpur, Shahdadkot Campus, Sindh. The authors gratefully acknowledge the institutional support and collaborative efforts that made this research possible. We extend our sincere appreciation to the farming communities for their time, trust, and valuable insights, as well as to the field teams for their dedication to data collection and coordination.

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