

Original Research

Do E-Credit and Institutional Support Drive Climate-Smart, Environmentally Sustainable Practices in Punjab's Agriculture?

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Abstract

This research investigates the role of digital e-credit and institutional support in facilitating the adoption of climate-smart agriculture (CSA) practices among rural smallholders in Punjab, Pakistan. The study analyzes how e-credit, alongside institutional backing and farmers' demographic attributes, influences the decision to embrace CSA practices and determines the extent of their adoption. Data from 420 farmers across five Punjab districts were analyzed using Multivariate Probit and Ordered Probit models. The findings emphasize the importance of e-credit and institutional support, including CSA training, soil testing services, seed certification, and market accessibility, to encourage the adoption of multiple CSA practices. In addition, the study establishes a positive correlation between the adoption of CSA practices and factors like farmer education, experience, landholding size, and tractor availability. The research underscores the need for enhanced access to e-credit, improved institutional infrastructure, and increased educational initiatives in rural areas to support climate-resilient farming practices.

Keywords: E-credit, climate-smart agriculture, environmental sustainability, Punjab agriculture, institutional support in environmental practices

Introduction

The unprecedented growth in the human population over the past few decades has exposed a significant

gap in food availability worldwide [1]. To address this, global indicators suggest a need for a substantial increase, approximately 70%, in food production by 2050 to meet the demands of an estimated 9 billion people [2]. This challenge has been a major concern for policymakers and is highlighted in the Sustainable Development Goals (SDGs) for 2030, which emphasize the importance of addressing climate change, hunger,

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and sustainability [1]. Agriculture, which provides a substantial portion of daily food requirements, is under threat due to the direct impacts of climate change [3]. Critical climate components such as rain and sunlight, essential for agriculture, are being altered by human activities, leading to a decline in agricultural production [4, 5].

In Pakistan, agriculture plays a pivotal role in the economy and livelihoods of its population [6]. The sector is experiencing significant setbacks due to climate change, leading to annual losses of around 3.8 billion dollars [7]. The decline in agricultural production not only affects the economic structure of Pakistan but also has broader implications for food security and the provision of raw materials for the industrial sector [8-10]. Given the importance of agriculture in providing major dietary staples like cereal crops, fruits, and vegetables, finding effective solutions to mitigate climate-related issues is crucial [11, 12].

The adoption of climate-smart agriculture (CSA) practices offers a viable solution to these challenges [13, 14]. CSA practices, as introduced by the Food Agriculture Organization (FAO), aim to provide a resilient and climate-friendly approach to agricultural production. In Pakistan, where agriculture is significantly impacted by climate change, the adoption of CSA practices is essential for maintaining production levels and ensuring income stability for farmers [15, 16]. However, the adoption of these practices is influenced by various factors, including cropping strategies, farming characteristics, and geographical differences [17].

In response to these challenges, the government of Punjab, Pakistan, initiated an interest-free digital e-credit policy aimed at boosting agricultural production and alleviating poverty in rural areas, particularly among the smaller and economically disadvantaged farming community. The government is extending support to small-scale farmers to alleviate credit constraints by offering cost-free registration at Suhulat Centres managed by the Land Record Management Information System (LRMIS) in collaboration with the Punjab Information Technology Board (PITB). This policy was launched to address challenges and limitations faced by small-scale farmers within the previous agricultural credit system. This credit initiative stands out by providing loans to tenants, women, and sharecroppers, a provision that was absent in earlier credit schemes. Its design focuses on broadening the accessibility of formal and digital financial services, aligning with the agenda of financial inclusion. Moreover, it aims to reduce farmers' reliance on high-cost, non-institutional credit sources.

Building on these developments, this study focuses on examining the impact of digital E-credit and institutional support on the adoption of Climate-Smart Agriculture (CSA) practices by rural small farmers in Punjab, Pakistan. It investigates how financial resources and institutional support, coupled with the demographic characteristics of farmers, influence their decision-

making and the intensity of CSA practice adoption. The objectives are to analyze the influence of E-credit and institutional support on CSA adoption, identify factors that intensify the adoption of these practices, and provide policy recommendations based on the findings. The novel contributions of this research lie in its comprehensive analysis of the roles of modern financial instruments like E-credit and institutional frameworks in promoting sustainable agriculture, filling a critical gap in the current understanding of CSA practice adoption in developing economies.

The rest of the paper is organized as follows: The subsequent section provides a Literature Review, exploring current research on Climate-Smart Agriculture. The Materials and Methods section provides details about the research methodology and data analysis. The Results section then presents the study's findings, followed by a Discussion section that analyzes these results concerning digital E-credit and institutional support. The paper concludes with a section summarizing the conclusions and their implications for future research.

Literature Review

Climate change poses a significant threat to agricultural sustainability, with drastic changes leading to widespread crop destruction and adversely impacting agricultural communities worldwide [7, 18]. In Pakistan, these challenges are particularly pronounced, given the country's dependence on agriculture for economic stability and food security [6]. The sector has been experiencing a decline in productivity due to various issues exacerbated by climate change, such as soil degradation, water stress, and nutritional deficiencies [19, 20]. This decline not only affects the livelihoods of farmers but also has broader implications for the country's economic structure and food supply [9, 12].

In response to these challenges, climate-smart agriculture (CSA) practices have been promoted as effective solutions [13, 14]. These practices, adapted to the specific context of Pakistani agriculture, include strategies like farmyard manure, crop rotation, deep plowing, zero tillage, and integrated weed management [21]. Each practice is designed to address specific climate-related challenges, aiming to enhance soil productivity and overall agricultural resilience [22-24]. Despite the potential benefits of CSA practices, their adoption varies among farmers, influenced by a range of factors including cropping strategies, farming characteristics, and geographical location [17].

A critical barrier to the widespread adoption of CSA practices is the lack of financial and institutional support [25-27]. Financial resources, particularly access to credit, are essential for farmers to adopt and sustain these practices [28]. In Pakistan, where a significant proportion of farmers are small-scale, access to financial capital is often limited [5, 29]. This limitation is further

exacerbated by procedural complexities and accessibility barriers associated with traditional credit facilities [30]. The potential role of modern credit facilities, such as e-credit, in facilitating the adoption of CSA practices remains largely unexplored in the literature.

Existing research underscores the importance of CSA practices in enhancing agricultural productivity and farmer income [21, 31-37]. Studies have shown positive outcomes, including increased crop production and efficiency, as a result of adopting CSA practices [38-40]. However, there is a need to further understand the factors influencing farmers' decisions to adopt these practices and the constraints they face. The literature provides insights into various socio-economic, land, and institutional drivers of CSA practice adoption [13, 41-49]. Nonetheless, the impact of modern credit facilities like e-credit on CSA adoption and the factors that intensify the adoption of these practices, especially in the context of Punjab, Pakistan, have not been adequately addressed [50, 51].

This study seeks to fill these gaps by analyzing the impact of socio-economic, land, and institutional characteristics, along with the availability of e-credit facilities, on the decision to adopt multiple CSA practices. It aims to identify the factors that intensify the adoption of CSA practices and to offer policy recommendations based on these findings. The exploration of e-credit and institutional support in the context of CSA adoption in Pakistan's agricultural sector, which faces imminent threats from climate change, constitutes a substantial contribution to the existing body of scientific literature.

Materials and Methods

Study Area and Data Collection

This study primarily focused on the factors affecting the adoption decision of climate-smart agriculture practices in the most important agricultural region Punjab, Pakistan. This region is a significant agriculture producer, providing around 57 percent of the country's agriculture production [52]. This research specifically examines the rice-wheat (RW) system in Punjab, a critical component of Pakistan's food security and a major contributor to the country's rice production. Encompassing about 2.1 million hectares, this system represents approximately three-fifths of Punjab's total agricultural area. Farmers in this region are more exposed to climate-related problems due to swift changes in climate patterns over the last few years [53]. Therefore, it is necessary to identify the major factors that influence the decision to adopt the CSA practices. If it is not explored in time, there is a likely possibility that farmers in the Punjab region could lose approximately 40% of farm production. However, this study has opened up a way forward to include novel factors such as e-credit facilities and institutional structure in CSA practice's decision process from

the Punjab perspective. Fig. 1 represents the map of the study area.

Data was collected using a questionnaire that included both quantitative and qualitative tools, and for the data collection process, a multistage random sampling technique was employed (See Fig. 2). Field surveys were conducted through face-to-face interviews with farmers, carried out by trained enumerators familiar with the local language and field conditions. In the first stage of the sample selection process, five districts from the Punjab region - Gujrat, Sialkot, Sheikhpura, Lahore, and Gujranwala - were selected for their significant role in the rice-wheat cropping system. In the second stage, one Tehsil was randomly chosen from each district. This was followed by selecting three union councils within each Tehsil, and from these, four villages per union council were identified. The final step involved selecting seven farmers from each village, culminating in intensive interviews with a total of 420 farmers. These interviews focused on gathering information about their socio-economic indicators, land characteristics, access to institutional support, and, crucially, the use of e-credit facilities.

Conceptual Framework

This study is based on the decision-making process in farm operations, considering farmers as the main stakeholders. These farmers encounter various risks during the operations of their farms. Farmers aim

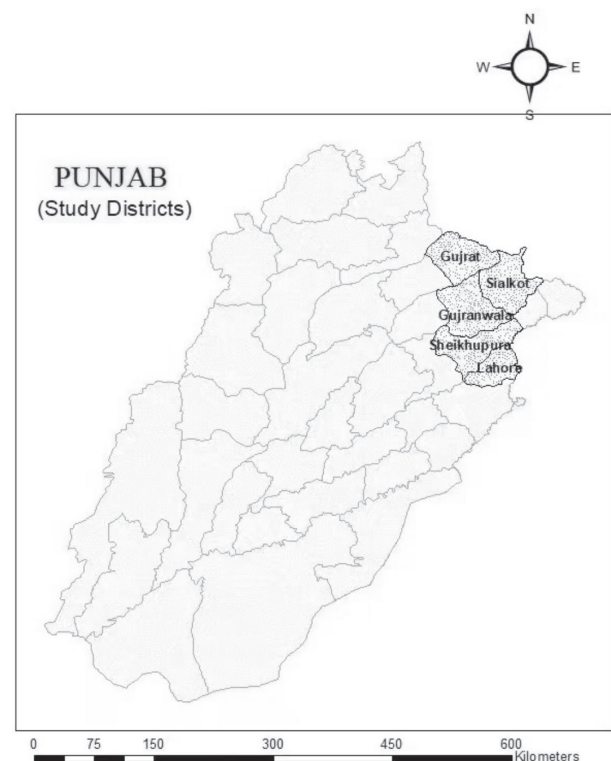


Fig. 1. Map of the study area.

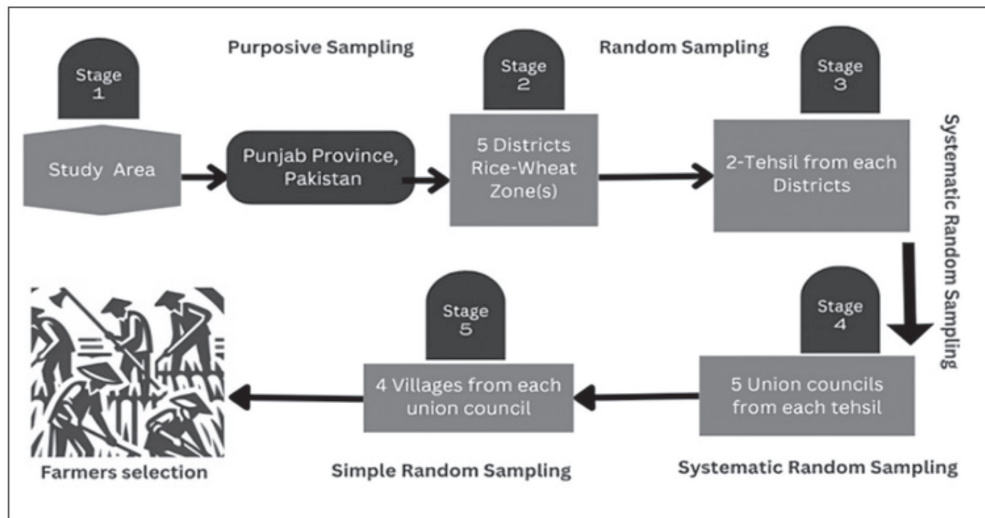


Fig. 2. Sampling technique.

to devise strategies that lower costs and increase farm income. While they can manage factors within their control, certain external elements, such as climate change, are beyond their influence and can pose a risk to farm productivity and profitability. Therefore, climate-smart agriculture (CSA) practices, as established previously, could be the best strategy to counter farmer risk and produce sustainable production. CSA practices are assumed to provide high revenues and food security for farmers. However, adopting such practices is attached to net benefits from farm operations. Consequently, observing net benefits is a far further thing, as they could be observed only if farmers adopt them. But the question here arises first: what are the basic factors that influence or constraints that stop farmers from the decision to adopt or not to adopt CSA practices? These factors are farmers' socioeconomics and farm characteristics, and more importantly, the financial capital the farmer holds. This study employed the e-credit facility that some farmers have as the primary financial resource, in addition to their diverse agricultural and demographic factors. These variables primarily assist farmers in making rational decisions about how to use such CSA approaches to achieve sustainable crop yield and profitability.

Empirical Strategy

This study used the Multivariate Probit Model (MVP) to examine the impact of several socio-economic factors, availability of the e-credit facility, and institutional structure on farmers' adoptions of climate-smart agriculture (CSA) practices following [54-57]. Climate-smart agriculture practices have been established as the most effective technological advancements in agriculture to avert climate-related risks and uncertainties [58]. However, these practices are influenced by different characteristics of farmers. It could also be assumed that these practices are not mutually exclusive and influence

the decision to uptake and substitute each other [59]. In crop cultivation, farmers face several agriculture constraints and climate change setbacks. Therefore, a set of combinations of different CSA practices are positively correlated (complementary) or negatively correlated (substitute) to each other. However, the use of a univariate model is not an effective way to explore the simultaneous and interdependent decision process; hence it would omit this useful economic information related to technological adoption [44]. This is why in this study we used MVP to firstly identify the impact of different factors on the adoption of CSA practices and secondly to explore the correlation between these practices.

Based on the theoretical aspect of the previous section, it could be assumed that farmers could potentially adopt the CSA practices if the benefits from uptaking are higher. So, let's say there are i^{th} number of farmers taking values as $i = \{1, 2, 3, \dots, N\}$ facing a choice of adopting CSA practice j^{th} where j are different climate-smart agriculture practices like Crop residues chopping in soil, Integrated weeds management, Sustainable irrigation water use, and Crop rotation. The decision to adopt these technologies would be influenced by different factors X_{ij} . Let's denote CSA practice as a latent variable Y_{ij} that takes binary values 0 to 1, where 0 indicates not adopted and 1 indicates the adoption of CSA practices. So, mathematically we can express this as follows:

$$Y_{ij} = \beta_j X_{ij} + \epsilon_i \quad (1)$$

Where Y_{ij} represents the outcome of the decision of CSA practice and X_{ij} denotes the several socio-economic indicators of farmers, institutional structure, and adoption of the e-credit facility. Meanwhile, β_j here is a coefficient representing the magnitude of the impact of factors on the decision to adopt the CSA practice to be estimated. Finally, ϵ_i represents the error term.

Thus, to simultaneously estimate the ‘n’ number of CSA practices following system of the equation would be estimated: Y_{i1}^*

$$Y_{i1}^* = \beta_1 X_{i1} + \varepsilon_i \quad (2)$$

$$Y_{i2}^* = \beta_2 X_{i2} + \varepsilon_i \quad (3)$$

$$Y_{i3}^* = \beta_3 X_{i3} + \varepsilon_i \quad (4)$$

$$Y_{i4}^* = \beta_4 X_{i4} + \varepsilon_i \quad (5)$$

Where, latent variables Y_{i1}^* , Y_{i2}^* , Y_{i3}^* and Y_{i4}^* are underlying CSA practices namely crop residue chopping in soil, integrated weeds management, sustainable irrigation water use, and crop rotation. However, X_{i1} , X_{i2} , X_{i3} , X_{i4} are factors such as farmer e-credit adoption, farm size, education, manager experience, adult female, off-farm employment, marital status, tube well owned, output market, seed, labor shortage, soil testing lab, NGO office, quality of land, insurance information, motorcycle, refrigerator, cart and tractor.

Extending this perspective further, it could be obvious to examine the factors that influence different CSA practices through MVP [60]. However, from the above-cited framework, it could be seen that farmers practice a mixture of adaptation. It is worth mentioning here that it is important to assess the intensity of the adoption of CSA practices, but the question arises here how to measure the intensity of the adoption of CSA practices? To answer the question this study used a modeling framework of several practices adopted by farmers following [61-63]. In this framework, it is hypothesized that farmers either adopt all of CSA practices or none of them. Alternatively, we can say whether he has adopted one, two, three, or four at the same time. Therefore, the dependent variable will take discrete values in order ranging from 0, 1, 2, 3, and 4. As the MVP model cannot determine or analyze the number of CSA practices adopted by farmers, therefore, there is a need for other analytical tools. Poisson regression fits perfectly to observe such a model where a discrete dependent variable is used, or where the possibility of number adoption is being observed [64]. However, the Poisson model only estimates the equal or potential possibility of adoption of all CSA practices and in our case, there might be the possibility of dependence of one CSA practice on another [63]. As we cited above CSA practices might be complementary or substitute for each other. Therefore, the ordered Probit model is considered the best choice in such circumstances. The ordered Probit model can be expressed as follows:

$$A^* = \beta Z_i + \bar{u}$$

Where A^* is unobserved and is given as

$$\begin{aligned} \theta_i &= 0 \text{ if } A^* \leq 0 \\ \theta_i &= 1 \text{ if } 0 < A^* \leq \alpha_1 \\ \theta_i &= 2 \text{ if } \alpha_1 < A^* \leq \alpha_2 \\ \theta_i &= 3 \text{ if } \alpha_2 < A^* \leq \alpha_3 \\ \theta_i &= 4 \text{ if } \alpha_3 < A^* \leq \alpha_4 \end{aligned}$$

Where $\alpha_1 < \alpha_2 < \alpha_3 < \alpha_4$ are cutoff or threshold parameters that are estimated using β . Furthermore, we assumed that \bar{u} is normally distributed with zero mean and unit variance. The probabilities of observing the outcome of dependent variables (j) are as follows:

$$p(A^* = j|x) = 1 - \Phi(\alpha_{j-1} - \beta Z_i)$$

Where Φ is the cumulative normal distribution function of \bar{u} .

Description of Variables

Table 1 represents a description of the variable used in the analysis; the first, half part represents the explanatory variables- all those factors purposively affect the decision to adopt CSA practices. Moreover, the last part represents the dependent variables. The mean value and standard deviation of all variables are represented in the extreme left column of the table. First, as an essential variable in this study, farmer willingness to accept e-credit was employed. This is a binary choice variable with a value ranging from 0 to 1, the mean value of the variable is 0.47, and the standard deviation is 0.50. In this context, farm size denotes the operational land held by the farmer in acres, with the mean value standing at 6.806 acres. Household education is measured in years for this study, and the mean value recorded is 7.286 years. Likewise, farmer manager experience is quantified by the number of years the household has dedicated to farming.

Adult females represent the number of adult female members in a household. Moreover, variables like tube well owned, output market, seed, labor Shortage, soil testing lab, NGO office, quality of land, insurance information, motorcycle, refrigerator, cart, and tractor represent the availability of these facilities. Our dependent variables have binary values 0 to 1 representing the adoption or not adoption of climate-smart agriculture practices. This study has used integrated weeds management, crop residue chopping in soil, sustainable water use, and crop rotation as CSA practices in this analysis.

Results

Results shown in Table 2 justified the relevance of using a multivariate Probit model to account for the

unobserved correlation across the decision to adopt several climate-smart agriculture (CSA) practices. The Wald test ($Wald(76)\chi^2 = 158.37; Prob>\chi^2 = 0.000$) rejects the null hypothesis that all coefficients in the equation are jointly equal to zero. Results further showed a heterogeneous impact of several explanatory variables on different CSA practices. E-credit adoption showed a statistically positive and significant impact on sustainable irrigation water use, integrated weeds management, and crop residue chopping in soil with a significance level of 1%, 5%, and 10% respectively. However, e-credit adoption was found to have a negative impact on the decision to adopt crop rotation as a CSA practice.

Farm size indicated a positive and statistically significant influence on the decision to adopt sustainable irrigation water use, integrated weed management, and crop residue chopping in soil and crop rotation. Results showed that education has positively influenced the decision to adopt crop rotation. Consequently, off-farm employment was found to have a negative influence on the decision to adopt CSA practices such as crop residue chopping in soil and sustainable irrigation water use. Moreover, Off-farm employment showed a negative impact on the decision to adopt crop residue chopping in soil and sustainable irrigation water use. However, no impact of off-farm employment was found on integrated weeds management and crop rotation.

Table 1. Description of variables and socioeconomic characteristics of household.

Variables	Description of variables	Mean	Standard deviation
Independent Variables			
Farmer e-credit adoption	Dummy, 1 if the household availed E-credit facility, 0 otherwise	0.476	0.500
Farm size	Continuous, Operational land holding of households in acres	6.806	2.342
Education	Continuous, Education of households in years	7.286	3.171
Manager experience	Continuous, Household experience in farming over the years	26.062	9.773
Adult female	Continuous, Number of adult females in the house	1.621	0.678
Off Farm Employment	Dummy, 1 if the household is involved in an off-farm employment activity, 0 otherwise	0.243	0.429
Marital status	Dummy, 1 if the respondent is married, 0 otherwise	0.112	0.316
Tube well owned	Dummy, 1 if the household has tube well ownership, 0 otherwise	0.433	0.496
Output market	Dummy, 1 if the household has easy access to the output market, 0 otherwise	0.581	0.494
Seed	Dummy, 1 if the household has easy access to certified seed, 0 otherwise	0.576	0.495
Labor Shortage	Dummy, 1 if the household has experienced an agriculture labor shortage, 0 otherwise	0.612	0.488
Soil testing lab	Dummy, 1 if the household has easy access to the Government soil testing laboratory, 0 otherwise	0.879	0.327
NGO office	Dummy, 1 if the household has easy access to the NGO office, 0 otherwise	0.019	0.137
Quality of land	Dummy, 1 if the household has good quality agricultural land, 0 otherwise	0.640	0.480
Insurance information	Dummy, 1 if the household has crop insurance information, 0 otherwise	0.636	0.482
Motorcycle	Dummy, 1 if the house owned a motorcycle, 0 otherwise	0.288	0.453
Refrigerator	Dummy, 1 if the household has owned a refrigerator, 0 otherwise	0.386	0.487
Cart	Dummy, 1 if the household has owned an agricultural cart, 0 otherwise	0.340	0.474
Tractor	Dummy, 1 if the household owned a tractor, 0 otherwise	0.014	0.119
Dependent Variables			
Integrated weeds management	Dummy, 1 if the household adopted Integrated weeds management, 0 otherwise	0.574	0.495
Crop residues chopping in soil	Dummy, 1 if the household adopted Crop residues chopping in soil, 0 otherwise	0.517	0.500
Sustainable water use	Dummy, 1 if the household adopted Sustainable irrigation water use, 0 otherwise	0.545	0.499
Crop rotation	Dummy, 1 if the household adopted Crop rotation, 0 otherwise	0.514	0.500

The findings also demonstrated that the availability of the output market has positively influenced the choice to adopt sustainable irrigation water usage. (1% level of significance), integrated weeds management (1% level of significance), crop residues chopping in soil (5% level of significance), and crop rotation (5% level of significance). Results showed that the availability of soil testing labs influenced farmers' decision to adopt integrated weed management at a 1 % level of significance. Comparatively, it has negatively influenced the decision to adopt crop rotation. The marital status of the farmer was found to be a positive driver of the decision to adopt sustainable irrigation water use. In contrast to it, there was a significant and negative impact of marital status on crop rotation. Moreover, a significant positive impact of education was found on the decision to adopt crop rotation.

Results indicated that certified seed availability has statistically positively related to the adoption of sustainable irrigation water use, integrated weeds management, and crop residue chopping in soil and crop rotation. Moreover, results revealed that the availability of awareness on CSA practices has increased the likelihood of adoption of sustainable irrigation water use, integrated weeds management, and crop rotation. Finally, the results of the study indicated a positive and significant influence of the availability of tractors on sustainable irrigation water use.

Table 3 presents the results of the pair-wise correlation coefficient of different CSA practices, which indicated that crop residues chopping in soil and integrated weed management are found as complementary to each other with 1 percent of level significance. The result further indicated that sustainable irrigation water use

Table 2. Multivariate probit estimation of farmer attributes on adoption of different sustainable technologies.

Variables	Integrated weeds management	Crop residues chopping in soil	Sustainable irrigation water use	Crop rotation
Farmer e-credit adoption	0.410** (0.199)	0.305* (0.185)	0.734*** (0.184)	-0.719*** (0.205)
Farm size	0.113*** (0.036)	0.063** (0.032)	0.091*** (0.033)	0.081** (0.036)
Education	-0.015 (0.024)	-0.011 (0.022)	-0.007 (0.022)	0.050** (0.024)
Manager experience	-0.004 (0.008)	-0.003 (0.008)	-0.001 (0.008)	0.002 (0.008)
Adult female	0.077 (0.099)	0.170* (0.096)	0.089 (0.096)	-0.010 (0.100)
Off Farm Employment	-0.241 (0.155)	-0.413*** (0.149)	-0.311** (0.146)	0.249 (0.162)
Marital status	0.319 (0.222)	0.302 (0.203)	0.450** (0.209)	-0.549** (0.228)
Tube well owned	-0.220* (0.133)	-0.294** (0.125)	-0.362*** (0.126)	-0.044 (0.131)
Output market	0.644*** (0.241)	0.504** (0.226)	0.747*** (0.224)	0.529** (0.243)
Seed	0.479** (0.241)	0.524** (0.226)	0.576*** (0.222)	0.455* (0.244)
Labor Shortage	0.150 (0.135)	0.098 (0.128)	0.065 (0.131)	0.144 (0.134)
Soil testing lab	0.379** (0.192)	0.063 (0.178)	0.320* (0.183)	-0.440* (0.204)
NGO office	-0.960* (0.573)	-0.348 (0.413)	-0.622 (0.859)	0.567 (0.491)
Quality of land	-0.006 (0.153)	-0.232 (0.145)	-0.299** (0.150)	0.117 (0.157)
Insurance information	0.148 (0.139)	0.013 (0.132)	0.030 (0.134)	-0.310* (0.138)
Motorcycle	0.135 (0.166)	-0.048 (0.153)	0.075 (0.150)	-0.242 (0.170)
Awareness of CSA practices	0.330** (0.158)	0.079 (0.146)	0.343** (0.151)	0.311* (0.159)

Table 2. Continued.

Cart	-0.266* (0.137)	-0.047 (0.129)	-0.202 (0.128)	-0.056 (0.139)
Tractor	-0.622 (0.601)	-0.859 (0.607)	1.392*** (0.529)	-0.996 (0.658)
Constant	0.490 (0.451)	0.426 (0.425)	0.376 (0.419)	-0.107 (0.469)
Number of observations				420
Log Likelihood value				-731.37
Wald $\chi^2(76)$				158.37***
Prob> χ^2				0.0000

*** p<0.01, ** p<0.05, * p<0.10.

Table 3. Correlation coefficients between sustainable agricultural technologies.

Technologies	Correlation coefficient	Standard error
Crop residues chopping in soil and Integrated weeds management	0.909***	0.020
Sustainable irrigation water use and Integrated weeds management	0.980***	0.007
Crop rotation and Integrated weeds management	-0.043	0.077
Sustainable irrigation water use and Crop residues chopping in soil	0.952***	0.015
Crop rotation and Crop residues chopping in soil	-0.030	0.075
Crop rotation and Sustainable irrigation water use	-0.010	0.074

Likelihood ratio test of $\rho_{21} = \rho_{31} = \rho_{41} = \rho_{32} = \rho_{42} = \rho_{43} = 0$: $\chi^2(6) = 62.0691$

Prob> $\chi^2 = 0.0000$

*** p<0.01, ** p<0.05, * p<0.10.

is complementary with integrated weeds management and crop residues chopping in soil with a higher level of significance. Moreover, crop rotation has shown insignificant correlation but found as a substitute for integrated weeds management, crop residue chopping in soil, and sustainable irrigation water use.

Table 4 represents the result of the order Probit model, which was used to determine the impact of different socioeconomics and land characteristics on the intensity of adopting CSA practices. Results of the study indicated the significant value of LR χ^2 as 90.88 and pseudo R² value as 0.068. This implies that the model is perfectly fit and all the threshold parameters are significant implying the natural ordering of dependent variables. Although the results of the coefficient of order Probit estimation are hard to interpret, this study used the marginal effect to interpret the impact of different farmer characteristics on the adoption intensity of CSA practices.

The study's results revealed that farmers' adoption of the e-credit facility significantly and positively increased the intensity of adopting CSA practices. In addition, the findings indicated that farmers utilizing e-credit were inclined to adopt more than one CSA practice, with the probability value of -13.16%, -10.08%, 1.06%, 10.08%, and 12.10% of none, 1, 2, 3, and 4 CSA

practices adoption, respectively. Similarly, farm size has a statistically significant influence on the adoption intensity of CSA practices. The number of adult females in the household also indicated a positive influence on adopting 3 and 4 CSA practices and a negative but statistically significant influence on none and 1 CSA practices.

The marital status of farmers, which has been taken here as a dummy variable, has intensified the adoption of CSA practices. Results indicated that married men are likely to adopt more than one CSA practice. Furthermore, the soil testing lab has also a statistically significant impact on adoption intensity. Results further revealed that the availability of a tractor also increases the intensity of adoption, Table 4 showed a highly significant and negative value of the probability of no adoption of any CSA practices and a significant and positive value of more than 1 CSA practice for those farmers who own a tractor.

Results further revealed that the education of farmers intensified the probability of adoption of CSA practices. Table 4 indicated the probability values of adoption of none, 1, 3, and 4 CSA practices as - 0.09, -0.8, 0.8, and 0.8, respectively, against the education of farmers. Finally, farm manager experience in farming has increased the adoption of more than 1 CSA practice;

Table 4. Ordered probit estimation of factors affecting the intensity of adoption of CSA practices.

Variable	Coefficient (Std. Err)	Marginal Effects				
		Prob (Y = 0 X)	Prob (Y = 1 X)	Prob (Y = 2 X)	Prob (Y = 3 X)	Prob (Y = 4 X)
Farmer e-credit adoption	0.642*** (-0.164)	-0.136***	-0.108***	0.016*	0.108***	0.121***
Farm size	0.068** (-0.028)	-0.014**	-0.012**	-0.002	0.012**	0.013**
Adult female	0.245*** (0.0825)	-0.0528**	-0.042**	0.007	0.043***	0.045**
Off Farm Employment	-0.145 (0.129)	0.0326	0.024	-0.006	-0.026	-0.025
Marital status	0.486*** (0.179)	-0.083***	-0.092**	-0.010	0.074**	0.111**
Tube well owned	0.0794 (0.106)	-0.016	-0.014	0.002	0.014	0.015
Output market	-0.228 (0.1901)	-0.048**	-0.040**	-0.006***	0.039**	0.043***
Seed	0.219 (0.1912)	-0.048	-0.037	0.007	0.038	0.039
Labour Shortage	-0.0182 (0.107)	0.003	0.003	-0.001	-0.003	-0.003
Soil testing lab	0.371** (0.160)	-0.092**	-0.054**	0.024	0.066**	0.057**
NGO office	0.0872 (0.377)	-0.017	-0.016	0.002	0.015	0.017
Quality of land	0.0693 (0.126)	-0.015	-0.012	0.002	0.012	0.013
Insurance information	0.0707 (0.111)	-0.015	-0.012	0.002	0.012	0.013
Motorcycle	-0.0116 (0.135)	0.002	0.002	0.000	-0.002	-0.002
Awareness of CSA practices	0.066** (0.126)	-0.014**	-0.011**	0.002	0.012***	0.012***
Cart	-0.223 (0.111)	0.050	0.037	-0.009	-0.039*	-0.039**
Tractor	0.846* (0.466)	-0.109***	-0.158**	-0.059	0.092***	0.236
Education	0.0445** (0.019)	-0.009**	-0.008**	0.001	0.008**	0.008**
Manager experience	0.0143** (0.006)	-0.003**	-0.002**	0.000	0.003**	0.003**
/cut1	0.233 (0.379)					
/cut2	1.103 (0.379)					
/cut3	1.811 (0.383)					
/cut4	2.594 (0.392)					

Number of observations = 420, LR $\chi^2(19) = 90.88^{***}$, Pseudo $R^2 = 0.0684$, Log likelihood = 618.792

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

it is shown in the table that units increase in the farmer experience increase the intensity of adoption as follows; 0.3 %, 0.2 %, 0.3% and 0.3% of none, 1, 3, 4 CSA practices adopted respectively. However, no significance has been found in the 2 CSA practices' adoption in time.

Discussion

This study critically examines the factors influencing Punjab farmers' adoption of sustainable practices in response to climate risks. Central to these findings is the role of e-credit facilities, which have emerged as a significant determinant in encouraging farmers to adopt a range of Climate-Smart Agriculture (CSA) practices. This highlights the importance of financial

capital in upgrading farm operations, where farmers with easier access to capital, especially through e-credit, are more likely to engage in sustainable practices. These results align with studies such as those by [29, 65, 66], which also underscore the positive impact of traditional credit facilities on sustainable farming. Moreover, this study sheds light on the environmental impact of e-credit in agriculture, demonstrating its potential to promote environmentally sustainable practices, thus contributing to the reduction of the agricultural sector's ecological footprint.

Results further revealed the positive influence of farm size on the adoption of multiple CSA practices and their intensity. Larger farms adopting CSA practices can significantly contribute to regional environmental sustainability through reduced use of chemical

fertilizers and pesticides and increased biodiversity. The reason could be found in the mechanism of land holding; a farmer with more land is likely to focus on his land productivity so they often alter techniques to produce agricultural products. CSA practices attract large landholders because farmers with large land have large capital to invest in such modern production techniques, it is as similar to found of [67]. Off-farm work was shown to have a negative impact on the choice to embrace numerous CSA practices and so has no likely effect on the number of CSA practices adopted. This means that farmers with off-farm employment are less likely to be interested in farm operations because they have less time after work; conversely, they have a secondary source of money therefore they are less concerned with farm profitability, which is exacerbated by the fact that they have a secondary source of revenue [43].

Awareness of CSA practices tends to influence the intensity of CSA practices adopted and multiple CSA practices positively as the more a person is aware of CSA practices more he tends to adopt the CSA practices. Rural areas are less exposed to new information and updates therefore if they have such awareness they tend to adopt more, relatively similar found by [65]. Moreover, farmer easy access to the output market also extend the intensity of adoption as well as influence the adoption of multiple adoption practices positively; it generally increases the cost of growing crops if the output market is inaccessible or far from the approach of farmers, but if farmer has easy access to output market they could invest more interest in their farm operation to produce more so they could get good profits [68]. Results indicated that access to certified seed has a positive impact on multiple CSA practices; this positive association was assumed because Farmer trusted in the high-quality certified seed to produce efficiently with modern techniques. The soil testing lab, however, has demonstrated a positive impact on the intensity of CSA adoption. This could be attributed to the reliability of soil for crop production and the increased awareness of soil type and deficiencies. However, the farmers having access to soil labs tend to adopt modern practices as they are aware of their land quality and its tolerance. Certified seed, soil testing labs, and awareness of CSA practices are related to institutional support; this implies that if farmers have more of this institutional support they tend to adopt more modern and sustainable agriculture practices. These results are consistent with prior research [69].

Results of the study indicated that education has a positive influence on adoption intensity as well as multiple CSA practices adopted, which seems plausible. The reason behind this is the composure a farmer gets in his decision process after getting an education. They are more likely to make rational decisions and stay updated on methods to enhance their farm operations, consistent with previous findings [66]. Similarly, farmers possessing more years of experience were observed

to engage in a greater number of CSA practices and positively influence the adoption of multiple CSA strategies. The accumulation of farming experience enables these farmers to better understand and recognize the benefits of CSA practices, thereby facilitating more informed decisions and effective implementation based on their enhanced agricultural expertise.

Conclusions

This study systematically assessed the determinants influencing the adoption of various climate change adaptation practices and the factors driving the intensity of CSA practice adoption in Punjab, Pakistan. Utilizing cross-sectional data collected from five districts in Punjab through multistage random sampling, the study unveiled key insights. It identified e-credit facilities, educational level, farming experience, awareness of CSA practices, usage of certified seeds, and access to soil testing labs as critical determinants in farmers' decision-making processes. Notably, several CSA practices were found to be complementary, underscoring the benefits of adopting multiple practices simultaneously for enhanced farm productivity, especially in an economy heavily reliant on agriculture.

The study's findings underscore that a farmer's financial and social capital significantly influence their decision-making capabilities. Farmers endowed with greater capital resources are more inclined to make informed, rational decisions regarding their farm operations. CSA practices are increasingly recognized as sustainable and resilient approaches in the face of climatic uncertainties. Yet, farmers' adoption decisions are closely tied to their available social and financial resources. This study deduces that farmers with access to e-credit facilities are better positioned to adopt CSA practices. E-credit not only facilitates individual practice adoption but also enables the integration of complementary CSA practices for augmented agricultural output. Furthermore, institutional support mechanisms—such as certified seed availability, structured awareness programs, and soil testing facilities—greatly enhance the likelihood of adopting multiple CSA practices, thereby boosting farm productivity. Additionally, the study highlights the pivotal role of farmers' social structures, particularly education and farming experience, in rationalizing and optimizing farm operations through the strategic selection of CSA practices.

Extending beyond the immediate findings, these insights open avenues for future research, particularly in examining the long-term impacts of integrated CSA practices on environmental sustainability and farm resilience. Future studies could explore the dynamics of E-credit adoption across different agricultural contexts and its broader economic implications. In addition, further research is necessary to understand how educational programs and institutional support can

be effectively scaled to enhance CSA practice adoption and their contribution to environmental conservation and sustainable farming. In light of these findings, the study proposes comprehensive policy recommendations for the agricultural sector. Firstly, it advocates for the expansion of e-credit facilities to rural households, enabling the adoption of multiple CSA practices and promoting sustainable, resilient agricultural practices. Secondly, the importance of institutional support in agricultural productivity enhancement necessitates policy initiatives aimed at transforming and upgrading the rural institutional framework. Finally, the study calls for a thorough review of the social structure of rural communities, with a particular focus on educational and technical training aspects. Enhancing educational opportunities is crucial for enabling farmers to make timely, rational decisions in their farm operations, thereby necessitating government focus on the educational advancement of the rural populace.

Conflict of Interest

The authors declare no conflict of interest.

References

1. WAASWA A., OYWAYA NKURUMWA A., MWANGI KIBE A., NGENO KIPKEMOI J. Climate-Smart agriculture and potato production in Kenya: review of the determinants of practice. *Climate and Development*, **14** (1), 75, **2022**.
2. KASSAYE A.Y., SHAO G., WANG X., BELETE M. Evaluating the practices of climate-smart agriculture sustainability in Ethiopia using geocybernetic assessment matrix. *Environment, Development and Sustainability*, **24** (1), 724, **2022**.
3. TEKESTE K. Climate-Smart Agricultural (CSA) practices and its implications to food security in Siyadebrina Wayu District, Ethiopia. *African Journal of Agricultural Research*, **17** (1), 92, **2021**.
4. DE PINTO A., CENACCHI N., KWON H.-Y., KOO J., DUNSTON S. Climate smart agriculture and global food-crop production. *PloS one*, **15** (4), e0231764, **2020**.
5. NYANG'AU J.O., MOHAMED J.H., MANGO N., MAKATE C., WANGECI A.N. Smallholder farmers' perception of climate change and adoption of climate smart agriculture practices in Masaba South Sub-county, Kisii, Kenya. *Heliyon*, **7** (4), e06789, **2021**.
6. GUL A., CHANDIO A.A., SIYAL S.A., REHMAN A., XIUMIN W. How climate change is impacting the major yield crops of Pakistan? an exploration from long-and short-run estimation. *Environmental Science and Pollution Research*, **29** (18), 26660, **2022**.
7. ZOUGMORÉ R.B., LÄDERACH P., CAMPBELL B.M. Transforming food systems in Africa under climate change pressure: Role of climate-smart agriculture. *Sustainability*, **13** (8), 4305, **2021**.
8. YAQOUB N., ALI S.A., KANNAIAH D., KHAN N., SHABBIR M.S., BILAL K., TABASH M.I. The effects of agriculture productivity, land intensification, on sustainable economic growth: a panel analysis from Bangladesh, India, and Pakistan. *Economies. Environmental Science and Pollution Research*, **1**, **2022**.
9. AWAN A.G., ASLAM A. Impact of agriculture productivity on economic growth: A case study of Pakistan. *Global Journal of Management and Social Sciences*, **1** (1), 57, **2015**.
10. HYE Q.M.A. Agriculture on the road to industrialization and sustainable economic growth: an empirical investigation for Pakistan. *International Journal of Agricultural Economics & Rural Development*, **2** (2), 1, **2009**.
11. RAZA S.A., ALI Y., MEHBOOB F. Role of agriculture in economic growth of Pakistan. *Munich Personal RePEc Archive*, 32273, **2012**.
12. IQBAL M.M., ARIF M. Climate-change aspersions on food security of Pakistan. *A Journal of Science for Development*, **15** (1), 15, **2010**.
13. PAGLIACCI F., DEFRANCESCO E., MOZZATO D., BORTOLINI L., PEZZUOLO A., PIROTTI F., PISANI E., GATTO P. Drivers of farmers' adoption and continuation of climate-smart agricultural practices. A study from northeastern Italy. *Science of the Total Environment*, **710**, 136345, **2020**.
14. ANGOM J., VISWANATHAN P., RAMESH M.V. The dynamics of climate change adaptation in India: a review of climate smart agricultural practices among smallholder farmers in Aravalli district, Gujarat, India. *Current Research in Environmental Sustainability*, **3**, 100039, **2021**.
15. AGBENYO W., JIANG Y., JIA X., WANG J., NTIM-AMO G., DUNYA R., SIAW A., ASARE I., TWUMASI M.A. Does the Adoption of Climate-Smart Agricultural Practices Impact Farmers' Income? Evidence from Ghana. *International Journal of Environmental Research and Public Health*, **19** (7), 3804, **2022**.
16. MAKATE C., MAKATE M., MANGO N., SIZIBA S. Increasing resilience of smallholder farmers to climate change through multiple adoption of proven climate-smart agriculture innovations. Lessons from Southern Africa. *Journal of Environmental Management*, **231**, 858, **2019**.
17. DAS U., ANSARI M., GHOSH S. Effectiveness and upscaling potential of climate smart agriculture interventions: Farmers' participatory prioritization and livelihood indicators as its determinants. *Agricultural Systems*, **203**, 103515, **2022**.
18. SHILOMBOLENI H. Political economy challenges for climate smart agriculture in Africa. *Springer*, **2022**.
19. ABBAS S. Global warming and export competitiveness of agriculture sector: evidence from heterogeneous econometric analysis of Pakistan. *Environmental Science and Pollution Research*, **29** (23), 34325, **2022**.
20. IL ISLAM D., RAHMAN A., SARKER N.I., SARKER S.R., JIANCHAO L. Factors Influencing Rice Farmers' Risk Attitudes and Perceptions in Bangladesh amid Environmental and Climatic Issues. *Polish Journal of Environmental Studies*, **30** (1), **2021**.
21. SARDAR A., KIANI A.K., KUSLU Y. Does adoption of climate-smart agriculture (CSA) practices improve farmers' crop income? Assessing the determinants and its impacts in Punjab province, Pakistan. *Environment, Development and Sustainability*, **23** (7), 10119, **2021**.
22. SCHALLER M., BARTH E.I., BLIES D., RÖHRIG F., SCHÜMMELFEDER M. Climate smart agriculture (CSA): farmyard compost. *International Center for Tropical Agriculture (CIAT); The Centre for Rural Development (SLE), Berlin*, **2017**.

23. NG'ANG'A S.K., RIVERA M., PAMUK H., HELLA J.P. Costs and benefits of climate-smart agriculture practices: Evidence from intercropping and crop rotation of maize with soybean in rural Tanzania. *CGIAR*, 306, **2020**.
24. SHIKUKU K.M., MWONGERA C., WINOWIECKI L.A., TWYMAN J., ATIBO C., LÄDERACH P. Understanding farmers' indicators in climate-smart agriculture prioritization in Nwoya District, Northern Uganda. *Publicación CIAT*, **2015**.
25. BERNIER Q., MEINZEN-DICK R.S., KRISTJANSON P.M., HAGLUND E., KOVARIK C., BRYAN E., RINGLER C., SILVESTRI S. Gender and institutional aspects of climate-smart agricultural practices: evidence from Kenya. *CCAFS Working Paper*, **2015**.
26. ZERSSA G., FEYSSA D., KIM D.-G., EICHLER-LÖBERMANN B. Challenges of smallholder farming in Ethiopia and opportunities by adopting climate-smart agriculture. *Agriculture*, **11** (3), 192, **2021**.
27. MEMARBASHI P., MOJARRADI G., KESHAVARZ M. Climate-Smart Agriculture in Iran: Strategies, Constraints and Drivers. *Sustainability*, **14** (23), 15573, **2022**.
28. ZOUGMORÉ R.B., TRAORÉ A.S., MBODJ Y. Overview of the scientific, political and financial landscape of climate-smart agriculture in West Africa. *CCAFS Working Paper*, **2015**.
29. MAKATE C., MAKATE M., MUTENJE M., MANGO N., SIZIBA S. Synergistic impacts of agricultural credit and extension on adoption of climate-smart agricultural technologies in southern Africa. *Environmental Development*, **32**, 100458, **2019**.
30. OSABOHIEN R., MORDI A., OGUNDIPE A. Access to credit and agricultural sector performance in Nigeria. *African Journal of Science, Technology, Innovation and Development*, **14** (1), 247, **2022**.
31. JAMIL I., JUN W., MUGHAL B., RAZA M.H., IMRAN M.A., WAHEED A. Does the adaptation of climate-smart agricultural practices increase farmers' resilience to climate change? *Environmental Science and Pollution Research*, **28** (21), 27238, **2021**.
32. GASHURE S., WANA D., SAMIMI C. Impacts of climate variability and climate-smart agricultural practices on crop production in UNESCO designated cultural landscapes of Konso, Ethiopia. *Theoretical and Applied Climatology*, **150** (3), 1495, **2022**.
33. NYASIMI M., KIMELI P., SAYULA G., RADENY M., KINYANGI J., MUNGAI C. Adoption and dissemination pathways for climate-smart agriculture technologies and practices for climate-resilient livelihoods in Lushoto, Northeast Tanzania. *Climate*, **5** (3), 63, **2017**.
34. WEKESA B.M., AYUYA O.I., LAGAT J.K. Effect of climate-smart agricultural practices on household food security in smallholder production systems: micro-level evidence from Kenya. *Agriculture & Food Security*, **7** (1), 1, **2018**.
35. KICHAMU-WACHIRA E., XU Z., REARDON-SMITH K., BIGGS D., WACHIRA G., OMIDVAR N. Effects of climate-smart agricultural practices on crop yields, soil carbon, and nitrogen pools in Africa: a meta-analysis. *Journal of Soils and Sediments*, **21** (4), 1587, **2021**.
36. ABEGUNDE V.O., SIBANDA M., OBI A. Effect of climate-smart agriculture on household food security in small-scale production systems: A micro-level analysis from South Africa. *Cogent Social Sciences*, **8** (1), 2086343, **2022**.
37. WICHMANN S. Economic incentives for climate smart agriculture on peatlands in the EU. *Proceedings of the Greifswald Mire Centre*, **1**, 2018, **2018**.
38. KHATRI-CHHETRI A., ARYAL J.P., SAPKOTA T.B., KHURANA R. Economic benefits of climate-smart agricultural practices to smallholder farmers in the Indo-Gangetic Plains of India. *Current Science*, 1251, **2016**.
39. PANGAPANGA-PHIRI I., MUNGATANA E.D. Adoption of climate-smart agricultural practices and their influence on the technical efficiency of maize production under extreme weather events. *International Journal of Disaster Risk Reduction*, **61**, 102322, **2021**.
40. AKROFI-ATITIANI F., IFEJIKI SPERANZA C., BOCKEL L., ASARE R. Assessing climate smart agriculture and its determinants of practice in Ghana: A case of the cocoa production system. *Land*, **7** (1), 30, **2018**.
41. ANUGA S.W., GORDON C., BOON E., SURUGU J.M.-I. Determinants of climate smart agriculture (CSA) adoption among smallholder food crop farmers in the Techiman Municipality, Ghana. *Ghana Journal of Geography*, **11** (1), 124, **2019**.
42. BEYENE A.D., MEKONNEN A., KASSIE M., DI FALCO S., BEZABIH M. Determinants of adoption and impacts of Sustainable Land Management and Climate Smart Agricultural Practices (SLM-CSA): Panel data evidence from the Ethiopian highlands. *Environment for Development*, 17, **2017**.
43. FRANCIS M.-T., JULIUS M., ABDIL K.E., EDWIN K. Determinants of adoption of multiple climate change adaptation strategies in Southern Malawi: An ordered probit analysis. *Journal of Development and Agricultural Economics*, **9** (1), 1, **2017**.
44. NEGERA M., ALEMU T., HAGOS F., HAILESLASSIE A. Determinants of adoption of climate smart agricultural practices among farmers in Bale-Eco region, Ethiopia. *Heliyon*, **8** (7), e09824, **2022**.
45. MTHETHWA K.N., NGIDI M.S.C., OJO T.O., HLATSHWAYO S.I. The Determinants of Adoption and Intensity of Climate-Smart Agricultural Practices among Smallholder Maize Farmers. *Sustainability*, **14** (24), 16926, **2022**.
46. MURIITHI L.N., ONYARI C.N., MOGAKA H.R., GICHIMU B.M., GATUMO G. N., KWENA K. Adoption determinants of adapted climate smart agriculture technologies among smallholder farmers in Machakos, Makueni, and Kitui Counties of Kenya. *Journal of Agricultural Extension*, **25** (2), 75, **2021**.
47. DIRO S., TESFAYE A., ERKO B. Determinants of adoption of climate-smart agricultural technologies and practices in the coffee-based farming system of Ethiopia. *Agriculture & Food Security*, **11** (1), 1, **2022**.
48. SAHA M.K., BISWAS A.A.A., FAISAL M., MEANDAD J., AHMED R., PROKASH J., SAKIB F.M. Factors Affecting to Adoption of Climate-smart Agriculture Practices by Coastal Farmers' in Bangladesh. *American Journal of Environment and Sustainable Development*, **4** (4), 113, **2019**.
49. NYANG'AU J.O., MOHAMED J.H., MANGO N., MAKATE C., WANGECI A.N., AHENDA S.O. Determinants of smallholder farmers' choice of climate smart agriculture practices to adapt to climate change in masaba south Sub-County, Kisii, Kenya. *Asian Journal of Agricultural Extension, Economics & Sociology*, **38** (May), 29, **2020**.

50. AUTIO A., JOHANSSON T., MOTAROKI L., MINOIA P., PELLIKKA P. Constraints for adopting climate-smart agricultural practices among smallholder farmers in Southeast Kenya. *Agricultural Systems*, **194**, 103284, **2021**.
51. TSIGE M., SYNNEVÅG G., AUNE J.B. Gendered constraints for adopting climate-smart agriculture amongst smallholder Ethiopian women farmers. *Scientific African*, **7**, e00250, **2020**.
52. BADAR H., GHAFOR A., ADIL S.A. Factors affecting agricultural production of Punjab (Pakistan). *Pakistan Journal of Agriculture Science*, **44** (3), **2007**.
53. MUMTAZ M., DE OLIVEIRA J.A.P., ALI S.H. Climate change impacts and adaptation in agricultural sector: the case of local responses in Punjab, Pakistan. *IntechOpen London, UK*, **2019**.
54. KURGAT B.K., LAMANNA C., KIMARO A., NAMOI N., MANDA L., ROSENSTOCK T.S. Adoption of climate-smart agriculture technologies in Tanzania. *Frontiers in Sustainable Food Systems*, **4**, 55, **2020**.
55. MWUNGU C.M., MWONGERA C., SHIKUKU K.M., ACOSTA M., LÄDERACH P. Determinants of adoption of climate-smart agriculture technologies at farm plot level: An assessment from Southern Tanzania. *Handbook of climate Change Resilience*, **1**, **2018**.
56. BOZ I., SHAHBAZ P. Adoption of climate-smart agriculture practices and differentiated nutritional outcome among rural households: a case of Punjab province, Pakistan. *Food Security*, **13** (4), 913, **2021**.
57. SHAHBAZ P., ABBAS A., AZIZ B., ALOTAIBI B.A., TRAORE A. Nexus between Climate-Smart Livestock Production Practices and Farmers' Nutritional Security in Pakistan: Exploring Level, Linkages, and Determinants. *International Journal of Environmental Research and Public Health*, **19** (9), 5340, **2022**.
58. MAGUZA-TEMBO F., EDRISS A.-K., MANGISONI J. Determinants of climate smart agriculture technology adoption in the drought prone districts of Malawi using a multivariate probit analysis. *Asian Journal of Agricultural Extension, Economics and Sociology*, **16** (3), 1, **2017**.
59. MUSAFIRI C.M., KIBOI M., MACHARIA J., NG'ETICH O.K., KOSGEI D.K., MULIANGA B., OKOTI M., NGETICH F.K. Adoption of climate-smart agricultural practices among smallholder farmers in Western Kenya: do socioeconomic, institutional, and biophysical factors matter? *Heliyon*, **8** (1), e08677, **2022**.
60. KHAN N.A., MA W., OWUSU V., SHAH A.A. Does ICTs-based farm advisory services improve farmers' adaptation to climate change? Evidence from Pakistan. *Climate and Development*, **1**, **2022**.
61. KHAN N.A., QIAO J., ABID M., GAO Q. Understanding farm-level cognition of and autonomous adaptation to climate variability and associated factors: Evidence from the rice-growing zone of Pakistan. *Land Use Policy*, **105**, 105427, **2021**.
62. TANEJA G., PAL B.D., JOSHI P.K., AGGARWAL P.K., TYAGI N.K. Farmers' preferences for climate-smart agriculture – An assessment in the Indo-Gangetic Plain. In *Climate Smart Agriculture in South Asia*, Springer, pp. 91, **2019**.
63. FAISAL M., CHUNPING X., ABBAS A., RAZA M. H., AKHTAR S., AJMAL M. A., ALI A. Do risk perceptions and constraints influence the adoption of climate change practices among small livestock herders in Punjab, Pakistan? *Environmental Science and Pollution Research*, **28** (32), 43777, **2021**.
64. ONI T.S., AFOLAMI C.A., OBAYELU A.E., IDOWU M.A. Effects of Adoption of Climate Smart Agricultural Practices on Food Insecurity among Rice Farming Households in the Savanna and Rainforest Agro-Ecological Zones in Southwest, Nigeria. *International Journal of Progressive Research in Science and Engineering*, **2** (03), 12, **2022**.
65. MUJEYI A., MUDHARA M., MUTENJE M.J. Adoption determinants of multiple climate smart agricultural technologies in Zimbabwe: Considerations for scaling-up and out. *African Journal of Science, Technology, Innovation and Development*, **12** (6), 735, **2020**.
66. MUSYOKI M.E., BUSIENEI J.R., GATHIACA J.K., KARUKU G.N. Linking farmers' risk attitudes, livelihood diversification and adoption of climate smart agriculture technologies in the Nyando basin, South-Western Kenya. *Heliyon*, **8** (4), e09305, **2022**.
67. KPADONOU R.A.B., OWIYO T., BARBIER B., DENTON F., RUTABINGWA F., KIEMA A. Advancing climate-smart-agriculture in developing drylands: Joint analysis of the adoption of multiple on-farm soil and water conservation technologies in West African Sahel. *Land Use Policy*, **61**, 196, **2017**.
68. MAINDI N., OSUGA I., GICHEHA M. Advancing climate smart agriculture: adoption potential of multiple on-farm dairy production strategies among farmers in Murang'a County, Kenya. *Livestock Research for Rural Development*, **32** (4), **2020**.
69. ARYAL J.P., RAHUT D.B., MAHARJAN S., ERENSTEIN O. Factors affecting the adoption of multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India. *Wiley Online Library*, **42** (3), **2018**.