

Nexus of climate change adaptation and household wealth in climate risk hotspots – Insights from rural farm households of Pakistan

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ABSTRACT

The agricultural sector is a cornerstone of economic development, particularly in low-income countries where smallholder farming supports livelihoods and food security. However, the increasing unpredictability of climatic factors poses significant challenges, threatening its capacity to bolster smallholder farmers' household wealth through food production. While climate adaptation measures have been widely promoted, there remains a notable lack of empirical evidence establishing the relationship between climate adaptation and household wealth. Addressing this critical research gap, this study examines the relationship between climate adaptation and household wealth among 400 wheat smallholder farmers in Sindh province, Pakistan. Using endogenous switching regression (ESR) and propensity score matching (PSM) for robustness, we estimate the average treatment effect on the treated (ATT). The results consistently show that climate adaptation significantly increases per capita household wealth, primarily through enhanced crop production. Counterfactual analysis reveals that non-adopting households could have reduced poverty severity by 15% and extreme poverty by 17% had they adopted adaptation measures. These findings provide compelling empirical evidence for policymakers to prioritize adaptation support frameworks—such as subsidized inputs or training programs—which are indispensable for safeguarding food production, reducing climate vulnerability, and lifting smallholders out of poverty. By demonstrating the dual benefits of adaptation—wealth accumulation and poverty alleviation—this study underscores the urgency of scaling up climate-resilient agricultural practices as a key strategy for reducing vulnerability and fostering sustainable livelihoods.

1. Introduction

The agriculture sector plays a central role in the economy of developing nations (Aker, 2011; Tang, Lee, Huang, & Zhou, 2022; Zezza & Tasciotti, 2010). Particularly, in Pakistan, it contributes 18.9 percent to GDP and absorbs 42.3 percent of the labor force (Azam

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& Shafique, 2017; Syed, Raza, Bhatti, & Eash, 2022). In addition, the sector is an important source of foreign exchange earnings and stimulates growth in other sectors by providing the raw material to industrial areas. In doing so, agriculture contributes to the welfare of farmers – improves household food and nutrition security (Mwalupaso, Wang, Eshetie, & Tian, 2020), augments household income (Sekabira & Qaim, 2017), and household wealth (Edirisinghe, 2015). Accordingly, agriculture potentially contributes towards the fight against hunger and eradication of poverty. However, given the direct effect that climate change bears on agricultural output, it stands as one of the most susceptible sectors to the adverse influence of climate change especially for farmers in developing nations. In fact, unlike large-scale, the impacts of climate change are more severe for smallholder farmers. Climate change affects rural per capita income and poverty levels by drastically reducing agricultural productivity (Esham & Garforth, 2013; Ozdemir, 2022). To minimize the unexpected effects of climate change, identification of the changes in climatic variables and adjusting the farming practices in a way that copes with the change is essential for the smallholder farmers.

For the last two decades, the agriculture sector growth (especially food production) of Pakistan's economy has adversely been affected due to unpredicted climatic changes (Aslam, 2016; Ishaque, Tanvir, & Mukhtar, 2022). Continuous increase in temperature, series of floods from 2010 to 2014, long span of droughts and occurrence of new pests and diseases has greatly affected the agricultural production (Abbas, Han, Adeel, & Ullah, 2019; Abid, Schilling, Scheffran, & Zulfiqar, 2016). It is worth noting that these unpredicted changes in climatic factors declined the agricultural production and gravely threatened the food security of the country. Consequently, this inconvenienced the livelihoods of agricultural stakeholders, and demanded creativity in innovating new and advanced technologies for combating the adverse impact of climate change on the agriculture sector (Rehman, Ozturk, & Zhang, 2019). The government focused on supporting small and marginalized farmers while advocating for adaptation.

Coincidentally, the country's population is growing at the rate of 2.4 percent per annum which implies massive pressure for farmers especially those producing staples – rice and wheat. Crop production plays a significant role in the value addition of the agriculture sector and GDP of Pakistan. According to the 2017/2018 Economic Survey, important crop (wheat, rice, sugarcane, maize, and cotton) accounts for 23.60 % and 4.45 % in the value addition of the agriculture sector and GDP respectively. Precisely, wheat is an important food and cash crop of Pakistan. It contributes 9.1 % of the value-added agriculture and 1.7 % GDP contribution (GoP, 2017-18). Thus, adaptation is a key strategy to alleviate the severity of climate change impacts on food production and also household wealth. Adger et al. (2007) advances that adaptation enhances resilience and this aids in increasing yield. Given that Pakistan's agriculture purpose has changed from self-sufficiency to commercialization, increased yield will culminate in increased income which is likely to augment household wealth.

According to Masud et al. (2017), adaptation in this sense refers to dealing with the destructive effects of a changing climate on agriculture, which might eventually decrease vulnerability or enhance resilience. Generally, the choice of adaptation methods applied is driven by not only the economic structure but also environmental, institutional and socio-economic factors. Some common adaptation strategies used are irrigation, improved crop varieties, minimum tillage, changing planting dates, planting trees and crop rotation with legumes. However, for most smallholder farmers in rural area, the capacity to adapt is uncertain on account of poor socio-economic conditions (Wood, Jina, Jain, Kristjanson, & DeFries, 2014). In addition, there is less comprehension among farmers on issues of climate change (Alam & Siwar, 2009) yet they are exposed to high climatic risks. Consequently, most rice and wheat farmers have a low adaptive capacity (Adger & Vincent, 2005; Nazari, Rad, Sedighi, & Azadi, 2015) which affects their yields and also income. Thus, poverty and hunger is persistent. To overcome the welfare losses, development of comprehensive program of actions to address the hostile effects of climate change is an essential prerequisite especially for farmers in rural areas.

In an effort to build up a policy framework to fight against climate change, scholars have approved that adaptation strategies are pivotal in aiding local communities to cope with associated climatic variations and extreme weather conditions (Adger et al., 2007; Alam & Siwar, 2009). In this regard, most studies focus on farmers' perception to climate change and behavioral intent to adapt. They argue that the ability of farmers to recognize climate change is essential for adaptation. While this is true, a story of the benefits of adaptation is not complete because up till now, the nexus of household wealth and adaptation has never benefitted from empirical evidence. Based on the theory of rational choice, the decision to adapt is made when the benefits derived outweigh that from not adapting. Therefore, to address this knowledge gap, this study aims at evaluating the nexus of adaptation and household wealth among wheat farmers. Consequently, the contribution of the study is two-fold. First, the link of adaptation and household wealth is important for policymakers to promote adaptation and also household wealth which are important for realizing climate action and eradicating poverty and hunger respectively. Finally, to the best of the researchers' knowledge, such a study has never been conducted especially for wheat production, yet it holds so much potential to ensure food security and alleviate rural households from poverty.

2. Materials and methods

2.1. Theoretical underpinning

This study is anchored in an integrated theoretical framework that combines Protection Motivation Theory (PMT), the Sustainable Livelihoods Framework (SLF), and the Agricultural Household Model to explain the mechanisms linking climate change adaptation to household wealth accumulation. These complementary theories collectively address the psychological, socio-economic, and production dimensions of farmers' adaptation decisions and their welfare impacts.

At the behavioral level, Protection Motivation Theory provides crucial insights into the cognitive processes driving adaptation decisions (Rogers, 1975). The theory posits that farmers undertake adaptive actions when they: (1) perceive climate threats as severe (threat appraisal), and (2) believe available adaptation measures are effective and feasible (coping appraisal). This psychological framework helps explain why some farmers adopt climate-smart practices while others do not, even when facing similar climatic risks

(Bazrafkan et al., 2022; Keshavarz & Karami, 2016; Mosavian, Rostami, & Tatar, 2023; Villamor, Wakelin, Dunningham, & Clinton, 2023). Our study extends PMT by demonstrating how these adaptive behaviors ultimately translate into measurable wealth gains.

Additionally, the Sustainable Livelihoods Framework then elucidates the pathways through which adaptation strategies enhance household wealth (Chambers & Conway, 1992). Climate-resilient practices function as investments that build five key livelihood assets: (1) natural capital (improved land/water resources), (2) human capital (skills/knowledge), (3) financial capital (income/savings), (4) physical capital (tools/infrastructure), and (5) social capital (networks/support systems). By strengthening these inter-linked assets, adaptation measures create virtuous cycles of productivity and income growth that elevate household economic status (Call & Sellers, 2019; Natarajan, Newsham, Rigg, & Suhardiman, 2022).

The Agricultural Household Model provides the microeconomic foundation for understanding production decisions under climate stress (I. Singh, Squire, & Strauss, 1986). This model conceptualizes farm households as integrated units making simultaneous production and consumption choices under resource constraints. Climate adaptation enters this framework as a risk management strategy that stabilizes production functions, enabling more optimal allocation of land, labor and capital (Below et al., 2012; Mukherjee & Fransen, 2024). The model predicts that adaptation leads to greater marketable surplus, which directly boosts household income and wealth accumulation potential (Ogada, Rao, Radeny, Recha, & Solomon, 2020).

The synergy of these theories offers a comprehensive explanation of the adaptation-wealth nexus: PMT explains the initial adoption decisions, SLF maps the asset-building pathways, and the Agricultural Household Model quantifies the production and income effects. This multi-layered theoretical approach not only addresses the psychological and structural factors influencing adaptation outcomes, but also provides policymakers with actionable insights for designing interventions that simultaneously enhance climate resilience and economic welfare.

2.2. Data and description of study site

The data used in this study is from a household survey conducted in Sindh Province of Pakistan. It is strategically located in the South Asian region, attracting massive investment in different sectors from developed countries (Chandio, Mirani, & Shar, 2019). The country's agricultural sector consists of five sub sectors – livestock, fisheries, major crops, minor crops and forestry (GoP, 2017-18). As earlier indicated, the major crops are cotton, wheat, sugarcane, rice and maize while the minor crops are bajra, jowar, gram, barely and tobacco. The contribution of these sectors towards agriculture value addition and GDP is significant. Additionally the contribution of other sub sectors like livestock, fisheries and forestry also have a meaningful contribution to GDP (Chandio, Yuansheng, & Magsi, 2016). Apart from water shortage, lack of improved seed and advanced technologies, and shortage of finance to buy the basic inputs for agriculture production, Pakistan faces serious climate related challenges. However, Sindh faces multiple climate-related challenges, including water scarcity, limited access to improved seeds, and financial constraints, all of which directly impact farmers' adaptive capacity and household economic outcomes.

To capture the heterogeneity in climate change adaptation and wealth accumulation among wheat farmers, a two-stage sampling technique was employed. First, four districts within Sindh were purposively selected based on their high exposure to climate risks. Within each district, 100 wheat-farming households were randomly selected, yielding a total sample of 400 respondents. Data collection was conducted using a structured and pretested questionnaire, administered by trained enumerators. Triangulation was employed to enhance data validity, incorporating focus group discussions (FGDs) with farmers and structured interviews with agricultural extension officers, farmer organization leaders, and other key stakeholders.

The selection of variables in this study is rooted in the theoretical framework comprising Protection Motivation Theory (PMT), the Sustainable Livelihoods Framework (SLF), and the Agricultural Household Model. The dependent variable, household wealth, aligns with SLF, which posits that wealth accumulation is shaped by the diversification and strengthening of livelihood assets. The explanatory variables were selected to reflect key determinants of adaptation decisions and their economic impacts, as supported by prior empirical studies.

The inclusion of cultivated land size captures production capacity, as larger farms typically have greater resource endowments to adopt climate adaptation strategies (Below et al., 2012). Extension contact reflects the role of institutional support in facilitating adaptation through knowledge dissemination (Ogada et al., 2020). Gender of the household head is considered, as male-headed households often have better access to productive resources and external support networks, influencing adaptation uptake (Natarajan et al., 2022). Social capital, measured through group membership, aligns with SLF's emphasis on networks as a crucial asset for sharing information and accessing collective resources (Call & Sellers, 2019).

Farmers' experience and education levels are included based on PMT, as they shape cognitive appraisals of climate risks and the perceived efficacy of adaptation measures (Bazrafkan et al., 2022; Villamor et al., 2023). Household size accounts for labor availability, which influences the feasibility of adopting labor-intensive adaptation strategies. Market distance is incorporated as it affects transaction costs and market access, which can determine the profitability of adaptive investments (Mukherjee & Fransen, 2024).

To directly assess adaptation decisions, we include variables such as access to credit, which determines financial liquidity for adaptation investments (Below et al., 2012). Climate information access reflects the frequency of receiving weather forecasts, a key factor in informed decision-making under climate uncertainty. Soil quality perception influences the adoption of soil conservation measures, while off-farm income measures diversification strategies that mitigate agricultural income risks (Amadu, McNamara, & Miller, 2020). Risk aversion (self-risk assessment) is included based on PMT, as risk perception influences the likelihood of adopting adaptation measures (Keshavarz & Karami, 2016). Finally, training on climate adaptation captures human capital development, which enhances the ability to implement effective adaptation practices.

By integrating these theoretically and empirically grounded variables, this study provides a robust assessment of the pathways

linking climate adaptation to household wealth. The descriptive statistics for these variables are presented in Table 1.

2.3. Measurement of key variables

Household wealth, the outcome variable of interest, is the current value of farmer's household assets, expenditure and income in the survey year. It is a continuous variable in Pakistani Rupee and measurement of household wealth in this manner was also done by Bedelian, Ogutu, Homewood, and Keane (2023).

Adaptation to climate change is the primary explanatory variable in the study. It is captured as a dummy where 1 represents farmers who have adapted to climate change and 0 otherwise. A farmer is considered as an adopter if they have implemented at least one of the following in the survey year: improved seed (stress tolerant varieties), crop rotation with legume, minimum tillage, changing planting dates and irrigation

2.4. Analytical framework and empirical strategy

To achieve the objectives of the study, endogeneous switching regression (ESR) and propensity score matching (PSM) were applied.

2.4.1. Endogeneous switching regression

Endogenous Switching Regression (ESR) is a statistical method designed to analyze both the factors influencing farmers' decisions to adapt to climate change and the effects of those decisions on household wealth. Farmers face two options: adapting to climate change or not adapting. Their choice is not random; it is influenced by various household and farm characteristics, as well as their perceptions of risk and opportunity. ESR takes this into account, ensuring the analysis captures both the decision-making process and its consequences. The method assumes that farmers choose to adapt only if they expect their household wealth to increase as a result.

The ESR process involves two main steps. In the first step, ESR models the farmer's decision to adapt as a binary choice: adapt (yes) or not adapt (no). This decision depends on factors such as farm size, training, and access to information. ESR identifies these determinants using a "selection equation," which explains why some farmers adapt and others do not. In the second step, ESR estimates household wealth for two groups—adopters and non-adopters. Crucially, ESR also goes a step further by conducting a "what-if" analysis. It estimates counterfactual scenarios, such as what the wealth of adopters would have been if they had not adapted, and what the wealth of non-adopters would have been if they had adapted. These counterfactuals provide insights into the true impact of adaptation.

A key strength of ESR is its ability to compute two important measures: the Average Treatment Effect on the Treated (ATT) and the Average Treatment Effect on the Untreated (ATU). ATT shows the additional wealth adopters gain by adapting, compared to what they would have gained had they not adapted. ATU, on the other hand, shows the wealth non-adopters could have gained if they had chosen to adapt. By accounting for selection bias and enabling counterfactual analysis, ESR provides a robust framework to evaluate the impact of adaptation decisions on household wealth while addressing the differences between those who adapt and those who do not. This makes ESR a powerful tool for understanding the causal effects of climate change adaptation strategies.

Table 1
Descriptive Statistics.

Variable category	Description	Pooled N = 400	Adopter N = 257	Non-adopter N = 143
Outcome variable				
Household wealth	The current value of farmer's household assets, expenditure and income in the survey year in Pakistani Rupee	67451.71 (45667.79)	71149.89 (45148.96)	60805.34 (45999.36)
Control Variables				
Cultivated Land	The size of the area used for wheat production in acres	1.691 (1.256)	1.761 (1.112)	1.566 (1.477)
Extension Contact	Contact with agricultural extension officer (1 = has contact)	0.275 (0.447)	0.284 (0.452)	0.259 (0.439)
Gender	The sex of household head (1 = male)	0.85 (0.358)	0.844 (0.363)	0.86 (0.348)
Social Capital	If a farmer belongs to a farmer group (1 = is a member)	0.907 (0.29)	0.883 (0.322)	0.951 (0.217)
Farmer Experience	The number of years of farmer experience	20.595 (11.723)	19.913 (9.815)	21.823 (14.501)
Household Size	The number of people in a household	6.023 (3.26)	5.514 (2.785)	6.937 (3.817)
Education	If a farmer has attained basic education (1 = has attained basic education)	0.632 (0.483)	0.58 (0.495)	0.727 (0.447)
Age	The age of the household head	40.635 (12.769)	38.693 (10.233)	44.126 (15.82)
Market	The distance to the nearest market in kilometers	8.287 (3.589)	8.222 (3.658)	8.406 (3.471)
Access to Credit	Formal loan access (1 = received agri-loan in past 2 years)	0.065 (0.247)	0.035 (0.184)	0.082 (0.274)
Climate Information	Access to climate information (1 = has access)	0.658 (0.475)	0.709 (0.455)	0.608 (0.489)
Soil fertility perception	Farmer self-reported soil fertility perception (1 = good)	0.275 (0.447)	0.259 (0.439)	0.284 (0.452)
off-Farm Income	Farmers' participation in off-farm employment (1 = participant)	0.873 (0.334)	0.909 (0.288)	0.852 (0.356)
Training	Training attendance on climate change and adaptation (1 = has attended training)	0.32 (0.467)	0.486 (0.501)	0.021 (0.144)
Selfrisk	Farmer self-reported assessment on risk aversion (1 = is risk averse)	0.522 (0.5)	0.447 (0.498)	0.657 (0.476)
Crop failure	Prior crop failure (1 = experienced crop failure before)	0.125 (0.331)	0.163 (0.37)	0.087 (0.283)

Notes: The number in the parenthesis is the standard deviation

With this in mind, we apply the ESR by simultaneously estimating the factors affecting adaptation (criterion function) and also the relationship between the outcome variables (household wealth) and technology adoption (adaptation) conditional on their selection criterion, using an efficient procedure developed by Lokshin and Sajaia (2004) that uses full information maximum likelihood (FIML) method. Guided by random utility theory, farmers choose between adaptation to climate change or not based on their expected net household wealth benefits. Intuitively, net household wealth is a latent variable (I^*) capturing the difference ($Y_{\text{Adopter}} - Y_{\text{Non-adopter}}$) between household wealth accruing from adaptation (Y_{Adopter}) and non-adaptation ($Y_{\text{Non-adopter}}$). Thus, only when the difference is positive will households adapt to climate change. The first stage of the ESR, which is climate change adaptation decision in a latent variable framework, is specified as follows:

$$I^* = G'\alpha + \varepsilon_v \text{ with } I = \begin{cases} 1 & \text{if } I^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Where I^* is not observable, but we observe a binary indicator variable (I) which is adaptation or not, G includes a range of household and farm characteristics and also farmers' attitude towards adaptation as captured in Table 1, α is a vector of parameters to be estimated, and ε_v is a random error term with mean zero and variance σ^2 .

Since farmers decide to adapt to climate change or not, the household wealth outcomes for each regime are specified as an endogenous switching regime model conditional on I as follows:

$$\text{Regime 1 : } Y_{\text{Adopter}} = X'\beta_{\text{Adopter}} + \varepsilon_u \text{ if } I = 1 \text{ and,} \quad (2)$$

$$\text{Regime 2 : } Y_{\text{Non-adopter}} = X'\beta_{\text{Non-adopter}} + \varepsilon_n \text{ if } I = 0. \quad (3)$$

Where X represents a vector of covariates, and β is a vector of parameters to be estimated.

To ensure proper identification in the Endogenous Switching Regression (ESR) model, the variables in (G') (the adaptation equation) and (X') (the outcome equations) are allowed to overlap. However, at least one variable in (G'), known as the instrumental variable (IV), must not appear in (X'). This exclusion is critical for identifying the causal relationship between adaptation and household wealth. In this study, we used two instrumental variables: Selfrisk (a farmer's self-reported risk aversion, where 1 = risk-averse) and Crop failure (whether the farmer has experienced crop failure before, where 1 = experienced crop failure). These variables were validated through a falsification test. The test confirmed that both instruments were strongly correlated with the likelihood of adaptation—Selfrisk ($\beta = -0.185$, ($p < 0.002$)) and Crop failure ($\beta = 0.782$, ($p = 0.035$)). Importantly, they exhibited weak and statistically insignificant correlations with household wealth—Selfrisk ($\beta = 0.162$, ($p = 0.142$)) and Crop failure ($\beta = 0.471$, ($p = 0.102$)). This ensures the validity of the instruments, as they influence the decision to adapt without directly affecting the outcome variable, household wealth. By satisfying these conditions, the ESR model effectively accounts for selection bias, allowing for reliable estimation of the impact of climate change adaptation on household wealth.

Finally, as part of the postestimation process, the ATT and ATU are calculated by comparing the expected household wealth outcomes for adopters and non-adopters under both real and hypothetical scenarios. In the real scenarios, the observed household wealth outcomes for adopters and non-adopters, based on their actual adaptation decisions, are compared with the counterfactual scenarios. In these counterfactual scenarios, hypothetical outcomes are estimated (Lokshin & Sajaia, 2004): for adopters, what would their household wealth have been if they had not adapted? For non-adopters, what would their household wealth have been if they had chosen to adapt?

Thus, ATT and ATU are computed as follows:

$$ATT = E(Y_{\text{Adopter}} | I = 1, X) - E(Y_{\text{Non-adopter}} | I = 1, X) \quad (4)$$

$$ATU = E(Y_{\text{Adopter}} | I = 0, X) - E(Y_{\text{Non-adopter}} | I = 0, X) \quad (5)$$

2.4.2. Propensity score matching-Robustness check

To ensure reliable estimates, we used Propensity Score Matching (PSM) to analyze the factors that influence farmers' decisions to adapt to climate change and to measure the impact of adaptation through the Average Treatment Effect on the Treated (ATT). When comparing two groups—those who adapted (treatment group) and those who did not adapt (control group)—the results can sometimes be misleading. This is because the two groups may differ in ways that affect both their decision to adapt and their household outcomes. For example, farmers who adapt may have better access to resources or information compared to those who do not, introducing a bias in the comparison.

PSM is a method developed by Rosenbaum and Rubin (1983) to address this bias. It works by pairing or “matching” farmers in the treatment group with similar farmers in the control group based on shared characteristics, such as farm size, education, or access to credit. By creating a more balanced comparison, PSM ensures that the two groups are as similar as possible, except for their decision to adapt. This allows us to isolate the impact of adaptation on household wealth and draw more accurate conclusions as follows:

$$Y = Y_1 - Y_0 \quad (6)$$

Where Y_1 the outcome (household wealth) is when the household is participates in a program (treated) and Y_0 is the outcome when the household doesn't participate (untreated).

However owing to the fact that only one potential outcome is observed for each household, this generates a fundamental assess-

ment problem which is resolved by using a technique that permits identification of appropriate impacts through counterfactual outcome calculations in the absence of data (Mullan, Kontoleon, Swanson, & Zhang, 2010). Thus, the observed outcome (Y) for any household is defined as:

$$Y = AY_1 + (1 - T)Y_0 \quad (9)$$

Where A denotes a dummy variable for participation in the program (1 for farmers who adapt to climate change and 0 is otherwise), and this is further expressed as a function of impact variables (X) and the error terms (U_1 ; U_0)

$$Y_1 = X + U_1 \text{ and } Y_0 = X + U_0 \quad (8)$$

There are two assumptions of PSM and where these hold, average treatment effect (ATE) and average treatment effect on the treated (ATT) can be estimated (Abadie & Imbens, 2006).

The first assumption being that given a set of observable covariates, potential outcome is independent of the treatment allocated. This is called conditional independence assumption (CIA) and is expressed as:

$$(Y_1), (Y_0) \perp T | X \quad (9)$$

The second and last assumption being that impeccable predictability is prevented by overlap condition or common support, and this is expressed as:

$$0 < P(T = 1 | X) < 1 \quad (10)$$

Since household wealth is the outcome variable while adaptation is the treatment variable, factors affecting adaptation and calculation of the average treatment effect of the treated (ATT) can be evaluated simultaneously. To estimate the impact of the adaptation on productivity, the model is expressed as follows:

$$Y_i = \delta A_i + X_i \beta + z \quad (11)$$

Where Y_i is the outcome variables (household wealth) of i farmer, X_i is a vector of impact variables for i farmer, and A_i is the treatment variable for i farmer. The coefficient δ measures the impact of adaptation on the outcome variables and z is the error.

$$ATT = E[E(Y|A = 1, X = x) - E(Y|A = 0, X = x) | A = 1] \quad (12)$$

3. Empirical analysis and discussion

3.1. Incidence of adaptation to climate change

Table 2 presents the adoption intensity of farmers who have adapted to climate change. Among the five adaptation strategies considered, the most implemented is changing of planting dates. This makes sense especially considering that low uptake of new innovation in most developing countries is attributed to risk aversion. It appears there is relatively less risk associated with change of planting dates because it is only a matter of decisions based on climate information a farmer is exposed to.

The lowest incidence is for farmers practicing minimum tillage which has the advantage of improving soil fertility and conserving the soil structures. It is argued among the supporters of climate smart agriculture that it significantly improves the crop yield. The same is said of use of stress tolerant varieties and crop rotation with legumes. Lastly since, most crops require water to be productive, irrigation is very important to promote crop growth. Generally, all the strategies adopted by farmers are critical for driving productivity. The overall adoption rate of about 64 % is low in the context that climate is changing and Pakistan relies on wheat for food and also for income earnings. In view of the growing population, more farmers need to adapt to climate change because it aids farmers to cope with extreme weather conditions and associated climatic variations (Adger et al., 2007).

3.2. Nexus of climate change adaptation and household wealth

To simultaneously evaluate the determinants of climate change adaptation and the average treatment effect on the treated and

Table 2
Adoption intensity.

Item	Adopters	%
Adaptation in General	257	64.25
<i>Adaptation strategies</i>		
Improved seed (stress tolerant varieties)	220	55
Crop rotation with legume	200	50
Minimum tillage	180	45
Changing planting dates	257	64.25
Irrigation	245	61.25

untreated, ESR was applied. The result of the criterion function in Table 3 reveals that gender, farmer experience, age, household size, size of cultivated land, self-assessed risk for adaptation and training on adaptation are significant factors stirring adaptation to climate change. Consistent with most studies, age and farmer experience are opposite in their impact on technology adoption. As farmers age, they become too rigid to change their farming practices but with more farming experience, they are well aware of the changes that need to be incorporated for auspicious agricultural outputs. Therefore, more experienced farmers are likely to adapt to climate change.

Interestingly, farmers with larger cultivated land for wheat production have a higher propensity for climate change adaptation. The reasoning is that the risk is very high for large farms if climate change had its devastating impact on production. So, in the interest of securing their production, adaptation is seen as a remarkable insurance. In support, Chang and Tsai (2015) affirm that in increasing agricultural production, and farmers' incomes, new technology plays a pivotal role. However, farmers who are more risk averse are less likely to adopt the technology. Sadly, according to Mao, Zhou, Ifft, and Ying (2019) high-risk aversion could eventually hinder development of modern agriculture especially in developing countries like Pakistan where diffusion of new technology has been slow on account of risk aversion. One possible solution is to intensify on training farmers on adaptation to climate change because farmers who have attended training on adaptation have a higher likelihood to adopt. This is consistent with the finding of Zamasiya, Nyikahadzo, and Mukamuri (2017) who indicated that farmers who are exposed to more climate and adaptation information are more likely to devise adaptation strategies. This is because such information empowers farmers to be capable of recognizing climate change, an essential prerequisite for adaptation.

Contrary to our expectation, as household size increases, the propensity to adapt decreases. Given that family members are also a great source of labor for the household, large households have more available workforce which eases implementation of most adaptation strategies. This could suggest the underutilization of available labor in households or that most members are too young to be engaged in labor. This view is supported by the result in that male headed households are more likely to adapt than their counterpart. As concluded by Rasheed, Mwalupaso, Abbas, Tian, and Waseem (2020) men are engaged in more physical farming works than women.

We also find that access to climate information, soil fertility perception and prior crop failure positive and significantly influence climate change adaptation. Access to timely and reliable climate information plays a critical role in shaping farmers' adaptation decisions. Climate information—such as seasonal forecasts, weather predictions, and early warning systems—enhances farmers' awareness of climate risks and enables them to make proactive adjustments in their farming practices (Deressa et al., 2009; Mabe et al., 2014). The positive and significant effect of this variable suggests that farmers who have better access to climate information are more likely to adopt adaptation strategies. This finding is consistent with previous studies that highlight the role of climate services in reducing uncertainty and improving decision-making in agricultural production (Hansen et al., 2011; Tesfaye & Seifu, 2016). Given the rapid advancements in digital communication technologies, improving farmers' access to climate information through mobile applications, radio broadcasts, and extension services could further enhance adaptation rates.

Farmers' perception of soil fertility significantly influences their decision to adopt climate change adaptation strategies. This relationship suggests that farmers who perceive their soil as fertile and productive may be more willing to invest in adaptation measures that sustain or enhance soil quality over time. Conversely, farmers who view their soil as degraded might perceive adaptation investments as less beneficial or too costly due to lower expected returns. This finding aligns with the Sustainable Livelihoods Framework (SLF), which posits that the availability of natural capital (such as soil fertility) is a fundamental determinant of livelihood strategies. Thus, policies that promote soil conservation, organic fertilization, and sustainable land management practices could

Table 3
Endogeneous switching regression estimation.

Explanatory variables	Criterion function		Non-adopter		Adopter	
	Coef	SE	Coef	SE	Coef	SE
Gender	0.506*	0.274	0.087	0.096	−0.054	0.066
Farmer Experience	0.060**	0.026	0.013***	0.005	0.003	0.005
Age	−0.075***	0.024	0.005	0.005	0.042***	0.015
Household Size	−0.003*	0.002	0.005*	0.002	0.002	0.001
Market Distance	−0.215***	0.050	−0.026**	0.011	−0.039*	0.021
Cultivated Land	0.434***	0.134	0.309***	0.026	0.214	0.248
Social Capital	0.041**	0.017	0.044***	0.017	0.039**	0.017
Education	0.361***	0.045	0.178**	0.079	0.045	0.053
Extension contact	0.260	0.209	0.173**	0.079	0.090*	0.051
Access to Credit	0.009	0.018	0.125***	0.048	0.251***	0.054
Climate Information	0.053***	0.019	0.026*	0.014	0.071***	0.021
Soil fertility perception	0.339***	0.047	0.021**	0.010	0.057***	0.017
off-Farm Income	0.006	0.004	0.004	0.009	0.012	0.024
Training	0.075**	0.029	0.337	0.386	0.202***	0.022
Selfrisk	−0.834**	0.287				
Crop failure	0.150***	0.027				
Constant	1.094***	0.093	1.079***	0.087	1.29***	0.182
LR test of indep. eqns.:	chi2(1) = 18.49***					
N	400					

Notes: Figures in parentheses are standard errors of the coefficient, while *, **, and *** indicate statistical significance levels at 10%, 5%, and 1%, respectively.

further encourage farmers to adopt climate adaptation strategies.

The significant and positive impact of prior crop failure on adaptation decisions underscores the role of experiential learning in shaping farmers' responses to climate risks. Farmers who have previously experienced crop failure due to extreme weather events or other environmental shocks are more likely to adopt adaptation measures to mitigate future risks. This aligns with Protection Motivation Theory (PMT), which suggests that individuals who perceive a high level of threat (e.g., crop failure) and believe in the efficacy of adaptive actions are more inclined to engage in protective behaviors. The positive effect of prior crop failure on adaptation suggests that farmers respond to past losses by implementing strategies such as crop diversification, improved irrigation, and climate-resilient seed varieties. However, the ability to adapt also depends on farmers' financial capacity and access to supportive resources, indicating that targeted policies—such as risk-sharing mechanisms (e.g., crop insurance), credit access, and extension services—could further facilitate adaptive responses.

These findings collectively reinforce the multi-dimensional nature of climate adaptation decisions, where access to information, resource perception, and past experiences all shape farmers' willingness and ability to implement adaptive measures. Policies that enhance climate information dissemination, promote soil fertility management, and support farmers recovering from crop failure could significantly strengthen agricultural resilience in the face of climate change.

The analysis presented in Table 3 also reveals important heterogeneities in the factors influencing household wealth between climate change adaptation adopters and non-adopters. These differences substantiate the application of the endogenous switching regression framework, which effectively accounts for selection bias arising from the self-selection of farmers into adaptation. The findings underscore the complexity of the adaptation-household wealth nexus, highlighting how adaptation interacts with various socio-economic and institutional factors to shape wealth outcomes.

Education and farmer experience emerge as critical yet contrasting determinants of household wealth across adopters and non-adopters. Notably, farmer experience is a significant driver of wealth accumulation among non-adopters. This suggests that non-adopters leverage their accumulated knowledge and skills to optimize resource allocation and farming decisions even in the absence of adaptation strategies. Experienced farmers may have developed resilience through trial-and-error approaches, diversified income streams, or informal knowledge-sharing networks, enabling them to sustain their wealth levels despite not actively engaging in climate adaptation practices (Curtin, Tobin, & Reynolds, 2024).

Conversely, basic education does not significantly enhance household wealth among adopters. This finding challenges the conventional expectation that formal education directly improves economic well-being in agricultural settings. One plausible explanation is that basic education alone may not equip farmers with the specialized knowledge and technical expertise necessary to adopt and implement productivity-enhancing agricultural technologies (Mwalupaso, Korotoumou, Eshetie, Alavo, & Xu, 2019). This aligns with prior studies that emphasize the importance of agriculture-specific training and extension services in complementing general education to improve farm performance and wealth accumulation.

Extension contact significantly contributes to household wealth among both adopters and non-adopters, reinforcing its role as a key driver of agricultural development. Extension services provide farmers with valuable technical knowledge, climate-smart farming techniques, and access to improved inputs, all of which enhance productivity and, ultimately, economic well-being (Kuehne et al., 2017). Notably, this effect parallels the impact of farmer experience, suggesting that both formalized knowledge transfer and hands-on farming experience act as complementary pathways through which farmers build resilience and accumulate wealth. The importance of extension services also supports the PMT, which posits that individuals are more likely to take adaptive action when they perceive both a high level of climate risk and have confidence in their ability to respond effectively (Rogers, 1975). Since extension services provide farmers with actionable solutions to climate threats, they enhance their coping appraisal, increasing the likelihood of wealth-enhancing adaptation decisions.

Importantly, several factors contribute directly to household wealth across both adopters and non-adopters, illustrating how broader structural and contextual elements influence economic well-being. These factors go beyond basic productivity measures like yield and income to address deeper, systemic drivers of wealth accumulation. Climate information plays a pivotal role in enabling farmers to make strategic decisions, such as optimal planting schedules and input applications. These decisions reduce the risks associated with unpredictable weather patterns and ensure better resource allocation, enhancing the long-term stability of household wealth. Access to timely and accurate climate information empowers farmers to adapt efficiently, mitigating losses and contributing to a gradual increase in financial security. Research also highlights the critical role of climate-smart information services in improving resilience and overall economic outcomes in farming households (C. Singh et al., 2018; Tall, Coulibaly, & Diop, 2018). On the other hand, the perceived fertility of soil is strongly linked to wealth accumulation. Farmers who view their land as fertile are more inclined to invest in sustainable land management practices, such as crop rotation or organic fertilization, that preserve the value of their natural assets. These investments not only enhance soil quality but also contribute to higher land valuations and better long-term asset management. This reflects the Sustainable Livelihoods Framework (SLF), which emphasizes natural capital—including fertile soil—as a foundational element of wealth generation and economic success (Kim & Bevis, 2019; Turner, 2016).

Social networks function as an informal but invaluable resource for farmers, providing access to collective knowledge, credit, and shared labor arrangements. These networks reduce the financial strain of individual investments and facilitate cooperation in farming communities, which enhances household wealth over time. Social capital enables farmers to access resources and knowledge that might otherwise be unavailable, fostering greater resilience and adaptability to external shocks. The importance of social capital in rural wealth accumulation is a well-documented feature of economic resilience literature (Natarajan et al., 2022). Lastly, proximity to markets exerts a nuanced and critical influence on household wealth. Farmers located nearer to markets benefit from reduced transportation costs, greater access to agricultural inputs, and higher revenue from their produce due to better price realization (Curtin et al., 2024; Ennis & Kim, 2017). Conversely, as market distance increases, transaction costs such as travel expenses and logistical

challenges rise, significantly eroding potential wealth gains. Improvements in transportation infrastructure and the development of rural marketplaces could thus play a transformative role in closing wealth gaps between geographically advantaged and disadvantaged farmers.

Together, these factors highlight the multifaceted ways in which climate adaptation strategies, combined with broader systemic enablers, contribute to household wealth accumulation. These findings not only validate the theories guiding this analysis but also provide actionable insights into pathways for economic development and resilience-building in rural communities.

3.3. Average treatment effects

On the link between adaptation and household wealth, the results of this study strongly reinforce the theoretical frameworks underpinning our analysis—PMT, SLF, and AHM—while offering robust evidence on the link between climate change adaptation and household wealth. Both the ATT and the ATU, as shown in Table 4, are statistically significant at the 1 % level, emphasizing the positive impact of adaptation strategies on household wealth.

For adopters, the findings reveal a wealth increase of approximately 30 % due to adaptation. This aligns with PMT, which posits that farmers' adaptation behavior is motivated by their perceived ability to cope with climate threats (coping appraisal) and the associated benefits. By adopting climate-smart practices, households achieve higher agricultural yields, as detailed in Appendix A (Table A1), which become a vital source of income and facilitate wealth accumulation (Akter et al., 2022; Amadu et al., 2020). This outcome also reflects the role of SLF's natural capital—such as improved land productivity—enabled through adaptation, which strengthens households' overall livelihood assets and economic resilience (Chambers & Conway, 1992; Lázár et al., 2015; Lopez-Ridaura et al., 2018).

For non-adopters, the ATU indicates that had they chosen to adapt, their household wealth could have increased by about 15 %. This unrealized potential demonstrates the critical role of adaptation in leveraging household assets to alleviate poverty, in line with SLF. Moreover, non-adopters' missed wealth gains underscore the importance of risk diversification as outlined by AHM. Adaptation facilitates stability in income and production, providing significant opportunities to mitigate poverty and hunger (Lopez-Ridaura et al., 2018).

These findings also speak to the policy implications for eradicating poverty and hunger in Pakistan. Expanding access to resources, credit, and training that enhance farmers' capacity to adapt can amplify the benefits observed for adopters and unlock the potential wealth gains for non-adopters. However, it must be emphasized that these results are context-specific to Pakistan's socioeconomic and environmental conditions. The mechanisms driving the adaptation-wealth relationship may vary in other regions, necessitating caution in generalizing these findings.

By firmly anchoring our results in PMT, SLF, and AHM, this study not only confirms the theoretical pathways through which adaptation enhances household wealth but also highlights its potential as a transformative tool for rural development.

3.4. Robustness check

PSM was applied as a robust check in estimating the average treatment effect on the treated (ATT). However, a number of tests were conducted to ensure that the matching was well achieved. Generally, PSM drops some observations that are off support and this means some observations are not part of the estimation. A good matching is achieved when few observations are off support and the characteristics of the two groups are comparable. Consequently, a region of common support must be imposed as shown in Fig. 1B after balancing of characteristics is achieved as shown in Fig. 1A. This means the bias emanating from observed variables is reduced after matching to a point that the two groups are comparable as shown in Figs. 1C and 1D. Therefore, the results of the PSM can be relied upon especially that a good match was achieved.

The preliminary analysis reveals a statistically significant difference ($p < 0.01$) in household wealth between adaptation adopters and non-adopters prior to matching, with adopters exhibiting 32 % higher wealth levels (Table 5). While this initial finding suggests a strong positive association between climate adaptation and economic outcomes, direct comparison remains methodologically problematic due to systematic differences in observed and unobserved characteristics between the two groups. After implementing propensity score matching (PSM) to control for observable heterogeneity, the results demonstrate that adaptation adopters achieve approximately 18 % greater household wealth relative to comparable non-adopters. This positive treatment effect aligns with but is slightly attenuated compared to the endogenous switching regression (ESR) estimates, reflecting PSM's inherent limitation in addressing unobserved confounders such as risk preferences, entrepreneurial motivation, and cognitive factors that simultaneously influence both adaptation decisions and wealth accumulation. The methodological divergence between PSM (18 % gain) and ESR (30 % gain) estimates underscores the importance of accounting for both observable and unobservable selection biases when evaluating

Table 4
ATT and ATU from ESR estimation.

Item	N	Mean Household wealth		Coef	SE	Change in %
		Adopters	Non-adopters			
ATT	254	11.121	8.591	2.53***	0.017	29.45 %
ATU	141	10.764	9.327	1.437***	0.104	15.41 %

Notes: *, **, and *** indicate statistical significance levels at 10%, 5%, and 1%, respectively.

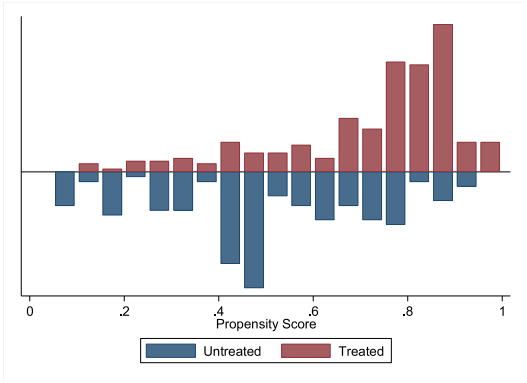


Fig. 1A.

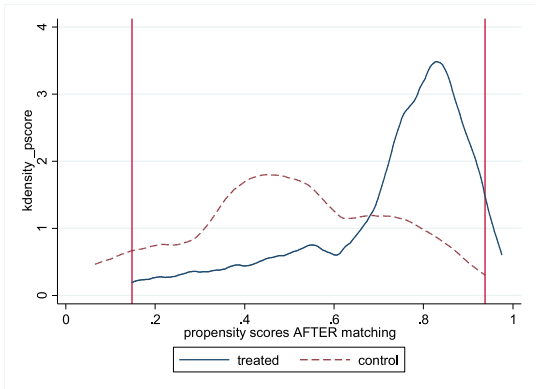


Fig. 1B. Region of common support.

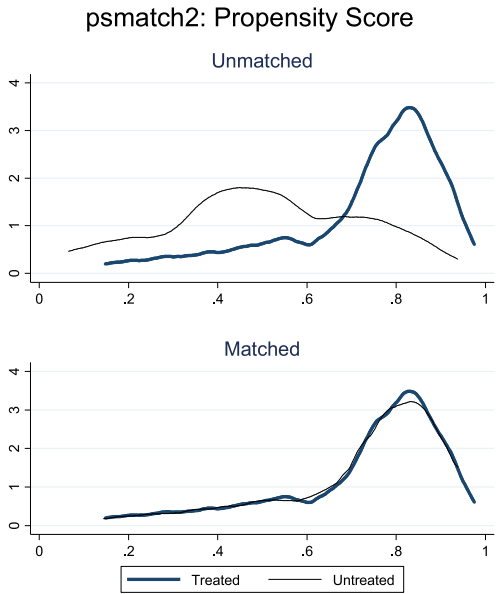


Fig. 1C. Kernal density before and after matching.

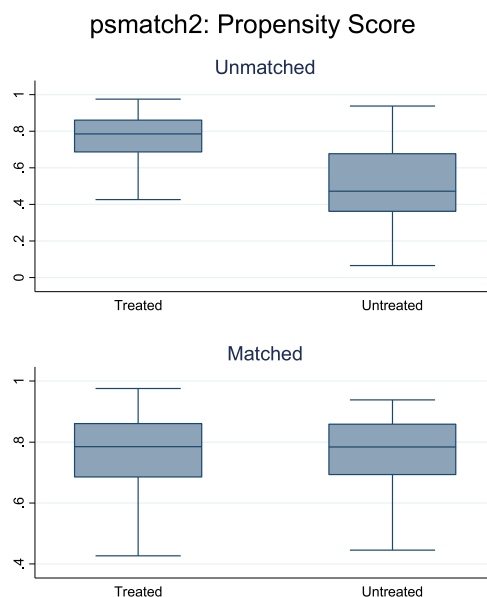


Fig. 1D. Box Plot before and after matching.

Table 5
Propensity score matching estimates.

Sample	Mean household wealth Treated	Controls	ATT	SE	Change in %
Unmatched	10.741	8.104	2.637***	0.151	32.54
Matched	10.189	8.628	1.561***	0.298	18.09

Notes: Figures in parentheses are standard errors of the mean, while *, and *** indicate statistical significance levels at 10%, and 1%, respectively.

climate adaptation impacts. These findings collectively provide robust, methodologically-consistent evidence that climate adaptation strategies generate economically meaningful returns for wheat producers in our study context, while simultaneously highlighting the superior capacity of ESR approaches to capture the full complexity of adaptation decision-making processes in smallholder agricultural systems.

3.5. Policy implication

The findings of the study present solution to two important policy and scholarly questions – (i) Is there a link between household wealth and adaptation to climate change by wheat farmers? And (ii) what are the determinants of climate change adaptation? It is widely agreed by policymakers and researchers alike that climate change is bound to happen regardless of the efforts made. For instance, while agriculture is inherently sensitive to climate change, it is also among the contributors to green-house gas (GHG) emissions. Thus, the solution is to adapt to climate change through implementing appropriate climate-smart strategies. The belief is that such strategies will enhance resilience and help farmers augment their yield. One of the major problems constraining adaptation is risk aversion of farmers and most likely this is a function of lack of accurate information and training. Therefore, policy support measures need to be put in place to support information circulation aimed at changing the risk perception of adaptation.

The aftermath is rapid intake of the various adaptation technologies which increase the per capita household wealth. When both PSM and ESR are applied, household wealth per capita is more for adopters than their counterparts (Table 6). In fact, had non-adopters

Table 6
ATT of household wealth per capita per annum.

Model	Item	Adopters	Non-adopters	Coef	SE	Change in %
ESR	ATT	54,043	34622.76	19420.24***	2015.78	56.09
	ATU	42514.61	22637.38	19877.23***	1025.58	87.81
PSM	Before matching	43274.4	29880.02	13394.39***	666.63	44.83
	After matching	38545.67	22652.5	15893.17***	1084.94	70.16

adapted to climate change their household wealth would increase by 34 % (19877.23 Pakistani Rupee = 119.05 United States Dollar and the exchange rate of 1 United States Dollar = 166.97 Pakistani Rupee) per annum. This translates to USD 0.326 per capital per day. In view of poverty severity (USD 2.15/Day poverty line) and extreme poverty (USD 1.90/Day poverty line), the augmented household wealth would authentically contribute to poverty alleviation by 15 % and 17 % respectively. Therefore, the nexus has important implication for poverty eradication.

4. Conclusion

On account of poor socio-economic conditions and validation of benefits derived, the capacity to adapt to climate change by smallholder farmers is uncertain. Despite much study on the perception of farmers on climate change and how efforts to adapt to climate change can help augment yield in the presence of climate, it is seldom emphasized and recognized that a nexus exists between climate change adaptation and household wealth for wealth farmers. Thus, this study makes use of 400 randomly selected smallholder wheat farmers from Sindh Province of Pakistan to establish the nexus.

Results indicate that both adopters and non-adopters would benefit from adaptation. Particularly, while adopting households are 29 % wealthier on account of adaptation, non-adopters would benefit about 15 % household wealth from adaptation to climate change. This value has important policy implication especially against the background of poverty eradication. Therefore, if information on adaptation is disseminated through training to a point that farmers realize that it is more risky not to adapt to climate change, household wealth per capita would augment. Consequently, this would contribute profoundly to the fight against poverty among the wheat smallholder farmers. By and large, to successfully guide policies that would accelerate adaptation to climate change by farmers and household wealth, adaptation strategies such as training programs and addressing risk aversion are essential.

While this study provides robust evidence of climate adaptation's wealth-enhancing effects among Pakistani wheat farmers, several limitations warrant consideration. First, the use of cross-sectional data restricts the ability to analyze household wealth trends over time. Since wealth is best understood as a dynamic measure, tracking changes over multiple periods through longitudinal studies would offer deeper insights into the effects of adaptation strategies. Incorporating time-series data in future research would therefore strengthen the evidence base and provide a clearer picture of how adaptation impacts wealth accumulation in the long term. Additionally, the scope of this research is geographically limited to Pakistan, which may affect the applicability of the findings in other regions. Expanding the study to include countries with varying climatic, economic, and institutional contexts could improve the generalizability of the results. Exploring adaptation strategies in diverse agricultural systems and socio-economic backgrounds would provide a more comprehensive understanding of the link between adaptation and household wealth. Finally, while the focus on wheat production provides valuable insights, future research could extend the analysis to other staple crops, such as rice and maize. This would corroborate the findings across different agricultural systems, strengthen the robustness of the results, and provide broader implications for food security and poverty alleviation. Despite these limitations, this study makes a critical contribution to the growing body of literature on climate adaptation and economic resilience. The findings lay a strong foundation for future research and offer actionable insights into the role of adaptation strategies in enhancing household wealth, reducing poverty, and promoting sustainable development.

CRedit authorship contribution statement

Shangao Wang: Writing – review & editing, Visualization. **Panhwar Ghulam Mustafa:** Writing – original draft, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Gershom Endelani Mwalupaso:** . **Zhou Li:** Supervision, Project administration, Funding acquisition.

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Declaration of competing interest

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

Appendix A

Table A1
Yield effects.

(continued on next page)

Table A1 (continued)

Status	N	With Adoption Kg/acre	Without Adoption Kg/acre	Treatment Effect Kg/ha	% Change
Status	N	With Adoption Kg/acre	Without Adoption Kg/acre	Treatment Effect Kg/ha	% Change
Adopter	257	2932.91	2011.66	ATT: 921.24*** (38.63)	45.8
Non-adopter	143	3118.39	2606.85	ATU: 511.53*** (43.35)	19.6

Notes: Figures in parentheses are standard errors of the mean, while *** indicate statistical significance levels at 1 %.

Data availability

Data will be made available on request.

References

- Abadie, A., Imbens, G.W., 2006. Large sample properties of matching estimators for average treatment effects. *Econometrica* 74 (1), 235–267.
- Abbas, Q., Han, J., Adeel, A., Ullah, R., 2019. Dairy Production under Climatic Risks: Perception, Perceived Impacts and Adaptations in Punjab, Pakistan. *International Journal of Environmental Research and Public Health* 16 (20), 4036.
- Abid, M., Schilling, J., Scheffran, J., Zulfikar, F., 2016. Climate change vulnerability, adaptation and risk perceptions at farm level in Punjab, Pakistan. *Science of the Total Environment* 547, 447–460.
- Adger, W. N., Agrawal, S., Mirza, M., Conde, C., O'brien, K., Pulhin, J., . . . Takahashi, K. (2007). Assessment of adaptation practices, options, constraints and capacity. *Adger, W.N., Vincent, K., 2005. Uncertainty in adaptive capacity. Comptes Rendus Geoscience* 337 (4), 399–410.
- Aker, J.C., 2011. Dial "A" for agriculture: a review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics* 42 (6), 631–647. <https://doi.org/10.1111/j.1574-0862.2011.00545.x>.
- Akter, A., Geng, X., Mwalupaso, G.E., Lu, H., Hoque, F., Ndungu, M.K., Abbas, Q., 2022. Income and Yield effects of climate-smart agriculture (CSA) adoption in flood prone areas of Bangladesh: Farm Level Evidence. *Climate Risk Management* 100455.
- Alam, M., Siwar, C., 2009. *Socioeconomic impacts and vulnerability of climate change on farming community: A study on Malaysian perspective*. Paper Presented at the Proceedings of the 3rd International Conference on Social Sciences and Humanities.
- Amadu, F.O., McNamara, P.E., Miller, D.C., 2020. Yield effects of climate-smart agriculture aid investment in southern Malawi. *Food Policy* 92, 101869.
- Aslam, M., 2016. Agricultural productivity current scenario, constraints and future prospects in Pakistan. *Sarhad Journal of Agriculture* 32 (4), 289–303.
- Azam, A., Shafique, M., 2017. Agriculture in Pakistan and its Impact on Economy. A Review. *Inter. J. Adv. Sci. Technol* 103, 47–60.
- Bazrafkan, K., Valizadeh, N., Khannejad, S., Kianmehr, N., Bijani, M., Hayati, D., 2022. What drives farmers to use conservation agriculture? Application of mediated protection motivation theory. *Frontiers in Psychology* 13, 991323.
- Bedelian, C., Ogutu, J., Homewood, K., Keane, A., 2023. Evaluating the determinants of participation in conservancy land leases and its impacts on household wealth in the Maasai Mara, Kenya: Equity and gender implications. *World Development* 174 (2024), 106442.
- Below, T.B., Mutabazi, K.D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., Tscherning, K., 2012. Can farmers' adaptation to climate change be explained by socio-economic household-level variables? *Global Environmental Change* 22 (1), 223–235.
- Call, M., Sellers, S., 2019. How does gendered vulnerability shape the adoption and impact of sustainable livelihood interventions in an era of global climate change? *Environmental Research Letters* 14 (8), 083005.
- Chambers, R., Conway, G., 1992. Sustainable rural livelihoods: practical concepts for the 21st century.
- Chandio, A.A., Mirani, A.A., Shar, R.U., 2019. Does agricultural sector foreign direct investment promote economic growth of Pakistan? Evidence from cointegration and causality analysis. *World Journal of Science, Technology and Sustainable Development*.
- Chandio, A.A., Yuansheng, J., Magsi, H., 2016. Agricultural sub-sectors performance: an analysis of sector-wise share in agriculture GDP of Pakistan. *International Journal of Economics and Finance* 8 (2), 156–162.
- Chang, S.C., Tsai, C.-H., 2015. The adoption of new technology by the farmers in Taiwan. *Applied Economics* 47 (36), 3817–3824.
- Curtin, I.J., Tobin, D., Reynolds, T., 2024. Do wealth and market access explain inconsistent relationships between crop diversity and dietary diversity? Evidence from 10 sub-Saharan African countries. *Sustainability* 16 (3), 1040.
- Edirisinghe, J.C., 2015. Smallholder farmers' household wealth and livelihood choices in developing countries: A Sri Lankan case study. *Economic Analysis and Policy* 45, 33–38.
- Ennis, S.F., Kim, Y., 2017. Market power and wealth distribution. Competition policy for shared prosperity and inclusive growth, A step ahead, pp. 133–153.
- Esham, M., Garforth, C., 2013. Agricultural adaptation to climate change: Insights from a farming community in Sri Lanka. *Mitigation and Adaptation Strategies for Global Change* 18 (5), 535–549.
- GoP. (2017-18). *Economic Survey of Pakistan*. Pakistan: Economic Survey of Pakistan Retrieved from http://finance.gov.pk/survey_1617.html.
- Ishaque, W., Tanvir, R., Mukhtar, M., 2022. Climate change and water crises in Pakistan: implications on water quality and health risks. *Journal of Environmental and Public Health* 2022 (1), 5484561.
- Keshavarz, M., Karami, E., 2016. Farmers' pro-environmental behavior under drought: Application of protection motivation theory. *Journal of Arid Environments* 127, 128–136.
- Kim, K., Bevis, L., 2019. Soil fertility and poverty in developing countries. *Choices* 34 (2), 1–8.
- Kuehne, G., Llewellyn, R., Pannell, D.J., Wilkinson, R., Dolling, P., Ouzman, J., Ewing, M., 2017. Predicting farmer uptake of new agricultural practices: A tool for research, extension and policy. *Agricultural Systems* 156, 115–125. <https://doi.org/10.1016/j.agry.2017.06.007>.
- Lázár, A.N., Clarke, D., Adams, H., Akanda, A.R., Szabo, S., Nicholls, R.J., Abedin, M.A., 2015. Agricultural livelihoods in coastal Bangladesh under climate and environmental change—A model framework. *Environmental Science: Processes & Impacts* 17 (6), 1018–1031.
- Lokshin, M., Sajaia, Z., 2004. Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal* 4 (3), 282–289.
- Lopez-Ridaura, S., Frelat, R., van Wijk, M.T., Valbuena, D., Krupnik, T.J., Jat, M.L., 2018. Climate smart agriculture, farm household typologies and food security: An ex-ante assessment from Eastern India. *Agric Syst* 159, 57–68. <https://doi.org/10.1016/j.agry.2017.09.007>.
- Mao, H., Zhou, L., Ifft, J., Ying, R., 2019. Risk preferences, production contracts and technology adoption by broiler farmers in China. *China Economic Review* 54, 147–159.
- Masud, M.M., Azam, M.N., Mohiuddin, M., Banna, H., Akhtar, R., Alam, A.F., Begum, H., 2017. Adaptation barriers and strategies towards climate change: Challenges in the agricultural sector. *Journal of Cleaner Production* 156, 698–706.
- Mosavian, S.H., Rostami, F., Tatar, M., 2023. Modeling farmers' intention to water protection behavior: A new extended version of the protection motivation theory. *Journal of Environmental Psychology* 90, 102036.

- Mukherjee, M., Fransen, S., 2024. Exploring migration decision-making and agricultural adaptation in the context of climate change: A systematic review. *World Development* 179, 106600.
- Mullan, K., Kontoleon, A., Swanson, T., Zhang, S., 2010. Evaluation of the Impact of Natural Forest Protection Programme on Rural Household Livelihood. *Environmental Management* 45 (3), 513–525.
- Mwalupaso, G.E., Korotoumou, M., Eshetie, A.M., Alavo, J.-P.-E., Xu, T., 2019. Recuperating dynamism in agriculture through adoption of sustainable agricultural technology-Implications for cleaner production. *Journal of Cleaner Production* 232 (C), 639–647. <https://doi.org/10.1016/j.jclepro.2019.05.366>.
- Mwalupaso, G.E., Wang, S., Eshetie, A.M., Tian, X., 2020. Ameliorating food and nutrition security in farm households: Does informatization matter? *Sustainability* 12 (2), 522.
- Natarajan, N., Newsham, A., Rigg, J., Suhardiman, D., 2022. A sustainable livelihoods framework for the 21st century. *World Development* 155, 105898.
- Nazari, S., Rad, G.P., Sedighi, H., Azadi, H., 2015. Vulnerability of wheat farmers: Toward a conceptual framework. *Ecological Indicators* 52, 517–532.
- Ogada, M.J., Rao, E.J., Radeny, M., Recha, J.W., Solomon, D., 2020. Climate-smart agriculture, household income and asset accumulation among smallholder farmers in the Nyando basin of Kenya. *World Development Perspectives* 18, 100203.
- Ozdemir, D., 2022. The impact of climate change on agricultural productivity in Asian countries: a heterogeneous panel data approach. *Environmental Science and Pollution Research* 1–13.
- Rasheed, A., Mwalupaso, G.E., Abbas, Q., Tian, X., Waseem, R., 2020. Women participation: a productivity strategy in rice production. *Sustainability* 12 (7), 2870.
- Rehman, A., Ozturk, I., Zhang, D., 2019. The causal connection between CO2 emissions and agricultural productivity in Pakistan: empirical evidence from an autoregressive distributed lag bounds testing approach. *Applied Sciences* 9 (8), 1692.
- Rogers, R.W., 1975. A protection motivation theory of fear appeals and attitude change¹. *The Journal of Psychology* 91 (1), 93–114.
- Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70 (1), 41–55. <https://doi.org/10.1093/biomet/70.1.41>.
- Sekabira, H., Qaim, M., 2017. Mobile money, agricultural marketing, and off-farm income in Uganda. *Agricultural Economics* 48 (5), 597–611. <https://doi.org/10.1111/agec.12360>.
- Singh, C., Daron, J., Bazaz, A., Ziervogel, G., Spear, D., Krishnaswamy, J., Kituyi, E., 2018. The utility of weather and climate information for adaptation decision-making: current uses and future prospects in Africa and India. *Climate and Development* 10 (5), 389–405.
- Singh, I., Squire, L., Strauss, J., 1986. The basic model: theory, empirical results, and policy conclusions. Extensions, applications, and policy, Agricultural household models, pp. 17–47.
- Syed, A., Raza, T., Bhatti, T.T., Eash, N.S., 2022. Climate Impacts on the agricultural sector of Pakistan: Risks and solutions. *Environmental Challenges* 6, 100433.
- Tall, A., Coulibaly, J.Y., Diop, M., 2018. Do climate services make a difference? A review of evaluation methodologies and practices to assess the value of climate information services for farmers: Implications for Africa. *Climate Services* 11, 1–12.
- Tang, S., Lee, H.F., Huang, X., Zhou, J., 2022. Poverty Stories of rural households in China: The case of North Jiangsu. *Journal of Rural Studies* 91, 1–9.
- Turner, M.D., 2016. Rethinking land endowment and inequality in rural Africa: the importance of soil fertility. *World Development* 87, 258–273.
- Villamor, G.B., Wakelin, S.J., Dunningham, A., Clinton, P.W., 2023. Climate change adaptation behaviour of forest growers in New Zealand: an application of protection motivation theory. *Climatic Change* 176 (2), 3.
- Wood, S.A., Jina, A.S., Jain, M., Kristjanson, P., DeFries, R.S., 2014. Smallholder farmer cropping decisions related to climate variability across multiple regions. *Global Environmental Change* 25, 163–172.
- Zamasiya, B., Nyikahadzoi, K., Mukamuri, B.B., 2017. Factors influencing smallholder farmers' behavioural intention towards adaptation to climate change in transitional climatic zones: A case study of Hwedza District in Zimbabwe. *J Environ Manage* 198 (Pt 1), 233–239. <https://doi.org/10.1016/j.jenvman.2017.04.073>.
- Zeza, A., Tasciotti, L., 2010. Urban agriculture, poverty, and food security: Empirical evidence from a sample of developing countries. *Food Policy* 35 (4), 265–273.