



## Original research article

# Assessing adaptive capacity of climate-vulnerable farming communities in flood-prone areas: Insights from a household survey in South Punjab, Pakistan

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## ABSTRACT

Climate change poses a significant threat to agricultural systems worldwide. In Pakistan, an agrarian country where the majority of the population relies on agriculture for their livelihoods, the impacts of climate change can be particularly devastating. Understanding the adaptive capacity of farmers is crucial in order to identify effective strategies for coping with the impacts of climate change. This study aimed to assess the adaptive capacity of farmers in Rajanpur and Dera Ghazi Khan, two flood-prone districts of South Punjab, Pakistan. Data were collected in October 2022 from 448 farmers through multistage stratified random sampling, and multivariate regression and bivariate probit models were used to analyze the likelihood of farmers adopting certain joint strategies and the impact of socioeconomic factors on their decision-making. Results indicated that concern for climate change and knowledge of market value of crops were significant determinants for farmers adopting joint strategies, while farmers with more experience and alternate sources of income were less likely to do so. Increased irrigation was a top strategy used despite its potential negative environmental impacts. Findings highlight the need for a holistic approach to climate adaptation that considers complex social, economic, and environmental factors and appreciates the complex decision-making process that farmers undergo. Understanding the local context is key to developing effective interventions to support climate resilience and sustainable livelihoods in agricultural communities.

## Practical Implications

Assessing the adaptive capacity of vulnerable communities to climate change, as well as factors affecting their decision-making process, can help decision-makers design better interventions and enable communities to make informed decisions to tackle climate change affects. The practical implications from the study are as follows:

- There is a need for capacity-building of farmers on post-production value chain in order to increase their business

acumen. This will expand their knowledge of the value of different products and may influence their crop selection.

- While alternative sources of income can boost the livelihoods of farmers, one unintended consequence is that they may be less likely to properly invest their time in farming activities or be incentivized to improve their farming practices.
- Similarly, farmers who have many years of experience and are set in their ways are likely to be resistant to changes in their practices and adopting different coping strategies. One way to tackle this is through more community engagement, especially positive peer pressure between farmers, as well as trying to engage more young people in the agriculture sector, who may be more likely to adopt new and innovative farming approaches.

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- Socio-economic factors should be considered when planning agriculture projects. A new technology which promises improved production and efficiency may not be enough of an incentive for farmers to change their practices, as human choices are not always driven by rational logic but by a multitude of external and internal factors. Behavior changes and social science concepts need to be better integrated into climate adaptation interventions for better success.

#### Data availability

Data will be made available on request.

## Introduction

Floods are one of the most frequent types of natural disasters and have affected more than 2 billion people globally between 1998 and 2017 (WHO, 2022). In 2021 alone, global flood disasters were 48% more than historic levels (1991–2020) and made up 56.13% of all major natural disasters that year, affecting 28% of the global population and causing the largest number of deaths (Govt. China et al., 2022). The South Asian region is particularly at high risk for climate-related hazards like flooding, especially the agriculture sector which is vulnerable to damages and resulting economic losses and food insecurity (Amarnath et al., 2017). Flood disasters have increased over the last three decades in South Asia due to factors such as climate change, environmental degradation, and increasing population growth (Shrestha and Takara, 2008). Climate change was found to be a major factor contributing to Pakistan's heavier monsoon rains in June 2022 which led to catastrophic flooding across the country (Otto et al., 2022).

Pakistan is no stranger to flood events (Shah et al., 2020) due to its geographic location and as host to a large portion of the Indus River. Between 1950 and 2023, Pakistan has witnessed 29 major flood events across the country, including the most recent 2022 floods (Federal Flood Commission, 2021). These floods submerged more than one-third of the country, affecting around 33 million people and resulting in nearly 1,700 deaths and over 1 million livestock losses (NDMA, 2022). Estimates suggest that 1.6 million hectares of farmland have been destroyed with reported economic losses between USD 30 to 35 billion, likely higher (Baloch, 2022). In Punjab province specifically, around 38% of the total population live in high-risk flood zones, notably in agricultural areas (Rentschler et al., 2022).

The agriculture sector is the largest in Pakistan and contributes around 24% of GDP and employs approximately half of the country's labor force (Pakistan Bureau of Statistics, n.d.). Flooding events pose a serious threat to communities living in flood-risk areas and can have a major negative impact on livelihoods, public health, water security, housing, infrastructure, energy access, and food security (Burke et al., 2023). Majority of communities affected by the 2022 floods in Pakistan were living in rural areas, in particular, small-scale farmers relying on agricultural production as their sustenance. The ripple effects of crop and livestock loss and land destruction is still being felt in 2023. Since early 2023, the country has faced the highest levels of inflation since the 1970s (Al Jazeera, 2023). Evidence also shows that low crop yields resulting from climate change events has led to increased migration into cities from rural areas (Lohano, 2016; Podesta, 2019). Ultimately, these negative impacts have pushed millions of Pakistanis into poverty and have led to overall socio-economic and political instability. Data from World Resources Institute's Aqueduct Flood interface – an online platform that measures and maps global flood risk – predicts that floods will continue to threaten lives and economies in the future and ranks Pakistan among the top ten countries with the highest increase in number of people to be affected by riverine flooding by 2030 (Kuzma and Luo, 2020).

As climate-driven flooding is now being recognized as the new norm, the government of Pakistan has taken steps to improve flood management, such as investing in flood protection infrastructure projects and implementing agricultural credit schemes. These technical and financial endeavors must also be coupled with appropriate and effective adaptation measures at the farming community or household level with an understanding of the drivers for adaptive capacity of communities to respond to future flood and other climate-extreme events (Adger et al., 2005; Aerts et al., 2018). This study adds to the literature on understanding farmers' adaptive capacity and barriers preventing adaptation at the farm-level in flood-prone areas of rural Pakistan.

#### Climate change adaptation strategies

The United Nations' Intergovernmental Panel on Climate Change (IPCC) defines adaptation as the "process of adjustment to actual or expected climate and its effects" and adaptive capacity as the "ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities or to respond to consequences (IPCC, 2022)." Essentially, adaptive capacity indicates to what extent climate adaptation can be successfully achieved and what factors hinder or promote adaptation. Adaptive capacity is affected by a multitude of factors such as geography, knowledge and information, availability of resources, perceived level of risk, and institutional support (Jongman, 2018). Adaptive capacity may also differ between the local, regional, and national levels of a country. Understanding the local context and practices of farmers affecting their adaptive capacity can feed into evidence-based decision-making and policy plans to ensure an effective response to climate change impacts.

There is extensive literature on climate change adaptation practices and determinants of adaptation in South Asia and beyond (Sterrett, 2011; Lwasa, 2015; Abbas et al., 2016a; Sitati et al., 2021; Fila et al., 2023). Studies range from focusing on identifying different adaptation measures adopted by farmers (Bryan et al., 2009; Karki et al., 2020; Abbas et al., 2022), reasoning behind adaptation uptake (Grothmann and Reusswig, 2006; Bryan et al., 2009; Gebrehiwot and Van Der Veen, 2013; Kibue et al., 2016), and the determinants which influence adaptation decisions (Alauddin and Sarker, 2014; Ahmad et al., 2016; Abid et al., 2016; Kuhlicke et al., 2020; Faisal et al., 2021).

Rural based studies in Pakistan have also assessed farmers' climate change perceptions, vulnerabilities, and adaptation strategies (Abid et al., 2015; Ali and Erenstein, 2017; Jamshed et al., 2019, 2017; Arshad et al., 2017; Khan et al., 2020). As reported in the literature, common strategies chosen by farmers in response to climatic events include adjustment in sowing and harvesting time, changes in agronomic practices, disease and pest management, switching to new crops, and changes in livelihood measures such as income diversification and choosing off-farm income options. Other specific flood adaptations in Pakistan such as plinth elevation, grain storage, and creating shelterbelts have also been observed (Aftab et al., 2021), as well as introducing flood-resistant crop varieties, spate irrigation, taking out loans, and migration (Qazibash et al., 2021).

Factors such as education level, age, agricultural resources, access to land, geographic location, access to extension services, years of farming experience, perceived flood or drought risk, and gender can all affect adaptation strategies of farmers and likelihood of uptake (Saqib et al., 2016; Jamshed et al., 2020; Ahmad and Afzal 2020a; Aftab et al., 2021). Community-based adaptation interventions and government schemes such as agricultural credit and crop insurance could help farmers improve their adaptive capacity (Bakare et al., 2023).

While some studies focus on the effects of adaptation measures on production or income (Ahmad and Afzal 2020b) other studies not specifically focused on rural farming families have looked at willingness of households to commit labor toward structural flood protection schemes (Abbas et al., 2016b), factors driving household flood vulnerability (Hamidi et al., 2020; Shah et al., 2020; Ullah et al., 2021), adaptation

measures at the household level (Ahmad and Afzal 2020a), and how flood events impact rural–urban linkages (Jamshed et al., 2021).

Further research to complement existing data on adaptation strategies is needed for rural farmers living in high-risk flood-prone areas of Pakistan, particularly in the context of assessing the likelihood of farmers adopting certain strategies over others, and which strategies may be jointly adopted or not. Punjab province, particularly south Punjab, is an important site for research due to its high vulnerability to climate-extreme events and that majority of its population are directly or indirectly linked to the agriculture sector (Nadeem et al., 2022). Punjab province is the agricultural hub of Pakistan, with 60% of its land cultivated for agriculture (The Urban Unit, Planning and Development Department, Government of Punjab, 2019). Moreover, continuous exposure to climate-driven events like floods will have negative long-term effects on coping abilities of farming communities as well as devastating impacts on production and livelihoods (Abid et al., 2016), as is already being seen present day. It is important to understand local adaptation contexts in order to inform nuanced and effective preventative measures rather than applying a ‘one-size-fits-all’ policy model.

Building off climate adaptation research in Pakistan, the current study is based on survey data of rural farming households in two flood-prone districts of South Punjab in order to answer the following research questions:

1. What are the main climate adaptation strategies farmers adopt to combat climate change?
2. What are farmers’ perceived climate-change risks and how does that affect which strategies they adopt?
3. Which combination of adaptation strategies are likely to be adopted simultaneously by farmers?

The main goal of this study is to quantify the marginal impacts of various explanatory factors on the probability of adopting different strategy combinations at the farm-level, which is currently missing in existing literature. The study aims to provide insight into farmer adaptive capacity and the determinants of adaptation strategy choice among farmers in the select districts, which can better inform tailored policies and climate change interventions. By developing and enhancing their adaptive capacity, farmers can become more resilient to the impacts of climate change and variability, and better able to sustain their livelihoods over the long term.

## Methodology

### Study area

Geographically, Punjab is located between 27.70°N – 34°N and 69.31°E – 75.38°E and can be classified as semi-arid to arid. The maximum annual mean temperature ranges from 29 °C – 31 °C and the minimum annual mean temperature ranges from approximately 16 °C – 18 °C (Abid et al., 2015, 2016). The province maintains a sub-tropical climate and houses five rivers. It is the most populous province of Pakistan with a population of around 127 million (PBS, 2023). The monsoon season lasts from June to September, and in 2022 the province witnessed 70% more rainfall than historical averages (PMD, 2022).

South Punjab was specifically selected as the study area for assessing adaptive capacity because it is highly vulnerable to floods (PDMA, 2022; NDMA, 2022) and has experienced consecutive flood events in the past decade causing infrastructure damage, loss of lives and livelihoods, food insecurity, and public health issues (NDMA, 2021). Additionally, south Punjab region was most recently affected and heavily impacted by a major flood event (PMD, 2022).

The study is further concentrated in two districts of Punjab, namely Rajanpur and Dera Ghazi Khan (DGK), which are in different flood-prone ecological regions. Rajanpur District lies on the western bank of the Indus River and covers an area of 12,318 km<sup>2</sup> with a population of

nearly 2 million (PBS, 2017). The district is made up of three tehsils: Rojhan, Jampur and Rajanpur (PBS, 2017). The major crops grown in Rajanpur include wheat, cotton, and sugarcane (Govt. of Punjab, n.d.).

DGK District is lies in a strip between the Indus River and the Koh-e-Suleman range of mountains separating it from the Balochistan Province. It covers an area of 11,922 km<sup>2</sup> with a population of 2.8 million distributed among three tehsils: Kot Chutta, Dera Ghazi Khan, and Koh Suleman (PBS, 2017). The main crops are cotton, wheat, rice, and sugarcane (Govt. of Punjab, n.d.).

### Identification of flood extent using Google Earth Engine

The maps for the study area (Fig. 1) were generated for assessing the extent of flood-affected areas within Rajanpur and DGK for further village selection. The flood extent maps were created using a change detection approach on Sentinel-1 Synthetic Aperture Radar (SAR) data (Zhang et al., 2020) via Google Earth Engine (GEE), a cloud-based geospatial data analysis platform used for processing remote sensing data on a large scale (Tamiminia et al., 2020). Maps were created through the following steps: study area selection, time frame and sensor parameters selection (pre- and post-flood time periods), data filtering, polarization, change detection and exporting data and final map layout (UN-SPIDER, n.d.). As shown in Fig. 1 the red highlighted areas are the 2022 flood-affected areas in both districts.

### Sampling and data collection

Based on the flood extent maps, a multi-stage stratified random sampling technique was used to refine the study areas. Within Rajanpur and DGK, two tehsils were randomly selected. In the next stage, 4 Union Councils (UC) were selected from each tehsil using stratified random sampling. A single UC contains several villages and two villages were randomly selected. Lastly, a total of 14 households were selected in each village for interviews through systematic random sampling, for a total of 448 households across Rajanpur and DGK (Table 1).

Data were collected using a structured survey through SurveyCTO, a tablet-based software, by a team of trained enumerators. The household member directly involved in agriculture activities and decision-making was selected for the household interview. Due to socio-cultural norms which place decision-making power predominantly with men, selected household members were all male. This is recognized as a limitation to the study and future research on gendered differences in climate adaptation strategies should be pursued, as women farmers play a vital role in the agriculture sector of Pakistan.

Ethical protocols of conducting human research were followed, including voluntary participation of respondents, informed consent, anonymity, and confidentiality. The purpose of the study and research objectives were explained prior to beginning the survey, and those respondents who did not consent were skipped and another household was visited. The survey themes included socio-economic characteristics, farming practices, risk factors associated to climate change, adaptation strategies, farmers’ capacity to adopt strategies, and constraints in adoption uptake.

### Econometric framework

Two models were used for econometric analysis: multivariate logistic regression and bivariate probit model. In order to investigate the adaptation strategies employed by farming households, a multivariate logistic regression model was used, as the study’s dependent variables are binary in nature, hence, making the distribution non-linear.

The estimated coefficients will inform us regarding the odds of strategy adoption according to each independent variable such as socio-economic characteristics, access to agricultural credit, market information, and weather information, while keeping all other variables constant.

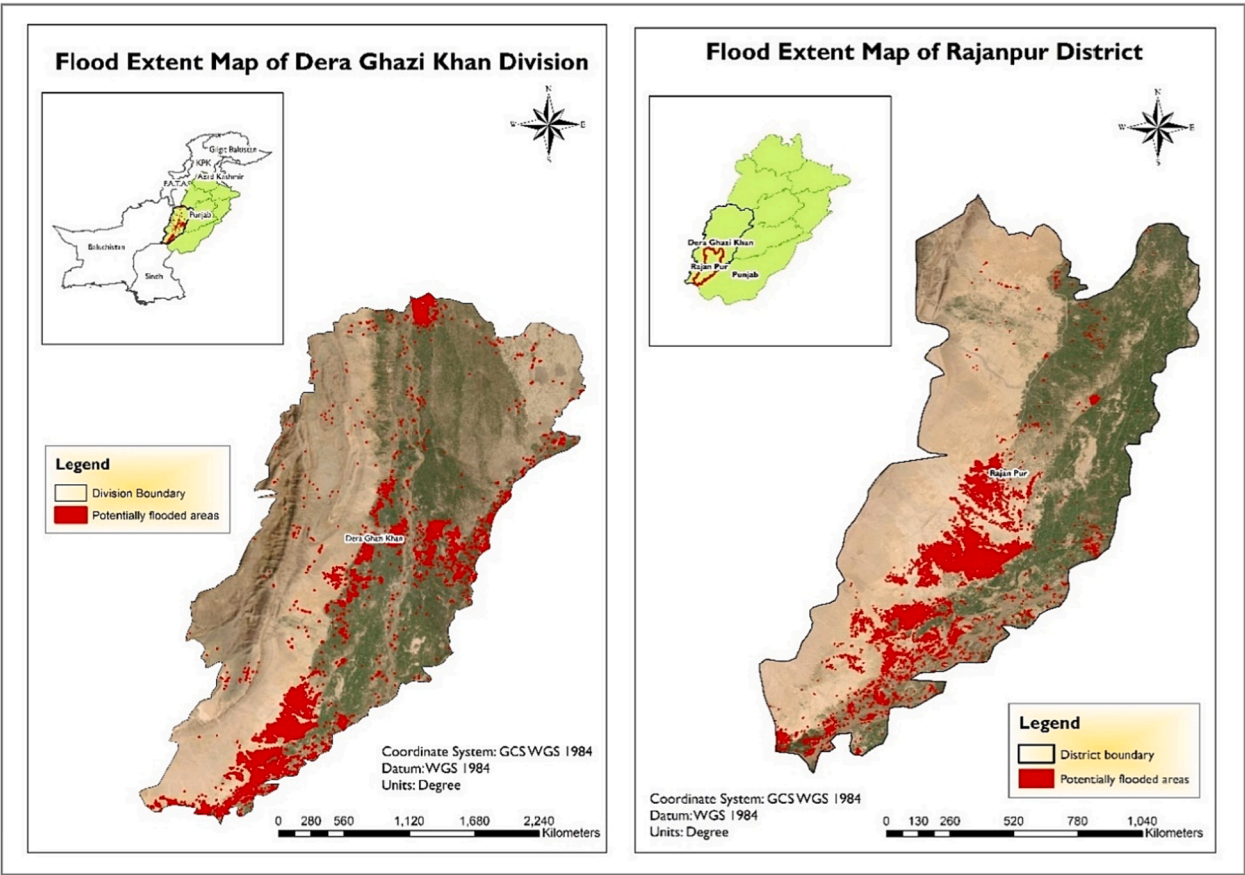


Fig. 1. Flood extent maps of study areas.

Table 1  
Sampling Overview.

Province	District	Tehsils	Union Councils	Villages	Villages per district	Interviews per village	Total interviews
Punjab	Rajanpur	Rojhan	4	2	8	14	112
		Jampur	4	2	8	14	112
	DGK	Jatoi	4	2	8	14	112
		Kot Chutta	4	2	8	14	112
	Total						448

$$\ln\left(\frac{P_i}{1-P_i}\right)=\beta_{10}+\beta_{11}Age_{bracket}+\beta_{12}Education_{bracket}+\beta_{13}Districts+\beta_{14}FamilySystem+\beta_{15}CCconcern+\beta_{16}Experience+\beta_{17}Agriculturecredit+\beta_{18}marketinformation+\beta_{19}weatherforecast+\beta_{19}occupation+\varepsilon_i$$

The multivariate logistics function can be specified as:

where  $\ln\left(\frac{P_i}{1-P_i}\right)$  denotes the dependent variables (various climate change adaptation strategies implemented by farm households) such as changed crop variety and type (CVT), changed planting dates and trees plantation (PDT), changed fertilizer and soil conservation (CFS), increased irrigation and crop conservation (ICD), and rented out crop with migration (RCM). The relationship of the dependent variables was assessed with the independent variables such as respondent age, education level, district, family system, climate change concern, farming experience, market information, and weather forecast, including constant ( $\beta_{10}$ ), and

( $\varepsilon_i$ ) error terms assumed to be normal standard distribution.

Past studies on farmers' adaptation strategies have mainly employed multivariate probit and binary logit models (Mittal and Mehar, 2016; Khan et al., 2020; Aftab et al., 2021) in order to assess factors that affect adaptation choices of farmers. Based on current literature, it has been established that farmers employ different climate change strategies and that these adoption measures are affected by various factors. To investigate the interdependent adaptation decisions implemented by farm households, the current study further employed a bivariate probit regression. This model is used analyze the relationship between two binary dependent variables, such as the decision of increased irrigation



and decision to change fertilizer type simultaneously (Greene, 2002). The results of the bivariate probit model provide insights into the relationship between two dependent variables being assessed, as well as the factors that influence each adaptation strategy separately and which would likely be adopted at the same time. The correlation coefficient estimated in the model is used to assess the degree of dependence between the two adaptations strategy.

The use of the bivariate probit model is scarce in adaptation literature (Rahman, 2008), especially in the context of Pakistan, but can offer insights on which combination of adaptation measures are most likely to be adopted and what are the motivating factors for farmers to do so. Another advantage of the model is the ease of calculating marginal effects on joint probabilities (Christofides et al., 1997). The multivariate logistics, bivariate probit regression and marginal effects are expected to produce a nuanced understanding of the mechanism of adaptation strategies farmers adopt to minimize the effects of climate change.

## Results

### Socioeconomic characteristics

The study collected information on the socioeconomic characteristics of households in Rajanpur and DGK and calculated their average and standard deviation values (Table 2). The average age of respondents was 42 and 46 years in Rajanpur and DGK, respectively, and they received on average only 8 and 7 years of schooling. Across both districts, majority participants lived in joint family systems and were engaged in farming as their main occupation. Respondents' average farming experience in Rajanpur and DGK was 8 and 7 years, respectively, while average experience of the household head was found to be 33 and 39 years, respectively.

The average operational land for farming was 3.6 hectares in both districts. In Rajanpur, the main source of income for households was on-farm work, accounting for around 81% of income, followed by financial remittance (29%), non-farm income (30%), and livestock and poultry (16%). In DGK, on-farm work accounted for 52% of income, followed by financial remittance (67%), non-farm income (40%), and livestock and

**Table 2**  
Socio-economics characteristics of respondents.

Characteristics of farm HH	Rajanpur Mean (SD)	DGK Mean (SD)
Respondent age	42.14 (12.35)	46.16 (13.91)
Education	8.31 (4.50)	7.92 (4.41)
Respondent years of experience in farming	22.32 (12.66)	25.13 (14.18)
Household head experience in farming	32.85 (15.17)	39 (16.23)
Total land in hectare for farming	3.80 (12.14)	3.88 (11.61)
Operational Land for farming	3.80 (12.14)	3.80 (12.14)
Percentage of annual source of income distribution	% (SD)	% (SD)
On-farm work	81% (66.34) N = 223	52% (33.93) N = 210
Livestock & Poultry	16% (15.93) N = 44	25% (23.09) N = 10
Financial Remittances	29% (19.38) N = 53	67% (21.76) N = 112
Non-farm income	30% (19.09) N = 96	40% (24.81) N = 96
Cash subsistence	Mean (SD)	Mean (SD)
Monthly minimum cash required for food & necessities of daily routine	PKR 38,553 (24576.24)	PKR 39,348 (66950.18)
Respondent occupation	<b>Rajanpur %</b>	<b>DGK %</b>
Farming	82%	77%
Public & Private employment	3%	8%
Own off business	4%	9%
Off-farm employment	10%	5%
Family System		
Joint	85%	95%
Nuclear	15%	5%

**Table 3**

Farm household concern over and observation of climate-driven events.

	Rajanpur	DGK
Respondent concerned about climate change	86% n = 193	96% n = 215
Respondent observed climate-driven event in last 10 years	67% n = 150	54% n = 122

poultry (25%). Households in DGK received more financial remittance and less on-farm income compared to those in Rajanpur, as many respondents in DGK were engaged in off-season labor work, and some households received foreign remittance. The minimum monthly cash subsistence required for fulfilling the necessities of daily life was reported as PKR 38,553 (USD 174) in Rajanpur and PKR 39,348 (USD 178) in DGK.

### Concern over and observation of climate-driven events

Results indicate that respondents were highly concerned about climate change, 86% in Rajanpur and 96% in DGK, while 67% and 54%, respectively, reported observing climatic changes in the past decade (Table 3). When asked about specific climate-related events, respondents in DGK reported observing high temperatures in summer (89%) with a mean frequency of 2.72, and low temperatures in winter (68%) with a frequency of 2.23. Respondents in Rajanpur reported less observation of high temperatures in summer (68%), but with a higher frequency of 3.70, and low temperatures in winter (40%) with a frequency of 2.95. The survey was conducted in flood-prone areas, and respondents reported observing floods in these areas (66% in Rajanpur/54% in DGK).

Furthermore, respondents in both districts reported experiencing droughts in both summer and winter, severe crop pests, human and animal diseases, insect attacks, soil problems, and new weeds. Findings suggest most farm households are highly concerned about floods, droughts, low and high temperatures in winter and summer seasons, as these events had a negative impact on crop production and contributed to an increase in human diseases. Table 4 summarizes reported climate change events experienced by respondents and their frequencies. Results are similar to trends observed in other studies (Abid et al., 2015,2019; Mase et al., 2017).

### Extent of rainfall pattern and temperature changes observed in summer and winter seasons

Respondents observed different precipitation patterns in summer

**Table 4**  
Reported climate change events experienced by respondents

	Rajanpur		DGK	
	Events observed (%)	Frequency Mean (SD)	Events observed (%)	Frequency Mean (SD)
Drought	22	1.88 (1.36)	35	2.69 (1.00)
High temperature	68	3.70 (2.54)	89	2.72 (1.62)
Low temperature	40	2.95 (1.39)	68	2.23 (1.22)
Flood	66	2.19 (1.29)	54	2.54 (1.77)
Severe crop pest	52	2.40 (1.49)	37	3.31 (2.49)
Human diseases	44	2.80 (0.97)	12	1.64 (1.59)
Animal diseases	66	2.85 (2.30)	51	2.25 (2.10)
Insect attack	65	2.22 (1.53)	46	2.98 (2.56)
Soil problem	41	1.89 (1.40)	9.8	2.17 (1.74)
New weeds	34	1.51 (0.579)	6.5	1.25 (0.463)

**Table 5**  
Households' observations of change in rainfall patterns

	Rajanpur			DGK		
	Increased	Decreased	Constant	Increased	Decreased	Constant
Change in summer rainfall patterns	43%	45%	12%	12%	79%	9%
Change in winter rainfall patterns	22%	55%	23%	14%	72%	14%

**Table 6**  
Households' reported extent of temperature change observed in last 10 years

	Rajanpur			DGK		
	Significantly warmed	Significantly cooled	Constant	Significantly warmed	Significantly cooled	Constant
Summer temperatures	86%	3%	11%	92%	3%	7%
Winter temperatures	33%	46%	21%	55%	34%	11%

and winter seasons, as well as different degrees of temperature change across both districts, as summarized in Table 5 and Table 6. In DGK, respondents reported that rainfall patterns had decreased in summer (79%) and winter (72%) compared to Rajanpur, where respondents reported a decrease in rainfall patterns of only 45% in summer and 55% in winter. On the other hand, Rajanpur reported increased rainfall patterns of 43% in summer and 22% in winter, while DGK had observed less increased rainfall in both seasons. However, respondents from both districts reported receiving late monsoon rainfall with high intensity, similar to trends found by Amir et al. (2020).

In terms of the extent of temperature changes observed, both districts reported similar trends. They observed a significant increase in summer temperatures, with 86% in Rajanpur and 92% in DGK reporting warmer temperatures and an extended summer period. Furthermore, they also reported a significant cooling of winter temperatures with cooler temperatures perceived in Rajanpur (46%) than DGK (34%).

#### Adaptation strategies employed by farmers and their implementation costs

Farm households have adopted various adaptation strategies at the farm level to combat the adverse impacts of climate change. Table 7 shows that most of the implemented strategies were related to changes

**Table 7**  
Climate change adaptation strategies and average implementation cost

	Rajanpur		DGK	
	Implemented	Mean Cost – PKR (USD)	Implemented	Mean Cost – PKR (USD)
Changed crop variety	39% n = 88	5,534 (25)	25% n = 57	5,035 (23)
Changed fertilizer	37% n = 84	6,827 (31)	40% n = 91	6,665 (30)
Increased irrigation	30% n = 69	59,853 (271)	24% n = 55	69,259 (313)
Changed planting dates	30% n = 68	3,809 (17)	46% n = 105	4,467 (20)
Planted shaded trees	29% n = 66	5,924 (27)	21% n = 48	8,354 (38)
Soil conservation	27% n = 61	6,926 (31)	24% n = 55	7,209 (33)
Mix cropping	20% n = 45	34,348 (155)	5% n = 10	30,500 (138)
Changed crop type	20% n = 44	6,877 (31)	1.3% n = 3	5,000 (23)
Rented out cropland	6% n = 13	–	1% n = 2	–
Migrate to urban area	7% n = 16	168,750 (764)	–	–

The average exchange rate for October 2022 (1 USD = 221 PKR) was used for calculation.

in cropping practices, including changed crop varieties, fertilizer choice, planting dates, crop type, and mixed cropping pattern.

The most implemented adaptation strategy reported in Rajanpur was changed crop variety (39%) followed by changed fertilizer (37%), while in DGK changed planting dates (46%) followed by changed fertilizer (40%) were the most common. In Rajanpur, the average cost of changed crop variety was valued at PKR 5,534 (USD 25) per crop production season, and in DGK the average cost of changed planting dates was valued at PKR 4,467 (USD 20). Interestingly, the average cost for changed crop variety in DGK was lower (PKR 5,035/USD 23) than in Rajanpur, but only 25% reported this adaptation strategy. Farmers in DGK may have less incentive to change crop variety as they receive more non-farming income as compared to farmers in Rajanpur. Changing fertilizer to maintain soil fertility was the second most implemented adaptation strategy in both districts, with an average cost value of PKR 6,827 (USD 31) in Rajanpur and PKR 6,665 (USD 30) in DGK. Price differences may vary across districts because fertilizer is supplied through the private sector.

Increased irrigation was implemented as the third adaptation strategy by farmers in Rajanpur (30%) in case of extreme drought and high temperature in summer, with an average cost of PKR 59,853 (USD 271) per crop production season. In DGK, the average price was much higher for increased irrigation (PKR 69,259/USD 313) and was the fourth adaptation strategy adopted by farmers (24%). Differences may be explained due to water pricing, source of water (tubewell or solar pump) farmers use for irrigation, or individual farmer preference.

In addition to these strategies, farmers also implemented advanced measures of land management like soil conservation and planting trees to maintain the productivity of the crop and soil fertility. Less common strategies adopted included mixed cropping, changing crop type, renting out cropland, and migrating to urban areas. Only 7% of respondents in Rajanpur reported migration as an adaptation strategy, while none from DGK reported ever migrating. This could be because in DGK farmers reported having more income sources other than farming, including receiving more remittance, so are less inclined to migrate than farmers in Rajanpur whose main source of income comes from farming.

#### Empirical results of implemented adaptation strategies

Multivariate logistics regression (Table 8) was used for all adaptation measures and bivariate probit logistics model (Table 9) for interdependent adaptation strategies, along with the probabilities of marginal values (Table 10 and Table 11), to assess the impact of various explanatory factors affecting farm households' adaptation strategy choice. Select similar adaptation strategies were combined and assessed as a single strategy, for example rented out cropland and migration to urban area and changed fertilizer and soil conservation. The multivariate model has proven to be sound in term of statistical diagnostics (Prob >  $\chi^2$ , Pseudo-R<sup>2</sup> of 0.0680–0.1248 and log likelihood ratio of –278.5044

**Table 8**  
Factors affecting adaptive capacity

Variables	Changed crop variety and type (CVT)	Changed planting dates and tree plantation (CPT)	Changed fertilizer and soil conservation (CFS)	Increased irrigation and crop diversification (ICD)	Rented out crop and migration (RCM)
DGK	0.470*** (0.102)	0.871 (0.194)	1.246 (0.281)	0.630** (0.147)	0.404* (0.202)
Concerned to climate change	2.035* (0.813)	7.454*** (3.303)	10.20*** (5.807)	4.089*** (2.125)	0.209*** (0.115)
Experience	0.983 (0.0117)	0.971** (0.0120)	0.968*** (0.0121)	0.970** (0.0127)	0.966 (0.0268)
Weather forecast	0.527 (0.211)	0.553 (0.229)	0.425** (0.177)	0.366** (0.157)	0.651 (0.577)
Market Understanding	0.890 (0.243)	1.575 (0.442)	1.481 (0.426)	1.925** (0.603)	1.827 (1.090)
31–40 Years Age	0.990 (0.331)	1.589 (0.549)	1.353 (0.463)	1.373 (0.469)	1.161 (0.759)
41–50 Years Age	1.939* (0.728)	1.209 (0.464)	0.780 (0.300)	0.895 (0.356)	1.994 (1.497)
51 and above Years Age	1.663 (0.764)	0.889 (0.420)	0.624 (0.297)	1.061 (0.524)	0.682 (0.805)
Primary	0.639 (0.208)	1.618 (0.533)	1.596 (0.525)	1.655 (0.559)	1.850 (1.352)
Matric	1.316 (0.406)	0.629 (0.198)	0.654 (0.210)	0.707 (0.244)	1.011 (0.811)
Higher	1.572 (0.541)	0.656 (0.229)	0.870 (0.304)	0.860 (0.323)	2.284 (1.801)
Public & private employment	0.403* (0.199)	0.284*** (0.130)	0.403** (0.185)	0.361* (0.209)	0.446 (0.504)
Own off business	0.856 (0.357)	0.187*** (0.0876)	0.191*** (0.0960)	0.388* (0.202)	–
Farming and off farming	0.756 (0.299)	0.768 (0.315)	0.398** (0.176)	0.426* (0.205)	0.401 (0.337)
Family system	1.492 (0.523)	1.307 (0.490)	1.112 (0.416)	0.666 (0.274)	1.594 (1.041)
Agricultural credit access	1.011 (0.223)	0.838 (0.189)	0.923 (0.210)	1.264 (0.298)	1.474 (0.663)
Constant	0.938 (0.578)	0.587 (0.379)	0.402 (0.294)	0.454 (0.322)	0.319 (0.374)
LR $\chi^2$ (13)	40.41	62.08	70.12	44.46	24.76
Prob > $\chi^2$	0.0001	0.0000	0.0000	0.0000	0.0248
Pseudo-R <sup>2</sup>	0.0680	0.1003	0.1142	0.0811	0.1248
Log likelihood	–278.5044	–278.3462	–271.9609	–251.942	–86.86255
Observations	448	448	448	448	448

Standard errors in parentheses \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

to –86.86255) (Noreen, 1989, 1988).

#### Climate adaptation choices across districts

DGK farmers are less likely to adopt changed crop variety/crop type (CVT), increased irrigation/crop diversification (ICD), and rented out cropland/migration to urban area (RCM) as compared to Rajanpur, and the relationship is statistically significant, while changed plantation dates/tree plantation (CPT) and changed fertilizer/soil conservation (CFS) have no significant difference across the two districts (Table 8). The bivariate probit model results show that DGK farmers are less likely to adopt CVT and PDT simultaneously, as well as CFS and ICD simultaneously, as compared to farmers in Rajanpur. The probability of the marginal values shows that DGK farmers are 11% less likely to adopt CVT and PDT and, 6% less likely to adopt CFS and ICD, at the same time, as compared to Rajanpur farmers. Overall, results suggest district location in itself does not have a significant effect on likelihood of adopting any of the strategies.

#### Farmer concern about climate change

One of the binary variables in the study is climate change concern (CCC), which is a crucial factor in determining the adaptation strategies of farm households. Results showed that respondents who express

concern about climate change are more likely to implement all the adaptation strategies listed Table 8 except for rented out cropland/migration to urban area, with all variables significant at 5% and 10% confidence level. Moreover, the highly significant coefficient of CCC indicates that the likelihood of adapting to climate change increases as the level of concern about climate change increases. Similarly, the bivariate probit result shows that farm households who are concerned about climate change are more likely to simultaneously adopt CVT with PDT and CFS with ICD, with significant results. The probability of the marginal values further show that increase in CCC will lead to a 22% increased probability of adopting CVT with PDT, and a 19% increased probability in adopting at least one adaptation strategy (Table 10). Further, increase in CCC will lead to a 21% increased the probability of adopting CFS with ICD adaptation strategy at the same time (Table 11).

#### Years of farming experience

As years of farming experience increase, there is decreased probability for adapting PDT, CFS, and ICD, which were found to be statistically significant. The remaining adaptation strategies (CVT, RCM) were insignificant. These findings are consistent with previous studies (Hisali et al., 2011; Ali and Erenstein, 2017). The bivariate model showed an inverse relationship between years of farming experience and likelihood

**Table 9**  
Results of Bivariate Probit Logistics Regression

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	CVT	PDT		CFS	ICD	
DGK	−0.444*** (0.132)	−0.110 (0.133)		0.0931 (0.134)	−0.270** (0.137)	
Concerned to climate change	0.486** (0.248)	1.203*** (0.252)		1.171*** (0.270)	0.728*** (0.261)	
Experience	−0.0105 (0.00723)	−0.0162** (0.00722)		−0.0192*** (0.00729)	−0.0162** (0.00764)	
Weather forecast	−0.384 (0.241)	−0.360 (0.247)		−0.471* (0.252)	−0.597** (0.261)	
Market understanding	−0.0680 (0.167)	0.279 (0.172)		0.246 (0.173)	0.407** (0.184)	
31–40 Years Age	−0.0101 (0.204)	0.295 (0.211)		0.260 (0.207)	0.139 (0.205)	
41–50 Years Age	0.412* (0.227)	0.114 (0.231)		−0.0757 (0.232)	−0.0943 (0.238)	
51 and above Years Age	0.310 (0.278)	−0.0779 (0.282)		−0.192 (0.284)	−0.00298 (0.293)	
Primary	−0.289 (0.197)	0.321 (0.197)		0.256 (0.196)	0.287 (0.198)	
Matric	0.179 (0.186)	−0.253 (0.187)		−0.213 (0.192)	−0.221 (0.201)	
Higher	0.275 (0.209)	−0.237 (0.209)		−0.101 (0.211)	−0.0532 (0.218)	
Public & private employment	−0.585** (0.298)	−0.747*** (0.274)		−0.484* (0.274)	−0.653* (0.335)	
Own off business	−0.114 (0.255)	−0.966*** (0.267)		−0.894*** (0.275)	−0.588** (0.299)	
Farming and off farming	−0.196 (0.248)	−0.162 (0.250)		−0.547** (0.251)	−0.443* (0.262)	
Family system	0.259 (0.217)	0.172 (0.227)		0.0332 (0.213)	−0.146 (0.229)	
Agricultural credit access	0.00783 (0.134)	−0.121 (0.135)		−0.0687 (0.138)	0.112 (0.141)	
athrho			0.521*** (0.0892)			1.516*** (0.154)
Constant	−0.0982 (0.378)	−0.344 (0.381)		−0.429 (0.399)	−0.398 (0.395)	
Wald $\chi^2$ (32)	115.96			90.11		
Prob > $\chi^2$	0.0000			0.0000		
Wald test of $\rho = 0$ : $\chi^2$ (1)	34.0539			97.3782		
Log likelihood	−526.07579			−421.13857		
Observations	448	448	448	448	448	448

Standard errors in parentheses \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

to adopt select adaptation strategy combinations (Table 9). The coefficients for CVT, PDT, CFS, and ICD are negative and statistically significant (except CVT), suggesting that more years of farming experience are associated with a lower probability of adopting the above-mentioned strategies. The coefficient for CVT is not statistically significant, suggesting that years of farming experience do not have a significant effect on the adoption of either strategy. The probability of the marginal values shows that with each 1% increase in years of farming experience, farmers are 0.5% less likely to jointly adopt CVT with PDT and 0.7% less likely to adopt CFS with ICD (Tables 10 and 11).

#### Availability of weather forecast information

Results show when farmers have access to information about weather forecast, they are less likely to adopt any of the adaptation strategies. The coefficients are insignificant for the rest of the strategies which means that having access to weather forecast does not affect the uptake of strategies (Table 8). The bivariate probit model result shows that farm households that have access to weather forecast information are less likely to adopt CVT with PDT and CFS with ICD, but the coefficient of ICD is statistically significant. The marginal effects show when farm households have weather forecast information, this will result in a 14% decreased probability of jointly adopting CVT and PDT and a 21% decreased probability of jointly adopting CFS and ICD (Table 10 and Table 11).

#### Information on crop value in market (market understanding)

Results show when farmers have increased market understanding, they are more likely to adopt all the adaptation strategies except for CVT, in line with previous research results (Abid et al., 2015, 2019). The bivariate probit model result shows that farm households who have better market understanding are more likely to adopt PDT and less likely to adopt CVT. The marginal effects show that better market understanding will result in a 2.5% increased probability to jointly adopt CVT and PDT. With better market understanding, farmers are more likely to adopt CFS or ICD, with the ICD variable significant. The marginal effects show that better market understanding will result in an 11% increased probability to jointly adopt CFS and ICD (Table 10 and Table 11).

#### Age

Results show that those farmers who are between 31 and 40 years are more likely to adopt PDT, CFS, ICD, and RCM as compared to those between 18 and 30 years old. Those who are 41–50 years old are more likely to adopt CVT, PDT, and RCM as compared to those between 18 and 30 years, with CVT statistically significant. Those who are 51 years and above are more likely to adopt CVT and ICD as compared to those between 18 and 30 years. These results are similar trends as in previous studies (Deressa et al., 2009).

The bivariate probit model result shows that farmers who are between the ages of 31–40 are more likely to adopt PDT and less likely to adopt CVT. The marginal effects show that those between 31 and 40



**Table 10**  
Probability of margin effects CVT & PDT.

	(1)	(2)	(3)	(4)
Variables	CVT = 0, PDT = 0	CVT = 0, PDT = 1	CVT = 1, PDT = 0	CVT = 1, PDT = 1
DGK	0.0941**	0.07314**	-0.0504**	-0.1168***
Concerned to climate change	-0.3661***	0.1975***	-0.0554	0.2239***
Experience	0.0058**	-0.0018	0.0006	-0.0046**
Weather forecast	0.1405**	0.0097	-0.0016	-0.1487**
Market understanding	-0.0595	0.0855**	-0.513	0.0253
31–40 Years Age	-0.0859	0.0894	-0.0301	0.0266
41–50 Years Age	-0.9265	-0.0628	0.0472	0.0108**
50 and above years	-0.0303	-0.0849	0.0613	0.0538
Primary	-0.0655	0.1670***	-0.0563**	-0.0451
Matric	0.0325	-0.1014**	0.0681**	0.0007
Higher and above	0.0095	-0.1161**	0.0847**	0.0218
Public & Private employment	0.2915***	-0.0930	-0.0035	-0.1948***
Own off business	0.2347***	-0.1915***	0.1243**	-0.1676***
Farming & off farming	0.0704	0.0030	-0.0064	-0.0069
Family System	-0.0810	-0.0198	0.0134	0.0874
Agricultural credit access	0.0303	-0.0333	0.0178	-0.0148
Observations	448	448	448	448

Standard errors in parentheses \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table 11**  
Probability of margin effects of CFS & ICD.

	(1)	(2)	(3)	(4)
Variables	CFS = 0, ICD = 0	CFS = 0, ICD = 1	CFS = 1, ICD = 0	CFS = 1, ICD = 1
DGK	-0.0096	-0.0268**	0.1009***	-0.0644
Concerned to climate change	-0.3427***	-0.0188	0.1454***	0.2162***
Experience	0.0074***	0.0009	-0.0019	-0.0055**
Weather forecast	0.1987**	-0.0124	0.0238	-0.2101**
Market understanding	-0.1063**	0.0114	-0.0220	0.1169**
31–40 Years Age	-0.0972	-0.0059	0.0486	0.545
41–50 Years Age	0.03115	-0.0016	-0.0003	-0.0291
50 and above years	0.05791	0.0156	-0.0569	-0.0166
Primary	-0.1052	0.0033	0.0008	0.1010
Matric	0.08361	-0.0020	-0.136	-0.0649
Higher and above	0.3663	0.0028	-0.0188	-0.0206
Public & Private employment	0.1936***	-0.0104	-0.0035	-0.1769***
Own off business	0.2915***	0.1511	-0.1160***	-0.1905***
Farming & off farming	0.2014***	0.0029	-0.0618	-0.1424***
Family System	-0.0031	-0.0099	0.0508	-0.0378
Agricultural credit access	0.0126	0.0141	-0.0509	0.0241
Observations	448	448	448	448

Standard errors in parentheses \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

years have a 2.6% increased probability to jointly adopt CVT and PDT. Those farmers between the ages of 41–50 are more likely to adopt CVT and PDT, with CVT statistically significant. The marginal effects show that those in this age bracket have a 1.8% increased probability to jointly adopt CVT and PDT, with joint adaptation probability statistically significant. Those farmers between the ages of 51 years and above are more likely to adopt CVT and less likely to adopt PDT. The marginal effects show that those in this age bracket have a 5.3% increased probability to jointly adopt CVT and PDT. The reference age bracket for the above is 18–30 years.

Farmers between the ages of 31–40 are more likely to adopt CFS and ICD. The marginal effects show this age group has a 5.4% increased

probability to jointly adopt CFS and ICD. Farmers aged 41–50 are less likely to adopt CFS and ICD. The marginal effects show this age group has a 0.2% decreased probability to jointly adopt CFS and ICD. Farmers aged 51 and above are less likely to adopt CFS and ICD, with marginal effects showing a 0.1% decreased probability to jointly CFS and ICD. Overall, the variables were insignificant, suggesting that age does not have a significant impact on adaptation choice.

#### Education level

Results indicate education is an important variable affecting adaptive capacity of farmers, as found in previous studies (Maddison, 2007; Deressa et al., 2009; Jha and Gupta, 2021). Multivariate logistic regression shows that as education level increases, farmers are more likely to adopt each adaptation strategy, as compared to farmers with no education (Table 8). The bivariate probit result shows that those with primary level education are more likely to adopt PDT, and less likely to adopt CVT. The marginal effects show that those with primary level education have 0.4% decreased probability to jointly adopt PDT and CVT. Those with matric level education are more likely to adopt CVT, and less likely to adopt PDT. The marginal effects show those with matric level education have 0.7% increased probability to jointly adopt PDT and CVT. Those with higher level education are more likely to adopt CVT, and less likely to adopt PDT, with marginal effects showing a 2.1% increased probability of jointly adopting CVT and PDT. Those with primary level of education are more likely to adopt CFS and ICD. Marginal effects show those with primary level education have a 10% increased probability of jointly adopting CFS and ICD. The remaining education levels show less likelihood to jointly adopt CFS and ICD, possibly due to the high costs of these adaptation strategies.

#### Income source other than farming

Results showed that those with an income source from public and private employment, own business, or both farming and off-farm employment are less likely to adopt CVT, PDT, CFS, and ICD compared with those whose income source is only farming, with statistically significant results (Table 8). The bivariate probit shows a negative but significant relationship between the variables, meaning income source other than farming will lead to decreased likelihood for adopting the strategies (Table 9). The margin effects show income source from public and private employment, own business, and farming and off-farming will result in a 19%, 16%, and 0.6% decreased probability of jointly adopting CVT and PDT, respectively (Table 10). Income source from public and private employment, own business, and farming and off-farming will result in a 17%, 19%, and 14% decreased probability to jointly adopt CFS and ICD, respectively, with highly significant results (Table 11).

#### Family system of farming household

Results show households living in a joint family system are more likely to adopt the adaptation strategies except ICD, as compared to those living within a nuclear family system. Relationships were found to be insignificant (Table 8), suggesting that family system does not have a significant effect on adaptation strategy choice. The bivariate model shows those living in a joint family system are more likely to adopt CVT, PDT, and CFS, and less likely to adopt ICD (Table 9). Marginal effects show that those in a joint family system have a 8% increased probability to jointly adopt CVT and PDT, and a 3% decreased probability to jointly adopt CFS and ICD (Table 10 and Table 11).

#### Access to agricultural credit (Loan Scheme)

The farm households with access to agricultural credit are more likely to adopt CVT, ICD, and RCM compared to those who do not have access to agricultural credit (Table 8). All variables were found to be insignificant, similar to previous findings (Abid et al., 2015; Di Falco et al. 2012), and suggesting that access to agricultural credit may not have a major impact on adaptation strategy choice. Similarly, bivariate

probit results show an insignificant relation among the dependent variables, including marginal effect values. However, there is mixed evidence in the literature on whether access to credit promotes climate-smart adaptation (Bakare et al., 2023; Ruben et al., 2019). Future research can assess different trade-offs to be considered among different adaptation strategies that are supported through agricultural credit.

## Discussion and conclusion

The aim of this study was to evaluate the adaptive capacity of farming communities in two districts of Punjab province to adjust and respond to changes in their environment, and their likelihood of adopting joint strategies. Results indicate that farmers in Rajanpur district are more likely to adopt all the discussed adaptation strategies as compared to those living in DGK. This higher level of adaptive capacity could be due to the district's heavier reliance on agriculture and farming, as well as being more severely affected by the recent floods than DGK.

The study results reveal that concern about climate change and market knowledge of crop value were the most significant determinants of farmers' adaptation choices. Farmers who displayed greater concern for climate change and had a better understanding of the local agricultural market were found to be significantly more likely to adopt the joint strategies, such as CVT and PDT, and CFS and ICD. These findings are logical, as farmers lacking these attributes would have less of a reason to alter their crop type or variety or change their farming practices. Based on these results, future interventions aimed at enhancing farmers' adaptive capacity should consider several factors. Firstly, interventions should prioritize raising awareness among farmers about the potential impacts of climate change on their crops and livelihoods. Secondly, interventions should consider improving access to information about the local agricultural market to enable farmers to make more informed decisions regarding crop selection and management practices. This could include providing training on market analysis and price forecasting or setting up information-sharing platforms that provide farmers with up-to-date information on market trends and demand. Thirdly, interventions should address the socio-economic factors that may be hindering the adoption of joint adaptation strategies. This could involve providing financial incentives, such as subsidies or loans, to support the adoption of new technologies or practices. Additionally, social safety nets and insurance schemes could be put in place to help farmers cope with the financial risks associated with climate change and other economic shocks.

Additionally, findings revealed that years of farming experience and sources of income other than farming exhibit a negative relationship with adaptation adoption. Farmers with more extensive years of farming experience and those with alternate income sources are less likely to adopt the joint adaptation strategies. The negative relationship observed between years of farming experience and adaptation adoption, as well as the relationship with alternative sources of income, may be attributed to several factors. For example, farmers with more years of experience may have established traditional farming practices that have served them well in the past. As such, they may be less open to change and less likely to adopt new strategies or technologies that deviate from their established methods. Moreover, farmers with alternative sources of income may have less of a motivation to adopt new adaptation strategies that require additional investments in time and resources. Lastly, there may be other social, cultural, or economic barriers that hinder the adoption of joint adaptation strategies, which may vary depending on the individual farmers' circumstances.

Another interesting finding is that out of the 448 total farmers surveyed, 32% (N = 143) had implemented none of the 10 listed adaptation strategies, while only 5% (N = 23) had implemented 7–10 strategies. The remaining had implemented either 1–3 strategies (40%) or 4–6 strategies (23%). Despite living in flood-prone and climate risk areas, and reporting concern about climate change, majority of the farmers in

the study area have overall low adaptive capacity. This may suggest that simply acknowledging the existence of climate change does not necessarily lead to taking concrete actions to adapt to its impacts. Other studies have also found that variables such as food insecurity and household expenses are more salient motivators for adaptation strategies than environmental concerns (Waldman et al., 2019).

This sheds light on the complex decision-making processes that farmers undergo and highlights the importance of recognizing the external factors that contribute to the gap between climate beliefs and actions. These factors may include a lack of institutional support or financial constraints. While the results suggest that farmers in the study area have low adaptive capacity, further investigation is necessary to identify the specific reasons for this limitation, such as insufficient personal motivation or inadequate institutional support. This emphasizes the need for interventions that not only address the environmental impacts of climate change but also the social and economic factors that influence farmers' adaptive capacity. Moreover, a better understanding of social and cultural norms, as well as religious influences on farming practices, may provide valuable insights for designing effective interventions.

Overall, interventions aimed at promoting the adoption of multiple adaptation strategies may need to focus on improving farmers' awareness and understanding of the risks and opportunities associated with climate change, as well as the potential benefits of combining different strategies in a holistic and integrated manner.

The results of this study contribute some understanding of the determinants of farmer adaptive capacity in the study area, but there is still a need for further research to fully understand the factors involved in the decision-making process itself. Adaptation decisions may be influenced by a range of social, economic, and environmental factors, and it is important to recognize that farmers, like all individuals, do not always make decisions based solely on rational thinking. Instead, their decisions may be influenced by factors such as social norms, peer pressure, values, beliefs, and emotions, as well as external pressures and constraints such as financial constraints and market dynamics.

For example, the survey highlighted that increased irrigation was the third and fourth most used adaption strategy in Rajanpur and DGK, respectively, despite the negative impacts increased irrigation may pose on the environment and water availability. While farmers may be aware of the potential negative impacts of increased irrigation, they may prioritize short-term economic gains over long-term sustainability, particularly if they are facing immediate financial pressures or have limited access to alternative adaptation options.

Therefore, it is important to consider the cognitive and emotional factors that may influence farmers' decision-making when developing policies and strategies to enhance their adaptive capacity. This requires a deeper understanding of the social and cultural contexts in which farmers operate, as well as an appreciation of the non-rational factors that may shape their decision-making processes. This will allow for the development of more effective approaches to promote the adoption of climate-resilient practices and enhance farmer adaptive capacity, for example incorporating social norms and values into extension programs, engaging with communities and peer networks, and addressing potential barriers to adoption, such as access to finance and information.

Additionally, interventions should also address the economic and institutional barriers that prevent farmers from adopting more sustainable practices. For example, providing farmers with access to more efficient and sustainable irrigation technologies, such as drip irrigation, can help reduce the negative environmental impacts of irrigation while still allowing farmers to meet their water needs. Similarly, providing farmers with access to credit, insurance, and other forms of institutional support can help reduce the economic risks associated with adopting more sustainable practices and encourage more environmentally friendly decision-making. Farmers are not solely responsible for making environmentally sustainable decisions, and governments and other stakeholders have a critical role to play in providing the necessary

infrastructure, policies, and regulations to support sustainable adaptation practices and ensure that environmental concerns are integrated into decision-making processes at all levels.

### Limitations of the study

The present study only selected farmers from two districts in South Punjab and surveyed them at a single point in time; future studies could select multiple districts and conduct a panel study to assess farmers' adaptation strategy choice over time. Additionally, future studies may employ mixed method approaches and conduct focus group discussions with farmers to gain deeper insight on the adaptation strategy decision-making process, which may uncover hidden determinants difficult to capture by a survey alone. Lastly, including female farmers and other underrepresented farming groups in future research can add more nuance to understanding farmers' behaviors and coping mechanisms in the context of climate change and ensure a more comprehensive understanding of the community's adaptive capacity.

### Ethical approval

This study was approved by the Ethics Review Board of Near East University, North Cyprus.

### Consent to participate

Informed verbal consent was taken from each eligible participant.

### Availability of data and materials

Data may compromise the privacy of study participants and may not be shared publicly. Data are available upon request to corresponding author Sohaib Aqib, Faculty of Economics and Administrative Science, Department of Economics, Near East university, North Cyprus, Cyprus, Email: sohaibaqib@yahoo.com.

### Author contributions

Study conception and design: Sohaib Aqib, Dr. Mehdi Seraj. Acquisition of data: Sohaib Aqib, Taimoor Ahmad. Analysis and interpretation of data: Sohaib Aqib, Taimoor Ahmad, Muhammad Haseeb Raza. Drafting of manuscript: Sohaib Aqib, Sidra Khalid. Critical revision: Huseyin Ozdeser, Sidra Khalid. All authors read and approved the final manuscript.

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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.

### Data availability

Data will be made available on request.

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