Journal of Agricultural Policy and Transformation (AgriPaT)
Journal homepage: http://www.ageconfrontiers.com/agripat

Climate Change and Agricultural Adaptation in Punjab, Pakistan

Muhammad Shakeel[1,*], Anwar-ul-Haq[1], Jannat Bibi[2], Zainab Sarfraz[1] & Huzaifa Naeem Bukhari[1]
[1]Institute of Agricultural and Resource Economics, University of Agriculture Faisalabad, Pakistan
[2] Department of Economics, Government College University, Faisalabad, Pakistan
* mshakeel187786@gmail.com

ARTICLE INFO

Keywords:
Climate Change
Adaptation
Agricultural Productivity
Punjab Pakistan
Smallholder Farmers
Binary Logistic Regression
Water-Efficient Irrigation

Received: 10 March 2026
Received in revised form: 29 April 2026
Accepted: 02 May 2026
Available online: 02 May 2026

ABSTRACT

Climate change poses a severe threat to agricultural productivity and rural livelihoods in Pakistan, yet farm-level adaptation responses remain insufficiently understood. This study examines climate change impacts and determinants of adaptation strategies among 100 randomly selected farmers in Punjab, Pakistan, using binary logistic regression. Results indicate substantial climate-induced production losses: cotton (40.6%), maize (35.1%), rice (33.4%), sugarcane (25.2%), and wheat (22.9%). Education emerged as the most consistent positive determinant of adaptation across all three strategies, change in sowing dates (OR = 1.345, $p < 0.05$), drought-resistant seeds (OR = 1.303, $p < 0.05$), and water-efficient methods (OR = 1.363, $p < 0.01$). Farm size significantly influenced only water-efficient method adoption (OR = 1.102, $p < 0.05$). Climate awareness and perceived yield losses showed large positive associations with adaptation, though statistical significance varied. These findings underscore that education and direct climate experience drive adaptive behavior, while capital-intensive adaptations require greater resource endowments. Targeted investments in extension services, climate information systems, and financing mechanisms for small-scale farmers are essential to enhance agricultural resilience in climate-vulnerable regions.

1. Introduction

Climate change represents one of the most pressing global challenges confronting agricultural systems, food security, and rural livelihoods, particularly in developing economies. Rising ambient temperatures, shifts in precipitation regimes, and the increased frequency of extreme weather events have fundamentally altered agro-ecological conditions worldwide. Staple cereals such as wheat, rice, and maize exhibit pronounced sensitivity to heat stress, with empirical evidence indicating that a 1°C increase in temperature could reduce global agricultural yields by 5 to 10 percent (Orlov et al., 2021). Furthermore, irregular rainfall, prolonged droughts, and flooding exacerbate water scarcity for irrigation, accelerate soil fertility degradation, and elevate crop failure risks. Extreme climatic events also damage agricultural infrastructure, disrupt supply chains, and generate substantial economic losses (Brempong et al., 2023).

The adverse effects of climate change propagate across multiple interconnected sectors, including water resources, energy, agriculture, food security, and human livelihoods (Liaqat et al., 2022). Consequently, sustainable agricultural systems necessitate long-term investments in infrastructure, improved irrigation networks, and climate-resilient technologies (World Bank, 2014). However, least developed and developing countries remain disproportionately vulnerable due to limited adaptive capacity, institutional constraints, and heavy reliance on climate-sensitive agriculture (Hansen et al., 2016). Global assessments, including the Global Climate Risk Index and IPCC reports, consistently highlight severe agricultural vulnerability across many regions, especially where resilience is low and exposure to climatic risks is high (Adil et al., 2025).

Beyond direct climatic pressures, agriculture faces additional structural challenges. Soil degradation from excessive fertilizer application and poor land management reduces arable land and threatens long-term food security (David Ra et al., 2025). Water scarcity, driven by over-extraction and pollution, constrains irrigation and crop growth (Matta et al., 2025). Smallholder farmers often lack access to modern technologies, quality seeds, credit facilities, and market information, thereby limiting their adaptive capacity (Branca et al., 2021). Climate change also increases pest and disease prevalence, raising production costs and further undermining agricultural sustainability (Raihan, 2023). According to the Intergovernmental Panel on Climate Change, global temperatures have already risen approximately 1.1°C above pre-industrial levels, with further warming projected unless greenhouse gas emissions are substantially reduced (Masson-Delmotte et al., 2022). These changes disrupt ecological balance by affecting water availability, soil fertility, and seasonal cycles critical for production, while also exacerbating desertification and land degradation (Hossain et al., 2020).

Within this global context, Pakistan presents a particularly salient case. Agriculture remains the backbone of Pakistan's economy, contributing approximately 23.54% to GDP and employing around 37% of the labor force (GOP, 2025). Over 60% of the rural population depends directly or indirectly on agriculture for their livelihoods. The sector supplies raw materials to major industries, notably textiles, and plays a critical role in food security, poverty reduction, and economic stability. Major crops such as wheat, rice, and cotton also contribute to export earnings and foreign exchange reserves, underscoring the sector's macroeconomic importance (GOP, 2025). Pakistan is ranked among the world's most climate-vulnerable countries, as evident by the devastating floods of 2010, 2022 and 2025. In response, the country has initiated several climate resilience measures, including engagement with global climate finance mechanisms such as the Loss and Damage Fund and commitments under COP-28. Pakistan has also set a target to shift 60% of its energy mix toward renewable sources by 2030. Nevertheless, effective climate adaptation requires equitable global energy transitions and increased concessional climate financing tailored to developing countries (Adnan et al., 2024).

In 2025, climate change severely affected Pakistan's agricultural production, with overall crop yields declining by 13.5%. Wheat production fell by 8.9% due to heat stress and dry spells, while cotton output dropped sharply by 30.7% because of excessive monsoon rainfall and reduced cultivated area (Amjad, 2025). Sugarcane and maize production also declined, and rice productivity fell despite an expansion in cultivated areas due to erratic weather and localized water shortages (Gosai et al., 2025). Rising temperatures intensified pest infestations, increased pesticide use, and reduced water availability during critical cropping seasons, further undermining productivity (Aeman et al., 2023). Indirect effects have been equally severe: reduced cotton output threatens Pakistan's textile industry, increases import dependence, and strains foreign exchange reserves. Declining food crop production raises concerns over food insecurity and price volatility, particularly affecting smallholder farmers who have experienced substantial income losses. Supply chain disruptions and shifts in cropping patterns further alter regional agricultural systems (Izuchukwu et al., 2025). Despite policy initiatives such as the National Climate Change Policy 2023, implementation of climate-smart agriculture remains constrained by financial limitations and institutional coordination challenges. Without timely interventions, climate change poses a serious threat to Pakistan's agricultural sustainability and economic stability (Amjad, 2025; Adom, 2024).

While the adverse impacts of climate change on crop productivity are widely acknowledged, the effectiveness and determinants of farmers' adaptation responses at the micro (farm) level remain insufficiently understood. Existing literature on climate change and agriculture in Pakistan has predominantly focused on macro-level assessments, simulation models, or aggregate yield impacts, often overlooking farm-level behavioral responses and decision-making processes. Moreover, many studies treat adaptation as a binary or aggregated outcome, failing to capture the diversity of adaptation strategies adopted by farmers such as adjustments in sowing dates, adoption of drought-resistant seeds, and water management practices. This limit understanding of how different socioeconomic and perceptual factors influence specific adaptation choices.

Against this backdrop, the present study examines the impacts of climate change on agricultural production and analyzes adaptation strategies adopted by farmers in Punjab, Pakistan, the country's agricultural heartland. By providing empirical evidence on crop losses and adaptation behavior, the study aims to inform policy interventions that strengthen agricultural resilience and promote sustainable development under changing climatic conditions. Given the critical role of agriculture in Pakistan's economy and society, and the sector's high sensitivity to climatic variations, it is imperative to understand and address the impacts of climate change. Research in this area is crucial for developing effective adaptation strategies, informing policy decisions, and ensuring the long-term sustainability of agricultural production. This study seeks to fill gaps in current knowledge by providing an in-depth analysis of how climate change is affecting the agricultural sector in

Pakistan, identifying key vulnerabilities, and proposing practical solutions to enhance resilience.

2. Methodology

Study Area Selection

This study investigates the impacts of climate change and agricultural adaptation strategies in Punjab, Pakistan, a region where agriculture constitutes a cornerstone of rural livelihoods and food security (GOP, 2025). As a representative case, District Toba Tek Singh, located in central Punjab, was purposively selected due to its diversified cropping system and documented exposure to climate variability (Amjad, 2025). According to the Pakistan Census 2022, the district has a population of 2,524,044 and covers an area of 3,252 km² (Pakistan Bureau of Statistics (PBS), 2023). The region receives an average annual rainfall of 462 mm, with pronounced seasonal fluctuations and peak precipitation during July and August. Agricultural production depends heavily on canal irrigation and groundwater extraction, rendering the area vulnerable to erratic rainfall, rising temperatures, and water scarcity (Matta et al., 2025). Major crops grown include wheat, rice, cotton, sugarcane, and maize, all of which exhibit high sensitivity to climatic stressors (Orlov et al., 2021; Aeman et al., 2023). These characteristics establish Toba Tek Singh as an appropriate case for analyzing climate change impacts and farm-level adaptation responses in Punjab.

Multistage Sampling Procedure and Sample Size

A multistage sampling procedure was employed to select respondents from District Toba Tek Singh. This approach ensures representativeness and minimizes selection bias by progressively narrowing the sampling frame from district level to individual farming households.

In the first stage Toba Tek Singh district was purposively selected due to its agricultural significance in central Punjab and its high exposure to climate change impacts, consistent with the study's focus on climate-vulnerable agricultural systems (Adil et al., 2025). In the second stage of the sampling procedure Toba Tek Singh tehsil was randomly selected among the four tehsils namely Toba Tek Singh, Gojra, Kamalia, and Pir Mahal. The third stage of the sampling procedure comprised of selection of Union Councils. Within the selected tehsil, three Union Councils (UC No. 38, 39, and 41) were randomly selected to provide a representative cluster of farming households. In the fourth stage, one village from each selected Union Council was selected at random. The final stage of the sampling procedure involved the selection of sampled farmers. Farmers were selected using simple random sampling from the three chosen villages. A total of 100 farmers were interviewed, providing sufficient data for statistical analysis and enhancing the reliability of the study findings.

The sample size was determined using the following equation (Eq. 1):

$$n = \frac{p(1-p)z^2}{e^2}$$

Where:
p = probability of the population being farmers,

z^2 = standard normal distribution value,

e = precision level.

Using the above equation with a 90% probability of the population being farmers and a 10% precision level, a total of 100 respondents were sampled for the present research. This sample size is consistent with farm-level studies examining adaptation determinants in climate-vulnerable contexts (Branca et al., 2021).

Data Collection

Primary data were collected through in-person interviews with sampled farmers using a structured questionnaire. The questionnaire was pre-tested with a small subsample (n = 10) to ensure clarity, relevance, and reliability, with modifications made accordingly. The instrument included both closed-ended and open-ended questions, capturing the following information:

- Socio-economic characteristics of farmers (age, education, income, family size)
- Farm-level information (land size, inputs, cropping patterns)
- Awareness and perception of climate change (Hansen et al., 2016)
- Adoption of climate-resilient practices (Liaqat et al., 2022)
- Observed changes in rainfall and temperature (Masson-Delmotte et al., 2022)
- Institutional support and access to extension services

Data Analysis

Data were analyzed using a combination of descriptive and econometric techniques. Descriptive statistics (means, percentages, and standard deviations) were employed to profile respondent characteristics. Cross-tabulations were used to examine bivariate relationships between variables. Binary logistic regression was applied to determine the influence of explanatory variables on the likelihood of adaptation, an approach widely used in farm-level adaptation studies (Branca et al., 2021; Eshetu and Mekonen, 2024).

Binary Logistic Regression

To assess the determinants of farmers' adaptation to climate change, a binary logistic regression model (logit model) was employed. The dependent variable is binary, coded as 1 if the farmer has adopted any climate change adaptation strategy and 0 otherwise. The study focused on the three most prevalent adaptation strategies: change in sowing dates, use of drought-resistant seeds, and use of water-efficient methods, each analyzed as a separate binary outcome. These strategies are commonly recognized as climate-resilient practices in water-scarce and heat-stressed agricultural systems (World Bank, 2014; Liaqat et al., 2022).

The model examined how various independent variables including age, education, annual income, farm size, awareness of climate change, perceived effects on crop yields, and increased cost of production affect the likelihood of adopting each strategy. The analysis provides insight into the socio-economic and behavioral factors that significantly influence farmers' decisions in responding to climate-induced agricultural challenges (Adom, 2024). The general form of the logit model is specified as follows (Eq. 2):

$$\text{Logit}\left(\frac{P}{1-P}\right) = \beta_0 + \beta_i X_i + e_i$$

Where:
P is the probability that a farmer adopts a specific adaptation strategy (e.g., change in sowing dates, use of drought-resistant seeds, or water-efficient methods), while $(1-P)$ is the probability of non-adoption. The left-hand side, $\text{Logit}(P/(1-P))$, represents the log-odds of adoption. On the right-hand side, β_0 is the intercept, β_i are the coefficients of the independent variables X_i, and e_i is the error term. This model estimates how different factors influence the likelihood of adopting each adaptation strategy.

Odds Ratios Interpretation

The odds ratio (OR) derived from logistic regression quantifies the change in odds of adopting a climate change adaptation practice with a one-unit increase in an explanatory variable, holding other variables constant (Ullah and Zubair, 2021):

- An OR > 1 indicates a positive association between the variable and adaptation behavior.
- An OR < 1 indicates a negative association.
- An OR = 1 suggests no effect.

Odds of an event are defined as the ratio of the probability that an event will occur to the probability that it will not occur. If the probability of an event happening is p, and the probability of the event not happening is $(1-p)$, then the odds are given by (Eshetu and Mekonen, 2024):

$$\text{Odds(Event)} = \frac{P}{1-P}$$

The odds ratio (OR) is a comparative measure of association between two odds relative to different events (Ullah and Zubair, 2021). For two events A and B:

$$\text{Odds}\{A \text{ vs } B\} = \frac{\text{odds}\{A\}}{\text{odds}\{B\}} = \frac{P_A/(1-P_A)}{P_B/(1-P_B)} \text{(Eq. 3)}$$

The OR is used to compare the relative odds of the outcome given exposure to the variable of interest (Eshetu and Mekonen, 2024). Additionally, OR can identify whether a specific exposure is a risk factor for a particular outcome and compare the magnitude of various risk factors. In logistic regression estimation, the regression coefficient (b_i) represents the change in the log-odds of the outcome per unit increase in the value of the exposure (Ullah and Zubair, 2021).

Variable Specification

i) Dependent Variables: Adaptation Strategies

- *Change in Sowing Dates:* Coded as 1 if the farmer has adjusted the timing of crop sowing in response to climate variability (e.g., heat stress or shifted rainfall patterns) and 0 otherwise. This strategy directly addresses temperature-induced phenological disruptions (Orlov et al., 2021; Masson-Delmotte et al., 2022).

- *Use of Drought-Resistant Seeds:* Coded as 1 if the farmer has adopted seed varieties more tolerant to drought conditions and 0 otherwise. Such varieties are key to maintaining yields under water stress (World Bank, 2014; Liaqat et al., 2022).

- *Use of Water-Efficient Methods:* Coded as 1 if the farmer employs techniques such as ridge-and-furrow irrigation or improved irrigation systems to conserve water and 0 otherwise. This practice is critical in contexts of groundwater depletion and erratic rainfall (Matta et al., 2025; Aeman et al., 2023).

ii) Independent Variables

- *Farm and Farm Household Attributes:* These socio-economic factors influence farmers' adaptation decisions and include age (measured in years), education (measured in years of formal schooling), annual income (measured in PKR), and farm size (measured in acres). These variables represent personal characteristics and resource capacity, which affect both the ability and willingness to adopt climate adaptation strategies (Branca et al., 2021; Adom, 2024).
- *Behavioral Factors:* This set includes variables related to farmers' perceptions and attitudes toward climate change: awareness of climate change, perceived effects on crop yields, and perceived increase in cost of production due to climate impacts. Perceptual factors are critical mediators of adaptation behavior, as farmers must recognize climatic changes and their consequences before undertaking adaptive actions (Hansen et al., 2016; Adil et al., 2025).

3. Results and Discussion

Descriptive Statistics of Farm Household and Farming Attributes

Table 1 presents the socio-economic profile of sampled farm households (N=100). The average age of respondents was 47.70 years (SD = 12.43), ranging from 20 to 80 years. Approximately 62% of respondents were above 40 years, indicating a mature and experienced farming population. This demographic profile is consistent with observations that individuals aged 40–60 years constitute the core farming cohort in developing-country agricultural systems (Rigg et al., 2020). Mean educational attainment was 5.54 years of schooling (SD = 5.52), with 55% of respondents having only primary education or no formal schooling. This limited educational background may constrain farmers' capacity to understand and adopt climate-smart agricultural technologies, consistent with evidence that education enhances climate awareness and adaptive capacity (Branca et al., 2021; Adom, 2024).

Table 1: Descriptive statistics of farm household attributes (N=100)

Household Profile	Minimum	Maximum	Mean	Std. Deviation
Age (years)	20	80	47.70	12.43
Education (years)	0	18	5.54	5.52
Annual household income (PKR)	75,000	1,200,000	485,150	241,200
Household family members (n)	3	22	8.46	3.97

Mean annual household income was PKR 485,150 (SD = 241,200), with approximately 60% of households earning below the mean, indicating substantial income disparity. This financial vulnerability can constrain the ability to implement adaptation measures, as climate-resilient technologies often require upfront investment (World Bank, 2014; Liaqat et al., 2022). Average household size was 8.46 members (SD = 3.97), with over 40% of households having more than 10 members. While larger families may provide greater labor availability for farming activities, they also create resource strain, potentially limiting investments in adaptive practices (Hansen et al., 2016).

Table 2 summarizes farming-related attributes. Mean farm size was 6.02 acres (SD = 8.38), with most farmers operating as smallholders. This is consistent with the structural characteristics of Pakistani agriculture, where land fragmentation and smallholdings predominate (GOP, 2025). Cultivated land averaged 88.65% of total landholdings (SD = 17.39), indicating efficient land use but potentially increasing susceptibility to climate-induced soil degradation (David Ra et al., 2024). The average number of household members engaged in farming was 1.71 (SD = 1.06), suggesting reliance on mechanization or off-farm income. Mean farming experience was 22.98 years (SD = 11.89), reflecting a well-established farming community with substantial traditional knowledge for coping with climate variability.

Table 2: Descriptive statistics of farming attributes

Farm Information	Minimum	Maximum	Mean	Std. Deviation
Farm size (acres)	1	50	6.02	8.383
Household members engaged in farming (n)	50	100	88.65	17.391
Area rented in (acres)	1	6	1.71	1.057
	1	50	7.55	10.843
Farming experience (years)	2	50	22.98	11.890

Crop Production Losses Due to Climate Change

Table 3 reports self-reported percentage losses in major crop production attributed to climate change. Cotton exhibited the highest average loss (40.55%, SD = 7.94, range: 30–65%), followed by maize (35.14%, SD = 9.26), rice (33.35%, SD = 7.28), sugarcane (25.20%, SD = 5.07), and wheat (22.89%, SD = 7.75). These findings align with national-level estimates reporting a 30.7% decline in cotton output and an 8.9% decline in wheat production due to heat stress and erratic rainfall (Amjad, 2025).

Table 3: Descriptive statistics of agricultural production losses due to climate change

Major Crop	Min (%)	Max (%)	Mean Loss (%)	Std. Deviation
Wheat	10.0	50.0	22.89	7.75
Sugarcane	20.0	40.0	25.20	5.07
Rice	20.0	50.0	33.35	7.28
Cotton	30.0	65.0	40.55	7.94
Maize	20.0	60.0	35.14	9.26

The substantial losses in cotton reflect its high sensitivity to extreme heat during flowering and boll formation stages, as well as increased pest infestations (e.g., bollworm outbreaks), consistent with observations by Aeman et al. (2023). Rice losses are attributable to high water requirements and sensitivity to erratic monsoon rainfall, with projections indicating potential yield declines of 3–22% by 2100 under high-emission scenarios (Gallé and Katzenberger, 2025). Wheat losses, while comparatively lower, remain significant given wheat's critical role in national food security (GOP, 2025). The high variability in maize losses (SD = 9.26) suggests that localized climate conditions, soil moisture availability, and management practices strongly influence outcomes (Gosai et al., 2025).

Determinants of Adaptation Strategies: Logistic Regression Results

Binary logistic regression was employed to identify factors influencing the adoption of three key adaptation strategies: (i) change in sowing dates, (ii) use of drought-resistant seeds, and (iii) adoption of water-efficient methods. Results are presented in Tables 4–6.

Change in Sowing Dates

Table 4 presents the determinants of adjustments in sowing dates. Education showed a positive and statistically significant relationship (β = 0.297, p = 0.023; OR = 1.345), indicating that each additional year of schooling increases the likelihood of adjusting sowing dates by 34.5%. This underscores the role of education in enhancing climate awareness and adaptive capacity (Branca et al., 2021). Annual income also exhibited a significant positive effect (β = 0.000, p = 0.029), though the coefficient's magnitude suggests minimal practical impact.

Table 4: Determinants of change in sowing dates as a climate change adaptation strategy

Variables	Coefficient	S.E.	Sig.	Exp(B)
Age	0.055	0.037	0.137	1.056
Education	0.297**	0.130	0.023	1.345
Annual Income	0.000**	0.000	0.029	1.000
Farm size (acres)	0.292	0.190	0.125	1.339
Awareness of climate change	2.762*	1.523	0.070	15.832
Effects on crop yields	2.356*	1.332	0.077	10.553
Increased cost of production	2.529*	1.479	0.087	12.545
Constant	-14.630	4.374	0.001	0.000

*Note: *p < 0.10, **p < 0.05, ***p < 0.01*

Awareness of climate change (β = 2.762, p = 0.070; OR = 15.83), perceived effects on crop yields (β = 2.356, p = 0.077; OR = 10.55), and increased production costs (β = 2.529, p = 0.087; OR = 12.55) all showed positive associations that were marginally significant (p < 0.10). These findings align with Leta and Meskerem (2025), who reported that 24% of farmers adjusted planting dates in response to climate variability. The strong odds ratios indicate that farmers who are aware of climate change are nearly 16 times more likely to adjust sowing dates than unaware farmers, highlighting the critical role of climate information dissemination (Hansen et al., 2016). Age and farm size were not statistically significant determinants, suggesting that these factors do not strongly influence this adaptation decision.

Use of Drought-Resistant Seeds

Table 5 reports determinants of drought-resistant seed adoption. Education again emerged as a significant positive predictor (β = 0.265, p = 0.011; OR = 1.303), confirming that more educated farmers are more likely to adopt resilient seed varieties. Awareness of climate change (β = 2.270, p = 0.065; OR = 9.68) and perceived increased production costs (β = 2.316, p = 0.079; OR = 10.13) showed marginally significant positive effects.

These results are consistent with Leta and Meskerem (2025), who found that 75% of farmers adopted drought-resistant crops as a primary adaptation strategy. The non-significance of age, income, and farm size suggests that adoption of drought-resistant seeds is driven more by knowledge and awareness than by resource endowments alone. This finding has important policy implications: targeted extension programs that build climate awareness may effectively promote adoption even among resource-constrained smallholders (World Bank, 2014).

Adoption of Water-Efficient Methods

Table 6 presents determinants of water-efficient method adoption. Education exhibited the strongest and most significant effect among socio-economic variables (β = 0.310, p = 0.009; OR = 1.363), indicating that each additional year of schooling increases adoption likelihood by 36.3%. Farm size also showed a significant positive effect (β = 0.097, p = 0.019; OR = 1.102), suggesting that larger landholdings facilitate investment in water-saving infrastructure, consistent with findings that larger farms have greater capacity to absorb adaptation costs (Adom, 2024).

Table 5: Determinants of drought-resistant seeds as a climate change adaptation strategy

Variables	Coefficient	S.E.	Sig.	Exp(B)
Age	0.020	0.031	0.529	1.020
Education	0.265**	0.105	0.011	1.303
Annual Income	0.000	0.000	0.131	1.000
Farm size (acres)	0.195	0.171	0.253	1.215
Awareness of climate change	2.270**	1.232	0.065	9.682
Effects on crop yields	1.775	1.166	0.128	5.903
Increased cost of production	2.316**	1.319	0.079	10.134
Constant	-10.058	2.985	0.001	0.000

*Note: *p < 0.10, **p < 0.05, ***p < 0.01*

Table 6: Determinants of efficient water use as a climate change adaptation strategy

Variables	Coefficient	S.E.	Sig.	Exp(B)
Age	0.002	0.033	0.946	1.002
Education	0.310***	0.119	0.009	1.363
Annual Income	0.000	0.000	0.149	1.000
Farm size (acres)	0.097**	0.162	0.019	1.102
Awareness of climate change	2.198**	1.322	0.015	9.010
Effects on crop yields	4.266***	1.503	0.005	71.244
Increased cost of production	0.907	1.237	0.463	2.476
Constant	-9.778	3.177	0.002	0.000

*Note: *p < 0.10, **p < 0.05, ***p < 0.01*

Perceived effects on crop yields demonstrated the largest coefficient among all variables ($\beta = 4.266$, $p = 0.005$; OR = 71.24), indicating that farmers who have directly experienced climate-induced yield losses are 71 times more likely to adopt water-efficient methods than those who have not. This finding strongly supports the hypothesis that personal experience with climate impacts is a powerful driver of adaptive behavior (Hansen et al., 2016; Adil et al., 2025). Awareness of climate change also showed a significant positive effect ($\beta = 2.198$, $p = 0.015$; OR = 9.01). The perception of increased production costs was not statistically significant, suggesting that water efficiency adoption is driven more by yield protection concerns than by input cost pressures. These results align with Shahzad et al. (2021), who reported that adoption of soil and water conservation practices increased farm net returns by 29–31%.

Discussion

The results collectively demonstrate that climate change has significantly affected crop productivity in Punjab, Pakistan, through increased water scarcity, yield reductions, and rising input costs confirming the region's vulnerability to climatic stresses (Amjad, 2025; Adil et al., 2025). Farmers are actively adopting adaptation measures within their capacity, but the extent and effectiveness of adaptation vary considerably across households. Among the determinants examined, education emerged as the most consistently significant factor across all three adaptation strategies. This finding underscores the importance of knowledge, awareness, and exposure to improved technologies in enhancing adaptive behavior, consistent with Branca et al. (2021) and Adom (2024). Farm size was significant only for water-efficient methods, suggesting that capital-intensive adaptations require larger resource bases, while knowledge-driven adaptations (e.g., sowing date adjustments) may be accessible to farmers regardless of landholding size.

Awareness of climate change and perceived yield losses showed positive associations with adaptation decisions, though statistical significance varied. Notably, the effect sizes (odds ratios) for these perceptual variables were large, indicating that while sample size constraints may have limited statistical power, the practical importance of climate awareness and personal experience cannot be dismissed (Masson-Delmotte et al., 2022; Orlov et al., 2021). This suggests that awareness alone is insufficient to drive adaptation without adequate economic resources and institutional support (Hansen et al., 2016; Liaqat et al., 2022).

The relatively low adoption of technologically sophisticated adaptations such as early warning systems and expert advisory services identified in the descriptive findings highlights critical gaps in extension services and climate information dissemination across rural Punjab. These gaps are consistent with broader institutional constraints documented in Pakistan's National Climate Change Policy 2023 implementation (Amjad, 2025; Hansen et al., 2016; Adil et al., 2025). Addressing these gaps requires targeted investments in agricultural extension, climate information systems, and concessional financing mechanisms to support smallholder adaptation (Adnan et al., 2024; World Bank, 2014).

4. Conclusion

Climate change poses a serious and growing threat to agricultural sustainability in Punjab, Pakistan, where farming livelihoods are highly sensitive to variations in temperature, rainfall, and water availability. This study examined the impacts of climate change on agricultural production and analyzed farmers' adaptation responses, focusing on adjustments in sowing dates, use of drought-resistant seed varieties, and adoption of water-efficient practices. Using primary data from 100 randomly selected farmers and binary logistic regression analysis, the study provides empirical evidence on the socio-economic and perceptual factors shaping climate change adaptation at the farm level.

The findings demonstrate that climate change has significantly affected crop productivity, with cotton (40.6%), maize (35.1%), and rice (33.4%) suffering the highest losses, confirming the vulnerability of Punjab's agriculture to climatic stresses. Farmers are actively adopting adaptation measures, but the extent and effectiveness of adaptation vary considerably across households. Education emerged as the most consistent and significant determinant of adaptation across all three strategies, underscoring the importance of knowledge dissemination and extension services. Farm size was significant only for water-efficient methods, reflecting the capital-intensive nature of irrigation investments. Although awareness of climate change and perceived yield losses showed positive associations with adaptation decisions, their effects were not always statistically significant at conventional levels, suggesting that awareness alone is insufficient without complementary economic resources and institutional support.

These findings carry important policy implications. First, investments in agricultural education and extension services should be prioritized to enhance climate literacy and promote adoption of knowledge-based adaptations. Second, financial mechanisms, including subsidized credit and climate risk insurance, are needed to enable smallholders to invest in capital-intensive adaptations such as water-efficient irrigation systems. Third, early warning systems and climate information dissemination networks require strengthening to translate climate awareness into effective action. Without such interventions, climate change poses a serious threat to Pakistan's agricultural sustainability, food security, and economic stability.

5. References

Adil, L., Eckstein, D., Künzel, V., & Schäfer, L. (2025). Climate Risk Index 2025.

Adnan, M., Xiao, B., Bibi, S., Xiao, P., Zhao, P., Wang, H., & An, X. (2024). Known and unknown environmental impacts related to climate change in Pakistan: An under-recognized risk to local communities. Sustainability, 16(14), 6108.

Adom, P. K. (2024). The socioeconomic impact of climate change in developing countries in the next decades. Center for Global Development, 139.

Aeman, H., Shu, H., Abbas, S., Aisha, H., & Usman, M. (2023). Sinking delta: Quantifying the impacts of saltwater intrusion in the Indus Delta of Pakistan. Science of the Total Environment, 880, 163356.

Amjad, H. (2025). How climate change threatens Pakistan's agricultural exports. Paradigm Shift.

Branca, G., Cacchiarelli, L., D'Amico, V., Dakishoni, L., Lupafya, E., Magalasi, M., & Sorrentino, A. (2021). Cereal–legume value chain analysis: A case of smallholder production in selected areas of Malawi. Agriculture, 11(12), 1217.

Brempong, M. B., Amankwaa-Yeboah, P., Yeboah, S., Owusu Danquah, E., Agyeman, K., Keteku, A. K., & Adomako, J. (2023). Soil and water conservation measures to adapt cropping systems to climate change-induced water stress in Africa. Frontiers in Sustainable Food Systems, 6, 1091665.

David Ra, A., Kumar, S., Kalambukattu, J. G., & Chatterjee, U. (2024). Land degradation and its relation to climate change and sustainability. In Climate crisis: Adaptive approaches and sustainability (pp. 121–135). Springer.

Eshetu, A., & Mekonen, A. A. (2024). Determinants of small-scale irrigation adoption in drought-prone areas of north-central Ethiopia in the context of climate change. Frontiers in Climate, 6, 1410527.

Gallé, J., & Katzenberger, A. (2025). Indian agriculture under climate change: The competing effect of temperature and rainfall anomalies. Economics of Disasters and Climate Change, 9(1), 53–105.

Gosai, H. G., Patel, J., Savalia, P., Narolkar, S., & Mankodi, P. (2025). India's Green Energy Perspective: Critical Overview. The Intersection of Global Energy Politics and Climate Change: A Comprehensive Analysis of Energy Markets and Economics, 133-165.

Government of Pakistan. (2025). Pakistan Economic Survey 2024–25. Ministry of Finance.

Hansen, J., Sato, M., Hearty, P., Ruedy, R., Kelley, M., Masson-Delmotte, V., & Lo, K. W. (2016). Ice melt, sea level rise and superstorms: Evidence from paleoclimate data, climate modeling, and modern observations. Atmospheric Chemistry and Physics, 16(6), 3761–3812.

Hossain, A., Krupnik, T. J., Timsina, J., Mahboob, M. G., Chaki, A. K., Farooq, M., & Hasanuzzaman, M. (2020). Agricultural land degradation: Processes and problems undermining future food security. In Environment, climate, plant and vegetation growth (pp. 17–61). Springer.

Izuchukwu, P. O., Zino Izu, O., Frank Chudi, A., Theresa Ojevwe, A., & Chinwe Sheila, N. (2025). The economic costs of climate disasters: Analyzing data from recent floods, wildfires, and hurricanes. Manuscripts on Sustainable Economics, Finance and Management, 2(3), 1–22.

Leta, K., & Meskerem, A. (2025). Farmers' perceived impacts of climate change on agricultural production and coping strategies in Arsi Negelle Woreda, Ethiopia. Ethiopian Journal of Development Research, 47(1), 1–32.

Liaqat, W., Barutçular, C., Farooq, M., Ahmad, H., Jan, M., Ahmad, Z., & Li, M. (2022). Climate change in relation to agriculture: A review. Spanish Journal of Agricultural Research, 20(2).

Masson-Delmotte, V., Zhai, P., Pörtner, H. O., Roberts, D., Skea, J., & Shukla, P. R. (2022). Global warming of 1.5°C: IPCC special report. Cambridge University Press.

Matta, G., Pant, G., Kamboj, N., Kumar, S., Kumar, A., Kumar, P., & Saini, H. (2025). Current challenges and solutions to achieving sustainable water security. In Water scarcity management: Enabling technologies (pp. 235–254).

Orlov, A., Daloz, A. S., Sillmann, J., Thiery, W., Douzal, C., Lejeune, Q., & Schleussner, C. (2021). Global economic responses to heat stress impacts on crop production. Economics of Disasters and Climate Change, 5, 367–390.

Pakistan Bureau of Statistics. (2023). 7th Population and Housing Census 2023. Government of Pakistan.

Raihan, A. (2023). A review of global climate change impacts, adaptation strategies, and mitigation options. Journal of Environmental Science and Economics, 2(3), 36–58.

Rigg, J., Phongsiri, M., Promphakping, B., Salamanca, A., & Sripun, M. (2020). Who will tend the farm? Interrogating the ageing Asian farmer. The Journal of Peasant Studies, 47(2), 306–325.

Shahzad, M. F., Abdulai, A., & Issahaku, G. (2021). Adaptation implications of climate-smart agriculture in rural Pakistan. Sustainability, 13(21), 11702.

Ullah, R., & Zubair, M. (2021). Irrigation water management under climate change: Local perceptions and adaptation. In Natural resource governance in Asia (pp. 353–363). Elsevier.

World Bank. (2014). Doing business 2015: Going beyond efficiency. World Bank Publications.