

## VULNERABILITY ASSESSMENT OF AGRICULTURAL COMMUNITIES TO CLIMATE CHANGE

<sup>1\*</sup>Muhammad Saleem, <sup>2</sup>Samrat Sikdar, <sup>3</sup>Syed Taimoor Shah, <sup>4</sup>Sana Shaukat

<sup>1</sup>Institute of Agriculture Extension, Education and Rural Development, University of Agriculture, Faisalabad

<sup>2</sup>School of Human Sciences, College of Agriculture & Life Sciences, Mississippi State University, Starkville, MS 39762, USA

<sup>3</sup>Lecturer Agriculture Extension, Balochistan Agriculture College Quetta

<sup>4</sup>Institute of Forest Sciences, Faculty of Agriculture and Environment, The Islamia University of Bahawalpur, 63100, Pakistan

### Article History

**Keywords:** Vulnerability Assessment, Agricultural Communities, Climate Change

### Article History

Received on 27 April 2026

Accepted on 19 May 2026

Published on 25 May 2026

Copyright @Author

Corresponding Author:  
[saleemshyk@gmail.com](mailto:saleemshyk@gmail.com)

### Abstract

Agriculture is highly vulnerable to climate change, and especially in developing countries, where farming is a large part of the livelihoods. Pakistan is one of the highly vulnerable countries to climate change even though it has a very low contribution in the global greenhouse gas emission. Increasing temperatures, frequently followed by droughts and irregular rainfall, floods and pest outbreaks in the region of Southern Punjab are all jeopardizing the agricultural productivity and rural livelihoods. This study evaluated the vulnerability of agricultural populations to climate change in four major agricultural districts of Southern Punjab (Muzaffargarh, Multan, Bahawalpur and Rahim Yar Khan) within the framework developed by Intergovernmental Panel on Climate Change (IPCC), which is based on three components: exposure, sensitivity and adaptive capability. A cross sectional survey was carried out with 160 farmers selected at random, with a structured questionnaire. Descriptive statistics, reliability analysis, confirmatory factor analysis (CFA), correlation analysis, multiple linear regression, one-way ANOVA, bootstrapped mediation analysis, and structural equation modeling (SEM) were used for data analysis. The measurement model was found to be reliable and valid, with  $\alpha$  range from 0.89 to 0.92 and CFI and RMSEA measure of model fit indices were acceptable. The level of farmers' exposure ( $M = 4.12$ ), sensitivity ( $M = 3.88$ ) and adaptive capacity ( $M = 3.19$ ) were high, moderate and relatively moderate, respectively. The results of



correlation and SEM showed that exposure ( $\beta = 0.52$ ;  $p < 0.001$ ) and sensitivity ( $\beta = 0.33$ ;  $p < 0.001$ ) significantly increased climate change vulnerability while adaptive capacity significantly reduced vulnerability ( $\beta = -0.47$ ;  $p < 0.001$ ). Multiple regression results showed that education, farm size, extension services and access to climate information were significant negative predictor variables of vulnerability while age had a positive association with vulnerability. The model accounted for 66% of the variability in the vulnerability (Adjusted  $R^2 = 0.64$ ). There were significant spatial variations between districts ( $F = 19.81$ ,  $p < 0.001$ ) with Muzaffargarh showing the highest vulnerability and Rahim Yar Khan showing the lowest. Additionally, mediation analysis showed that extension services partially mediated the relationship between extension services and climate change vulnerability. The results highlight the need to bolster adaptive capacity to climate change to decrease farmers vulnerability to climate change, such as by enhancing agricultural extension services, providing timely climate information, farmer education, institutional support, and climate resilient agricultural policies. The study offers empirical evidence in favor of adaptation planning and policy interventions at the district level for improving the resilience of agriculture communities in climate sensitive areas of Pakistan.

**Key Words:** Climate, Vulnerability, Impact, Community

## Introduction

Climate change has become one of the most serious challenges to the food security, rural incomes and sustainable agricultural development in the 21st century. Global warming has become faster than ever, and it is a result mainly of anthropogenic greenhouse gas emissions that have led to a wide range of changes in precipitation, temperature, and in the frequency and intensity of extreme climate events (Intergovernmental Panel on

Climate Change [IPCC], 2022). The agriculture sector is one of the most vulnerable sectors to these changes, because the sector is very sensitive to climatic conditions for crop production, water supply and ecosystem services (Schmidhuber & Tubiello, 2007). Worldwide, weather events associated with the climate, such as frequent droughts, irregular monsoons, extreme flooding, abnormal frost, and increased pest infestations, are already affecting crop yields and food security for



billions of people (Lobell et al., 2011; Wheeler & Von Braun, 2013). The impacts are not uniform: Smallholder farming communities in developing countries are hit hardest and earliest, with the lowest contribution to global emissions (Morton, 2007; Thornton et al., 2014).

While Pakistan is among the top ten climate change-susceptible countries in the world, it contributes less than one per cent of global greenhouse gas emissions (Eckstein et al., 2021; Khan et al., 2020). The agriculture sector of the country accounts for around 22% of the national Gross Domestic Product (GDP) and provides employment to nearly 44% of the nation's labour Force, thus playing a pivotal role in the national economy (Government of Pakistan, 2022). But, the climate change stress is further compounded on the agricultural sector in Pakistan because the mean annual temperature has been raised by 0.5°C in last 50 years, and the prediction is that by the end of 21st century, it will be increased by 1.5-3°C under moderate emission scenarios (Chaudhry, 2017; Siddiqui et al., 2012). These shifts are already impacting yields of key crops such as wheat, cotton, rice, sugarcane and maize, on which the livelihoods of millions of rural households are directly dependent (Mubeen et al., 2020; Sultana et al., 2009). The devastating floods of 2022 that inundated over a third of the country's territory and damaged agriculture to the tune of more than USD 3.7 billion, only further highlights the magnitude of the

climate crisis and the need for a comprehensive assessment of vulnerability in India (United Nations, 2022).

The districts of Muzaffargarh, Multan, Bahawalpur, and Rahim Yar Khan which form Southern Punjab are one of the most important and climate-vulnerable areas in Pakistan regarding agriculture. The region falls under an agro-climatic zone of arid and semi-arid climate with extreme summer temperature that often exceeds 45°C, high Evapotranspiration rate, frequent occurrence of droughts and increasing monsoon precipitation variability (Qaisrani et al., 2022; Sultana et al., 2009). Most farming households in Southern Punjab are smallholders who are working on very narrow margins, are heavily dependent on canal and ground water irrigation, and are not able to avail of formal credit and insurance facilities and institutional support systems (Abid et al., 2015). The structural conditions severely limit the ability of the farming communities to absorb and recover from climate-shocks, making them one of the most vulnerable agricultural communities in South Asia (Arshad et al., 2017). It is recognized from the literature survey that systematic multi-district vulnerability assessment, which considers socioeconomic, institutional, and perceptual dimension, is very limited in the published literature, especially in the region of study despite its economic importance and high exposure to climate risks.

Vulnerability to climate change has been theorized and operationalized in the academic literature to a great degree. The IPCC (2022) describes vulnerability as the tendency or susceptibility of a system to be harmed by climate change and includes three components: exposure, sensitivity, and adaptive capacity. Exposure is the occurrence of climate hazards (droughts, floods, heat waves, irregular precipitation, etc.) that a system or population is exposed to. Sensitivity refers to the extent of the adverse impacts of climate variability on agricultural systems, livelihood opportunities and human health. Adaptive capacity is defined as the ability of individuals, households and communities to adjust to climate change, reduce potential damages, take advantage of new opportunities and manage impacts (Adger, 2006; Smit & Wandel, 2006). The vulnerability formula ( $\text{Vulnerability} = \text{Exposure} + \text{Sensitivity} - \text{Adaptive Capacity}$ ) is a useful and widely used approach for empirical measurement and policy analysis (IPCC, 2022; Turner et al., 2003). This framework acknowledges that exposure and sensitivity contribute to vulnerability, but also suggests that adaptive capacity is a major moderating factor which can significantly mitigate the final effects of climate hazards on human systems (Brooks et al., 2005; O'Brien et al., 2004). There is a large number of empirical literature which has discussed the factors influencing the vulnerability to climate change and adaptive capacity of smallholder farmers in the developing countries. A variety of socioeconomic factors

have been found to be significant underlying factors shaping farmers' adaptive capacity and vulnerability outcomes, including education, farm size, household income, extension service access, access to climate information, farmer organizations, and land ownership (Below et al., 2012; Deressa et al., 2009; Hahn et al., 2009). Agricultural extension services, especially, have been found to be one of the strongest predictors of adaptive behaviors, with extension contact helping farmers become more aware of climate risks, have a more complete understanding of adaptation options and are more likely to implement improved agricultural practices (Abid et al., 2015; Davis et al., 2012). Likewise, reliable climate information allows farmers to make timely and informed choices about the planting date, the type of crops to grow and the mitigation measures that should be taken to minimize losses from the climate (Roudier et al., 2011; Zamasiya et al., 2021). Institutional factors such as extension service, agricultural credit and farmers association membership have been proved to be important factors affecting their adaptive capacity and vulnerability to climate change for major crop farmers in the Pakistani context (Abid et al, 2016; Arshad et al, 2017).

In terms of methodology, the evaluation of the vulnerability of agricultural communities to climate change has also undergone a significant change in the last few decades. Initial efforts were largely limited to biophysical indicators and combined national or regional indices

with little indication of the micro-level factors that create vulnerability for individual households and farming communities (Hahn et al., 2009; O'Brien et al., 2004). More recent scholarship, however, has called for survey-based, household-level approaches that combine farmers' perceptions of climate change, measured socioeconomic characteristics and institutional access variables within psychometrically sound frameworks (Abid et al., 2015; Tessema et al., 2013). Structural equation modeling (SEM) and confirmatory factor analysis (CFA) have been increasingly used to test hypothesized causal relationships between exposure, sensitivity, adaptive capacity and vulnerability outcomes, and to assess the latent construct of vulnerability, with greater methodological rigor than the simple regression approach (Arunrat et al., 2017; Bryan et al., 2013). Despite these progressions, the majority of vulnerability studies in Pakistan are methodologically constrained with the use of descriptive statistics and basic regression models that do not take into account mediation pathways, or multi-group comparisons across districts (Abid et al., 2016; Qaisrani et al., 2022). While a significant amount of literature has emerged on climate change and agriculture in Pakistan, there are still some important research gaps. Firstly, most of the studies conducted so far were focused only on a single district or crop, and hence their results can only be applied in a small area as compared to the regional context. (Abid et al., 2015; Mubeen et al., 2020). Second, very few studies have explicitly dealt with all three components of vulnerability (exposure, sensitivity and adaptive capacity) with

specific measurement and validation process including confirmatory factor analysis, convergent and divergent validity testing, and common method bias testing (Sultana et al., 2009; Siddiqui et al., 2012). Third, the mediating mechanism of adaptive capacity between institutional factors (extension service and climate information etc.) and vulnerability outcomes was poorly explored in the Pakistani literature (Arshad et al., 2017; Khan et al., 2020). Lastly, the evidence base is lacking in comparative vulnerability assessments across multiple districts of Southern Punjab, from which a spatially differentiated policy recommendation could be made. This study aims to directly tackle these gaps.

## **2- Methodology**

### **2.1 Research Design**

A cross sectional survey research design approach was used in order to examine the vulnerability of the Agricultural communities exposed to climate change in Southern Punjab, Pakistan on quantitative basis. Primary data pertaining to farmers' perceptions of climate change, climate change induced risks, sensitivity of farmers' production systems, adaptation capacity and vulnerability of their livelihoods were gathered using a survey-based method.

### **2.2 Study Area**

The study was carried out in four main Agricultural Districts of the Southern Punjab namely Muzaffargarh, Multan, Bahawalpur and Rahim Yar Khan. These districts have been selected purposively as they are considered as one of the most important agricultural areas of the Punjab and are highly



susceptible to climate change effects like increase in temperature, long spells of drought, irregular rains, floods, water scarcity, and pests. The process of selection of the districts has been done in such a way that they cover the different agro-ecological zones and major cropping systems of Southern Punjab.

These districts are primarily agricultural, with wheat, cotton, rice, sugarcane, and maize being the key crops, playing a crucial role in Pakistan's agricultural economy.

### 2.3 Study Population

The target groups were the major farmers of the selected district areas who cultivated crops. The study included farmers cultivating wheat, cotton, rice, sugarcane, maize and other field crops, as their livelihood is very much dependent on the agricultural production which is sensitive to climate.

### 2.4 Sampling Procedure

The respondents were selected by a multistage sampling technique.

In the first phase, four districts namely Muzaffargarh, Multan, Bahawalpur and Rahim Yar Khan were purposively picked for the study, due to their importance in agriculture and vulnerability to climate threats.

In the second stage, lists of major crop farmers were secured from the District Agriculture Extension Department's help.

The third stage involved simple random sampling method for randomly selecting 40 farmers from each district.

Therefore, the total number of samples were 160 farmers (40×4 districts).

### 2.5 Data Collection Instrument

The primary data was gathered through a structured interview schedule (questionnaire), which was developed after a thorough literature review on the topic of vulnerability to climate change and agricultural adaptation. The questionnaire was divided into the following sections:

The socio-economic attributes of farmers are assessed. Socio-economic attributes of the farmers are evaluated.

Knowledge and understanding of climate change.

- Exposure to climate-related hazards
- Sensitivity of agricultural production systems
- Adaptive capacity

The first consideration is to implement strategies to adapt to climate change.

Institu. support and extension services

The majority of attitudinal statements were on a five point Likert scale, ranging from:

- 1 = Strongly Disagree
- 2 = Disagree
- 3 = Neutral
- 4 = Agree
- 5 = Strongly Agree

The Instrument was pre-tested during the planning phase.

The questionnaire was pre-tested with 20 big farmers of crop in a neighbouring district which was not part of the sample. Before final survey, the necessary modification was done to improve the clarity, validity and relevance of the questionnaire.

The instrument has a high degree of reliability.



Cronbach's Alpha coefficient was used to test the internal consistency of the questionnaire. The reliability coefficient that was obtained was considered acceptable at 0.70 or above, this shows satisfactory reliability of the research instrument.

**2.6 Data Collection Procedure**

The primary data were collected by the researcher during field visits through the face-to-face interview method. The respondents were briefed on the purpose of the study prior to each interview and their informed consent were obtained. Ensuring respondents' confidentiality and anonymity was maintained throughout research process.

**2.7 Variables of the Study**

**Independent Variables**

1. Age
2. Education
3. Farming experience
4. Household size
5. Farm size
6. Land ownership
7. farm income
8. Access to irrigation
9. Ability to gain access to extension services
10. Access to climate information.
11. Speaking positively of farmer organisations
12. Availability of farming loans

**Dependent Variable**

**Table 1. Socio-economic Characteristics of the Respondents**

Variable	Category	Frequency	Percentage
Age	<35 years	28	17.5
	35–50 years	84	52.5
	>50 years	48	30.0
Education	Illiterate	32	20.0

**Climate Change Vulnerability**

The vulnerability assessment was performed on three dimensions:

**Exposure:** Frequency and intensity of climate-related hazards (droughts, floods, heat waves, irregular rainfall, pest infestation etc.).

**Sensitivity:** Extent of the impact of climate variability on farming activities and livelihoods.

**Adaptive Capacity:** Farmers' ability to respond and adapt – access to technology, financial resources, extension services, climate information and diversified livelihood options.

The overall vulnerability was conceptualized within the framework of:

$$\text{Vulnerability} = \text{Exposure} + \text{Sensitivity} - \text{Adaptive Capacity}$$

**Data Analysis**

Collected data were coded and analyzed using SPSS (Version 26) from IBM.

A multiple linear regression analysis was used to analyze the data.

One-way ANOVA used to compare the differences in vulnerability between the four districts.

Independent samples t-test (if appropriate)

All statistical analyses were conducted at 5% significance level (p<0.05).



	Primary	41	25.6
	Secondary	46	28.8
	Higher Secondary	24	15.0
	Graduate and Above	17	10.6
Farm Size	Small	68	42.5
	Medium	59	36.9
	Large	33	20.6

**Table 2. Descriptive Statistics**

Variable	Mean	Std. Dev.	Min	Max
Exposure	4.12	0.55	2.45	5.00
Sensitivity	3.88	0.61	2.10	5.00
Adaptive Capacity	3.19	0.72	1.50	5.00
Climate Change Vulnerability	3.74	0.46	2.44	4.91

**Table 3. Reliability and Convergent Validity of the Measurement Model**

Construct	Items	Cronbach's $\alpha$	CR	AVE
Exposure	8	0.91	0.93	0.66
Sensitivity	7	0.89	0.91	0.62
Adaptive Capacity	9	0.92	0.94	0.69
Vulnerability	10	0.90	0.92	0.65

Note: CR = Composite Reliability; AVE = Average Variance Extracted.  
Criteria:  $\alpha > 0.70$ , CR > 0.70, AVE > 0.50.

**Table 4. Model Fit Indices of the Confirmatory Factor Analysis**

Fit Index	Recommended Value	Obtained Value
Chi-square / Degrees of Freedom	<3.00	2.11
Goodness-of-Fit Index (GFI)	>0.90	0.93
Adjusted Goodness-of-Fit Index (AGFI)	>0.90	0.91
Comparative Fit Index (CFI)	>0.95	0.97

Tucker–Lewis Index (TLI)	>0.95	0.95
Root Mean Square Error of Approximation	<0.08	0.051
Standardized Root Mean Square Residual	<0.08	0.043

**Table 5. Correlation Matrix among the Variables**

Variables	1	2	3	4
1. Exposure	1			
2. Sensitivity	0.63**	1		
3. Adaptive Capacity	-0.54**	-0.47**	1	
4. Climate Change Vulnerability	0.76**	0.69**	-0.72**	1

Note: \*\*  $p < 0.01$  (two-tailed).

**Table 6. Multiple Regression Analysis of Factors Affecting Climate Change Vulnerability**

Predictor	Std. Beta ( $\beta$ )	t-value	p-value
Age	0.11	2.21	0.028
Education	-0.19	-3.88	<0.001
Farm Size	-0.24	-4.66	<0.001
Extension Services	-0.28	-5.19	<0.001
Access to Climate Information	-0.31	-6.01	<0.001
Adaptive Capacity	-0.41	-7.84	<0.001

**Table 7. Comparison of Climate Change Vulnerability among the Four Districts (One-Way ANOVA)**

District	Mean	Standard Deviation
Muzaffargarh	3.94	0.42
Multan	3.69	0.37
Bahawalpur	3.61	0.44
Rahim Yar Khan	3.28	0.38

**Table 8. Structural Equation Modeling (SEM) Results**

Hypothesized Relationship	$\beta$	t-value	p-value	Decision
Exposure and Climate Change Vulnerability	0.52	8.11	<0.001	Supported
Sensitivity and Climate Change Vulnerability	0.33	6.02	<0.001	Supported
Adaptive Capacity and Climate Change Vulnerability	-0.47	-8.74	<0.001	Supported

Note: Model fit –  $\chi^2/df = 2.19$ , CFI = 0.97, RMSEA = 0.049. All paths significant at  $p < 0.001$ .

**Table 9. Mediation Analysis Using Bootstrapping**

Path	Direct Effect	Indirect Effect	Total Effect	95% CI	Result
Extension Services Adaptive Capacity and Climate Change Vulnerability	-0.18	-0.16	-0.34	(-0.24, -0.09)	Partial Mediation

Note: 95% Bias-Corrected Confidence Intervals reported. CI not spanning zero indicates significant indirect effect.

### 3- Discussion

The aim of this study was to map the vulnerability of the major crop farmers in four districts of Southern Punjab in relation to climate change, while at the same time identifying socioeconomic and institutional factors that underlie this vulnerability. The findings confirm the theoretical framework proposed, but also highlight a number of obvious regional and structural trends that need to be unpacked. It is important to make note of the good measurement model before discussing the substantive results. Cronbach's alpha scores > 0.89 for all four constructs and composite

reliability scores > 0.90 and AVE scores > 0.60 (Table 3) suggest that survey items measured what they were designed to measure. CFA indices (Table 4) (CFI = 0.97, RMSEA = 0.051) are acceptable as per the convention (Arunrat et al., 2017; Bryan et al., 2013). This is important as a lot of the existing vulnerability literature from Pakistan was based on descriptive statistics and simple regression without prior formal validation of constructs (Abid et al., 2016; Qaisrani et al., 2022). The present findings provide greater confidence that "exposure," "sensitivity" and "adaptive capacity" are being measured as separate, coherent



constructs that are not proxies for the same underlying attitude. The correlation matrix (Table 5) and the SEM results (Table 8) support the hypothesized relationships of exposure with vulnerability, and sensitivity with vulnerability, while adaptive capacity is hypothesized to have a negative relationship with vulnerability. This is in line with the IPCC (2022) framework and with the results of Ethiopia and Mozambique who found that adaptive capacity is the most effective buffer against climate shocks (Deressa et al., 2009; Hahn et al., 2009). The relative size of these path coefficients is informative: adaptive capacity had the strongest link to vulnerability among the three constructs, indicating that actions to increase farmers' capacity to respond in the event of a crisis may have a larger impact than actions to reduce exposure (which are very difficult to implement in an arid to semi-arid region where summers are already 45°C; Qaisrani et al., 2022; Sultana et al., 2009).

Extension services ( $\beta = -0.28$ ) and access to climate information ( $\beta = -0.31$ ) are the two most positive institutional factors in reducing vulnerability compared to the other factors, as seen in the regression results (Table 6). This is in line with the previous Pakistani evidence that the extension contact is one of the most consistent predictors

of adaptive behavior (Abid et al., 2015; Arshad et al., 2017) and consistent with the findings from West Africa and Zimbabwe on the importance of timely climate information for planting and input decision (Roudier et al., 2011; Zamasiya et al., 2021). The direct implication is that, among the levers that policy makers can act on in the near term, extension coverage and the provision of climate information turn out to be the most promising, as changing farm size and land ownership take a generation, while changing education takes longer. It must be acknowledged that there is a limitation in this: the  $R^2$  for the model is 0.66 (Table 6), which indicates that two-thirds of the variance in vulnerability is explained by the model, but a third is not. This survey does not try to capture all of the factors that influence the results, and other factors such as informal credit access, off-farm income, local water-table depth, or household labor migration are potential candidates that are not included here but must be tested specifically in future studies instead of assuming that the current model is exhaustive.

The results of ANOVA (Table 7) show that Muzaffargarh had the highest mean vulnerability (3.94) while Rahim Yar Khan had the lowest mean vulnerability (3.28), which is statistically significant and supported by the Tukey post hoc test. This is the paper's



most clear-cut policy message: vulnerability isn't equal even within an agro-climatic zone and a regional-wide adaptation programme would not distribute resources optimally. The differences between the four districts are more likely to be due to differences in institutional access and adaptive capacity across districts than to exposure itself, and the current cross-sectional design does not fully support this hypothesis, but the mediation results do offer some support for this hypothesis.

Thus, the bootstrapped mediation analysis (Table 9) indicates that extension services have both direct (-0.18) and indirect (-0.16) effects on vulnerability, where the indirect pathway does not contain the null value. This is partial mediation, not full, as extension has an impact on vulnerability which is not fully captured by adaptive capacity. That's an important distinction because it is extension contact doing something for farmers beyond just capacity building, and possibly doing something that impacts exposure to losses directly (e.g., through early warning systems or pest advisories) or indirectly (e.g., farmer-centered innovation and experimentation). This is an aspect that is frequently overlooked in studies that only examine direct effects (Abid et al., 2016; Bryan et al., 2013), and is one of the more

methodologically useful aspects of this paper.

Combined with the socioeconomic profile in Table 1, which indicates that 45.6% of farmers lacked access to more than primary school education and 42.5% participated in small farms, the picture of this policy is pretty clear: this is a population with structurally low adaptive capacity and extension services and climate information are helping keep their vulnerability low. Both these institutional pathways would be expected to increase the vulnerability materially faster in high-exposure districts such as Muzaffargarh as compared to relatively lower vulnerability districts such as Rahim Yar Khan if weakened.

#### 4- Conclusion

The vulnerability of agriculture communities to climate change was measured in four major agricultural districts of Southern Punjab, Pakistan, in this study, based on IPCC vulnerability framework which includes exposure to climate change, sensitivity, and adaptive capacity of the communities. The results showed that different climate hazards such as rise in temperature, droughts, irregular rainfall and floods in the study area pose high risks to the agricultural productivity and rural livelihoods of farmers. Farmers were moderately adaptive, but this was not enough to overcome adverse impacts of climate change

variability, leading to high vulnerability to climate change. The empirical evidence validated the findings of the exposure and sensitivity, and adaptive capacity was found to have a significant influence in reducing climate change vulnerability. The results of the structural equation modeling also indicated that adaptive capacity is the strongest determinant influencing farmers' vulnerability, with a significant role in improving farmers' resilience. Multiple regression analysis revealed that educating farmers, farm size, better access to agricultural extension services, timely information of climate and adaptive capacity greatly mitigated farmers' vulnerability. On the other hand, the vulnerability was positively associated with increasing age implying that the older farmers might experience more difficulties in practicing Climate-smart Agriculture. The study also found a considerable variability at the district level in the vulnerability of the four districts. The farmers of Muzaffargarh were found to be the most vulnerable and farmers from Rahim Yar Khan were comparatively less vulnerable. The findings of these spatial differences suggest that there is a need to take district-wise climatic conditions, institutional support, and socioeconomic features into

account when implementing climate adaptation policies.

In addition, the mediation analysis revealed that the effect of agricultural extension services on climate change vulnerability is mediated by Adaptive capacity. This discovery shows that extension services not only increase the adaptive capacity of farmers, but also provide direct assistance like climate advisories, early warning information and farm management recommendations, which decreases vulnerability. Hence, enhancing agricultural extension systems is one of the most promising agricultural policy options for mitigating climate risks.

Overall, this study is a valuable addition to the existing literature by applying comprehensive measurement models that have been validated and sophisticated data analysis techniques such as confirmatory factor analysis, structural equation modelling, and mediation analysis to the household level of climate change vulnerability. The results offer strong empirical basis for evidence-based climate adaptation planning, and also pinpoint the need for institutional bolstering mechanisms for enhancing the resilience of agricultural communities in Southern Punjab and other climate-sensitive areas of the country.

## 5-Recommendations



The conclusions drawn from this study point to the need for a holistic and integrated approach between the government, Research institutions, extension institutions and the farming community to reduce the vulnerability of agricultural communities to climate change. Extension services need to be strengthened to increase the number of trained extension staff as well as regular extension capacity building programs on climate smart agriculture, sustainable crop management, integrated pest management, water conservation and efficient resource use. Extension agents should also help spread new farming techniques and adaptation strategies through demonstration plots, farmer field schools and online extension services.

Second, farmers should be able to easily access farmers' weather forecasting systems, early warning services, mobile phones, radio, television and social media with timely and reliable climate information. Precise climate data can help farmers make informed choices on crops, planting timings, timing irrigation, fertilizing, pest control and other practices that reduce the climate variability risk to their production.

Moreover, enhancing farmers' adaptive capacity should be a main goal of agricultural development policies. This can be done through better education and technical

knowhow of farmers, plantation of climate-resilient crop varieties, crop diversification, and better access to modern irrigation technologies, as well as good soil and water conservation practices. Investments in farmer training and institutional support in building adaptive capacity are likely to yield significant long-term benefits as this was identified as the most effective driver of reducing climate vulnerability.

There is also a need for the government to offer greater access to agricultural credit, crop insurance schemes, and financial support for investing in technologies that are climate resilient, or for recovery from climate-induced losses, to farmers. Strengthening farmer organisations and building farmer cooperatives could further contribute to better information sharing, collective action, market access and adoption of innovations. Such institutional mechanisms may enhance the ability of farmers to withstand shocks, as they enable the exchange of knowledge and boost their bargaining power.

With high risk levels between the four districts, location-specific adaptation measures should be planned and implemented instead of blanket measures for the entire Southern Punjab. Spending on adaptation, investments and institutional support should be prioritized for highly vulnerable





districts like Muzaffargarh. Vulnerability mapping should form part of provincial and national agricultural planning to optimally allocate resources based on regional vulnerability and risk.

Finally, future studies should use more diverse and larger samples, and longitudinal studies and mixed methods to better understand fluctuations in vulnerability over time. Other factors of vulnerability to be explored in future research include gender, social capital, migration, groundwater extraction, off-farm earnings and psychological adaptability. Advanced analytical methods such as multilevel modeling, geospatial analysis, and longitudinal structural equation modeling would lead to a better understanding of the cross-cutting synergies between climate risks, adaptive capacity, and agricultural livelihoods. The recommendations will boost the resilience of the farming communities, promote sustainable agriculture, ensure food security, and facilitate climate-resilient rural development in Pakistan through their implementation.

## References

1. Abid, M., Ngaruiya, G., Scheffran, J., & Zulfiqar, F. (2016). The role of social networks in agricultural adaptation to climate change: Implications for sustainable agriculture in Pakistan. *Climate*, 4(4), 56.
2. Arshad, M., Amjath-Babu, T. S., Kächele, H., & Müller, K. (2017). What drives the willingness to pay for crop insurance against extreme weather events in Pakistan? A hypothetical market approach. *Climate and Development*, 9(3), 234–244.
3. Abid, M., Scheffran, J., Schneider, U. A., & Ashfaq, M. (2015). Farmers' perceptions of and adaptation strategies to climate change and their determinants: The case of Punjab province, Pakistan. *Earth System Dynamics*, 6(1), 225–243. <https://doi.org/10.5194/esd-6-225-2015>
4. Abid, M., Scheffran, J., Schneider, U. A., & Ashfaq, M. (2015). Farmers' perceptions of and adaptation strategies to climate change and their determinants: The case of Punjab province, Pakistan. *Earth System Dynamics*, 6(1), 225–243.
5. Adger, W. N. (2006). Vulnerability. *Global Environmental Change*, 16(3), 268–281. <https://doi.org/10.1016/j.gloenvcha.2006.02.006>
6. Ali, Y. (2012). Role of agriculture in economic growth of Pakistan.
7. Arunrat, N., Wang, C., Pumijumnong, N., Sereenonchai, S., & Cai, W. (2017). Farmers' intention and decision to adapt



to climate change: A case study in the Yom and Nan basins, Phichit province of Thailand. *Journal of Cleaner Production*, 143, 672–685.

8. Below, T. B., Mutabazi, K. D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., & Tscherning, K. (2012). Can farmers' adaptation to climate change be explained by socioeconomic household-level variables? *Global Environmental Change*, 22(1), 223–235.

9. Brooks, N., Adger, W. N., & Kelly, P. M. (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Global Environmental Change*, 15(2), 151–163.

10. Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., & Herrero, M. (2013). Adapting agriculture to climate change in Kenya: Household strategies and determinants. *Journal of Environmental Management*, 114, 26–35.

11. Chaudhry, Q. Z. (2017). Climate change profile of Pakistan. Asian Development Bank. <https://doi.org/10.22617/TCS178435-2>

12. Davis, K., Nkonya, E., Kato, E., Mekonnen, D. A., Odendo, M., Miiro, R., & Nkuba, J. (2012). Impact of farmer field schools on agricultural

productivity and poverty in East Africa. *World Development*, 40(2), 402–413.

13. Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., & Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change*, 19(2), 248–255.

14. Eckstein, D., Künzel, V., & Schäfer, L. (2021). Global Climate Risk Index 2021: Who suffers most from extreme weather events? Germanwatch.

15. Government of Pakistan. (2022). Pakistan economic survey 2021–22. Ministry of Finance. [https://www.finance.gov.pk/survey\\_2022.html](https://www.finance.gov.pk/survey_2022.html)

16. Hahn, M. B., Riederer, A. M., & Foster, S. O. (2009). The livelihood vulnerability index: A pragmatic approach to assessing risks from climate variability and change—A case study in Mozambique. *Global Environmental Change*, 19(1), 74–88.

17. Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, 333(6042), 616–620.

18. Morton, J. F. (2007). The impact of climate change on smallholder and subsistence agriculture. *Proceedings of the*



- National Academy of Sciences, 104(50), 19680–19685.
19. Mubeen, M., Ahmad, A., Hammad, H. M., Awais, M., Abbas, F., Nasim, W., & Hoogenboom, G. (2020). Evaluating the climate change impacts on water use efficiency of cotton-wheat under semi-arid conditions using DSSAT model. *Journal of Water and Climate Change*, 11(4), 1661–1675. <https://doi.org/10.2166/wcc.2019.064>
20. O'Brien, K., Leichenko, R., Kelkar, U., Venner, H., Aandahl, G., Tompkins, H., Javed, A., Bhadwal, S., Barg, S., Nygaard, L., & West, J. (2004). Mapping vulnerability to multiple stressors: Climate change and globalization in India. *Global Environmental Change*, 14(4), 303–313.
21. Roudier, P., Sultan, B., Quirion, P., & Berg, A. (2011). The impact of future climate change on West African crop yields: What does the recent literature say? *Global Environmental Change*, 21(3), 1073–1083.
22. Schmidhuber, J., & Tubiello, F. N. (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences*, 104(50), 19703–19708.
23. Siddiqui, R., Samad, G., Nasir, M., & Jalil, H. H. (2012). The impact of climate change on major agricultural crops: Evidence from Punjab, Pakistan. *Pakistan Development Review*, 51(4), 261–274
24. Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, 16(3), 282–292. <https://doi.org/10.1016/j.gloenvcha.2006.03.008>
25. Sultana, H., Ali, N., Iqbal, M. M., & Khan, A. M. (2009). Vulnerability and adaptability of wheat production in different climatic zones of Pakistan under climate change scenarios. *Climatic Change*, 94(1–2), 123–142.
26. Sultana, H., Ali, N., Iqbal, M. M., & Khan, A. M. (2009). Vulnerability and adaptability of wheat production in different climatic zones of Pakistan under climate change scenarios. *Climatic Change*, 94(1–2), 123–142.
27. Tessema, Y. A., Aweke, C. S., & Endris, G. S. (2013). Understanding the process of adaptation to climate change by smallholder farmers: The case of east Hararghe Zone, Ethiopia. *Agricultural and Food Economics*, 1(1), 13.
28. Thornton, P. K., Ericksen, P. J., Herrero, M., & Challinor, A. J. (2014). Climate variability and vulnerability to



ISSN Online: 3006-2047

ISSN Print: 3006-2039



Volume. 5, Issue No. 2 (2026)

climate change: A review. *Global Change Biology*, 20(11), 3313–3328.

29. Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Kasperson, J. X., Luers, A., Martello, M. L., Polsky, C., Pulsipher, A., & Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences*, 100(14), 8074–8079.

30. Wheeler, T., & Von Braun, J. (2013). Climate change impacts on global food security. *Science*, 341(6145), 508–513.