Research Article

Multidimensional Climate Change Index for Assessing Vulnerability of Farm Households in Pakistan

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Abstract | This research aims to assess the vulnerability of Farm Households (HHs), and to climate change through Multidimensional Climate Change Index (MCCI) of vulnerability in Pakistan. For this survey of 5,775 Farm HHs, and Geographic Information System (special mapping) to map vulnerability indicators were used. The MCCI was developed to measure vulnerability, ecological, social, economic, political, and cultural dimensions of climate change. The study highlights that Climate Change (CC) can lead to more severe weather conditions, like changes in ecosystems, wildlife populations, affect global food systems and water supplies. The MCCI values provide valuable insights into the impact of CC across different provinces of the Pakistan. The data highlights that Balochistan has the highest headcount ratio (0.99) and Azad Jammu and Kashmir has the highest intensity (0.66) of CC impacts. The MCCI values (0.52) show that Sindh is the most vulnerable province to CC, followed closely by Punjab (0.49) and Khyber Pakhtunkhwa (0.48). The spatiotemporal vulnerability level of HHs in different provinces of Pakistan, categorized into five levels and Punjab has the highest number of HHs in the medium vulnerability category. Sindh and Khyber Pakhtunkhwa have the highest number of HHs in the high and extremely high vulnerability category respectively. The research highlights the need for targeted interventions to enhance the resilience of HHs in vulnerable regions and to reduce their exposure to external shocks by emphasizing on improving water management, ecosystem, adaptive strategies and developing early warning systems to help communities to prepare for extreme weather events.

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Introduction

Climate change (CC) is one of the biggest threats to achieving the Sustainable Development Goals (SDGs), adopted by the United Nations in 2015 to end poverty, protect the planet, and ensure prosperity for all (Hales and Birdthistle, 2023). The SDGs goal 13, climate action is also linked to several other SDGs, including clean energy (Goal 7), sustainable cities and communities (Goal 11), and responsible consumption and production (Goal 12) (Subroto and Datta, 2023; Thapa *et al*., 2023). The SDGs recognize that CC is a global problem that requires urgent action (Salhi, 2023) and SDGs, Goal 13 specifically calling for countries to take urgent action to combat CC and its impacts (Albitar *et al*., 2023). This goal recognizes that CC poses a threat to sustainable development and that it is essential to reduce greenhouse gas emissions and increase resilience to the impacts of CC (Lyytimäki *et al*., 2023).

CC is an undeniable and pressing issue that is affecting the world in various ways (Mavrodieva *et al*., 2019; Méndez, 2020; Lobo *et al*., 2021; Hacquard *et al*., 2022). Pakistan, being situated in Southeast Asia, is highly vulnerable to floods and droughts caused by CC and the country's agriculture sector, ground water, nutrition, soil quality, soil organic matter, health conditions, and poverty are adversely affected by the variations in climate (Harris *et al*., 2020) and particularly in terms of its agricultural sector is facing significant yield reduction (Chandio *et al*., 2023). The social vulnerability further contributes to the country's disaster risk (Hussain *et al*., 2023). It is therefore important to consider the various factors that contribute to this vulnerability to create a climatic-resilient farming system.

Farming is a way of life for 56% of the population in Pakistan, and their livelihoods are directly tied to the land and the weather patterns that govern it. As CC continues to disrupt these patterns, it is increasingly important to understand the vulnerabilities of the population and to develop strategies to help them adapt. The physical effects of CC are becoming more and more evident with each passing day, and population around the globe are noticing these changes first-hand (Masson-Delmotte *et al*., 2021). Rising temperatures are causing population to experience more frequent and severe heatwaves (Tartarini *et al*., 2022), while changes in precipitation patterns (Coates *et al*., 2022) are causing droughts (Dibi-Anoh *et al*., 2023) and floods (Duchenne-Moutien and Neetoo, 2021) to become more common. CC is also causing sea levels to rise, melting of glaciers and ice sheets (Woolway *et al*., 2020; Sesana *et al*., 2021), resulting in more frequent storms and floods around the world (Bulthuis *et al*., 2019). This is causing sea levels to rise, which is causing even more flooding and storm damage. Also shifts in the distribution and behaviour of plant and animal species, leading to biodiversity loss (Dhungana *et al*., 2020) coupled by the cultivated crop land use and changes in the yields and quality of the crops (Hock and Huss, 2021).

CC has ecological dimension (De Frenne *et al*., 2021) and have effects on natural events such as flowering, migration, and hibernation (Cianconi *et al*., 2020). These events are critical for the survival of many plant and animal species, and changes in their timing could have severe consequences. As temperatures rise and precipitation patterns change, certain species may be unable to survive in their current habitats (Ponti and Sannolo, 2022), affect the growth and yield of crops (Detzel *et al*., 2022). This, in turn, can affect food security and the livelihoods of farmers and communities that depend on agriculture. CC has also been linked to the decline in the number of certain species (Detzel *et al*., 2022) and the loss of their habitats due to human activities such as deforestation and urbanization can exacerbate the problem. Changes in ecosystem services, such as clean water and pollination, are other ecological effects of CC. The warming of the oceans, for instance, can affect the distribution and abundance of marine organisms, leading to changes in fishing patterns and food security and hence affect the productivity of marine ecosystems (Ahmed *et al*., 2019).

The CC extreme weather events, changes in air and water quality, and the spread of diseases affects human health (Mogos *et al*., 2021; Sherratt, 2021). The loss of property and crops, increased healthcare costs, and displacement/migration of people due to sea level rise and drought are some of the ways in which climate change affects infrastructure (Tabe, 2019; Romanello *et al*., 2021). The rising temperatures and extreme weather patterns caused by CC can lead to economic damages (Botzen *et al*., 2019; Frame *et al*., 2020). The political dimension of CC is a critical aspect that cannot be overlooked (Scoville-Simonds *et al*., 2020). It is essential to understand the role that international cooperation and coordination play in addressing CC and the public opinion on CC can significantly influence political decision-making (Howe *et al*., 2019). Climate-related litigation, such as lawsuits against governments or corporations, is also an essential part of the political dimension of CC (Latulippe and Klenk, 2020).

The CC can bring about changes in cultural attitudes towards nature, such as the belief in the intrinsic value of the natural world (Shrivastava *et al*., 2020). Values such as individualism or collectivism can also change in response to CC (Rondhi *et al*., 2019). The communities must understand that CC can lead to changes in their behaviours related to the environment (Shrivastava *et al*., 2020). CC can also affect cultural identity, such as national or regional identity (Kipp *et al*., 2019). Furthermore, indigenous knowledge and practices related to the environment can change due to CC, leading to a loss of cultural heritage and practices (Dwivedi *et al*., 2022). Religious beliefs can also influence attitudes towards the natural world and the role of humans in caring for the environment (Kipp *et al*., 2019). It is essential for communities to recognize the cultural dimension of CC and how it affects their perception and response to this global issue (Rondhi *et al*., 2019).

The impact of CC is being felt around the world, and it is essential to take action to adapt to the changes that are already happening (Stern and Stern, 2007) through the adaptation agricultural practices (Verlie, 2019). Farmers can use their knowledge of adaptation and mitigation strategies to grow completely new crop varieties that are more resilient to the effects of CC (Pelling, 2010; Mustafa *et al*., 2019). They can also rear or raise new types of animals that are better suited to the changing climate (Grote *et al*., 2021). Another important aspect of adaptation is access to weather forecasts and information (Verlie, 2019). This can help farmers make informed decisions about when to plant and harvest their crops, as well as how to manage water resources (Mustafa *et al*., 2019). Warning information can also be crucial in helping farmers prepare for extreme weather events, such as droughts or floods (Pelling, 2010). By investing in research and development of new agricultural practices, can help ensure that the food supply is secure even in the face of a changing climate (Mustafa *et al*., 2019).

The preceding paras underscores the significant and multifaceted impacts of CC on farm HHs, affecting their economic stability, social well-being, and the environment they depend upon. While existing methods for assessing CC vulnerability offer valuable insights, they often fall short in capturing the intricate and context-specific nature of vulnerability at the farm level within Pakistan. Limitations such as a lack of focus on micro-level dynamics, the neglect of internal factors influencing adaptation, data constraints, and challenges in addressing the multidimensionality of vulnerability necessitate a more comprehensive approach. A multidimensional index offers a robust framework to overcome these shortcomings, providing a more nuanced and holistic understanding of the various factors that contribute to the vulnerability of farm HHs. Therefore, to address the identified gaps and to provide a more accurate and comprehensive assessment of the challenges faced, this research aims to develop a MCCI for assessing vulnerability of farm HHs in Pakistan. This index will integrate economic, social, political, cultural and environmental dimensions, offering a valuable tool for researchers, and practitioners to design and implement more effective strategies for CC adaptation and resilience building in Pakistan's agricultural sector.

Research significance

The rising threat of CC poses a profound challenge to global agricultural systems, with particularly severe consequences for vulnerable regions such as Pakistan. Ranked 7th among the countries most susceptible to climate-related disasters, Pakistan's predominantly agrarian economy and large rural population are highly exposed to the adverse effects of a changing climate. The agricultural sector, a cornerstone of the national economy, contributes significantly to the gross domestic product and provides livelihoods for a substantial portion of the population, making the resilience of farm HHs a critical concern for national food security and economic stability. However, assessing the vulnerability of these HHs through traditional economic indicators alone offers a limited perspective on the complex realities they face. These indicators may not adequately reflect the exposure to environmental shocks, the sensitivity of livelihoods dependent on natural resources, or the adaptive capacities of communities at the micro-level. Therefore, this research argues that the MCC vulnerability index specifically tailored for farm households in Pakistan holds significant research importance. This importance stems from the inherent limitations of existing assessment approaches and the increasingly recognized multifaceted nature of CC impacts on vulnerable populations. The multidimensional approach, of this research will articulate the significance of such an index in providing a more accurate, comprehensive, and relevant understanding of vulnerability, ultimately paving the way for more effective adaptation and mitigation strategies at the farm HHs level vulnerability assessment.

Objectives of the research

The objectives of vulnerability measurements of

Pakistani farm HHs with reference to CC may include to assess the current level of vulnerability of farm HHs in Pakistan to the impacts of CC and to identify the key indicators contributing to the vulnerability. Also, to develop a vulnerability index based on special mapping, to quantify the level of vulnerability.

Materials and Methods

The research methodology for assessing the vulnerability of Pakistani farm HHs to CC involve a comprehensive literature review (Table 1) conducted to gather relevant data on vulnerability measurements indicators, CC impacts, and coping strategies and adaptation measures being used by farm HHs. A survey method was used to collect primary data from a representative sample (6000), with 1000 HHs each from Khyber Pakhtunkhwa, Punjab, Sindh, Balochistan, Azad Jammu and Kashmir and Gilgit Baltistan through random sampling, using face to face interview method. The survey data were analysed for 5775 HHs, based on the response received, while 4% of the respondents were reluctant to give the information. The SPSS statistical software was used to analyse the data for the descriptive statistics calculation and also the Multidimensional climate change index (MCCI) for measuring the HHs vulnerability.

Table 1: *Dimensions/ Indicators weight and deprivation cut-off of Climate Change (CC) vulnerability in Pakistan.*

Dimensions (weight)	Indicators	Weight	Deprivation cut-off	Reference
Physical (1/7)	HHs observing area rising temperatures	1/84	If yes	(Coates *et al*., 2022)
	HHs looking at the changes in precipitation patterns	1/84	If yes	(Coates *et al*., 2022)
	HHs see frequent and severe droughts	1/84	If yes	(Hock and Huss, 2021; Dibi-Anoh *et al*., 2023)
	HHs observing floods, and storms	1/84	If yes	(Duchenne-Moutien and Neetoo, 2021)
	HHs observing expand and sea levels to rise	1/84	If yes	(Woolway *et al*., 2020; Sesana *et al*., 2021)
	HHs observing the glaciers and ice sheets to melt	1/84	If yes	(Bulthuis *et al*., 2019; Bolibar *et al*., 2022)
	HHs observing frequent and severe heatwaves	1/84	If yes	(Hock and Huss, 2021)
	HHs observing droughts, floods, hurricanes	1/84	If yes	(Hock and Huss, 2021)
	HHs facing extreme weather events	1/84	If yes	(Hock and Huss, 2021)
	HHs obverse shifts in the distribution and behavior of plant and animal species	1/84	If yes	(Dhungana *et al*., 2020)
	HHs observed biodiversity loss	1/84	If yes	(Dhungana *et al*., 2020)
	HHs cultivated crop land use affected	1/84	If yes	(Hock and Huss, 2021)
Ecological (1/7)	CC affects timing of natural events, i.e. flowering, migration, and hibernation change	1/42	If yes	(Ahmed *et al*., 2019; Cianconi *et al*., 2020)
	HHs observe shifts in the geographic range of plant and animal species	1/42	If yes	(Cianconi *et al*., 2020)
	HHs looking CC effect on the production of crops and other plant-based resources	1/42	If yes	(Ponti and Sannolo, 2022)
	HHs observe that some species decline in number or go extinct	1/42	If yes	(Potter and Röös, 2021)
	HHs observing Changes in ecosystem services, such as clean water, pollination,	1/42	If yes	(Potter and Röös, 2021; Detzel *et al*., 2022)
	HHs observing the change can affect the productivity of marine ecosystems	1/42	If yes	(Ahmed *et al*., 2019; Potter and Röös, 2021)
Social (1/7)	CC effect HHs Health (through extreme weather events, changes in air and water quality, the spread of diseases)	1/42	If yes	(Mogos *et al*., 2021; Sherratt, 2021)
	CC affects infrastructure, loss of property and crops, and increased healthcare costs	1/42	If yes	(Tabe, 2019; Torres *et al*., 2021)
	CC cause displacement and migration, as people are forced to leave their homes due to sea level rise, droughts	1/42	If yes	(Tabe, 2019; Clayton, 2020)

Table continues on next page........

Links Researchers

Dimensions (weight)	Indicators	Weight	Deprivation cut-off	Reference
	CC affect cultural practices and traditions	1/42	If yes	(Clayton, 2020)
	HHs observing coordinated response at the local, national, and international levels for CC	1/42	If no	(Matewos, 2022)
	HHs observing the strengthening of communities' ability to adapt to changing conditions	1/42	If no	(Frame *et al*., 2020; Matewos, 2022)
Economics (1/7)	CC can cause economic damages that require adaptation measures	1/42	If no	(Botzen *et al*., 2019; Frame *et al*., 2020)
	CC greenhouse gas emissions require significant investments in low-carbon technologies and infrastructure	1/42	If no	(Frame *et al*., 2020; Orlov *et al*., 2020)
	Energy sector is a major contributor to greenhouse gas emissions	1/42	If yes	(Abbass *et al*., 2022)
	CC affect cultural practices and traditions	1/42	If yes	(Orlov *et al*., 2020; Abbass *et al*., 2022)
	HHs have Investment in low-carbon technologies	1/42	If no	(Abbass *et al*., 2022)
	CC affect economic growth through its impact on natural resources, infrastructure, and human health.	1/42	If yes	(Rondhi *et al*., 2019; Orlov *et al*., 2020)
Political (1/7)	HHs have knowledge of international cooperation and coordination of CC	1/42	If no	(Scoville-Simonds *et al*., 2020)
	HHs know about the National climate policy	1/42	If no	(Howe *et al*., 2019; Scoville-Simonds *et al*., 2020)
	HHs know about the statements and actions of government officials and political candidates on CC	1/42	If no	(Latulippe and Klenk, 2020)
	HHs consider that public opinion on CC can influence political decision-making	1/42	If no	(Scoville-Simonds *et al*., 2020)
	HHs have climate-related litigation, such as lawsuits against governments or corporations' knowledge	1/42	If no	(Howe *et al*., 2019; Rondhi *et al*., 2019)
	HHs have say in advocacy groups and the level of public engagement in environmental issues	1/42	If no	(Scoville-Simonds *et al*., 2020)
Cultural (1/7)	CC affect HHs cultural attitudes towards nature, such as the belief in the intrinsic value of the natural world	1/42	If yes	(Rondhi *et al*., 2019; Shrivastava *et al*., 2020)
	HHs value the Cultural values, such collectivism for CC	1/42	If no	(Scoville-Simonds *et al*., 2020)
	CC change HHs behaviors related to the environment	1/42	If no	(Shrivastava *et al*., 2020; Dwivedi *et al*., 2022)
	HHs consider that CC affect the cultural identity, such as national or regional identity	1/42	If no	(Kipp *et al*., 2019; Verlie, 2019)
	CC affect HHs Indigenous knowledge and practices related to the environment change	1/42	If yes	(Kipp *et al*., 2019; Rondhi *et al*., 2019)
	HHs religious beliefs can influence attitudes towards the natural world and the role of humans in caring for the environment	1/42	If no	(Shrivastava *et al*., 2020; Grote *et al*., 2021; Dwivedi *et al*., 2022)
Adaptation (1/7)	Adaptation/mitigation strategies knowledge	1/42	If no	(Mustafa *et al*., 2019; Verlie, 2019)
	Grow completely new crop variety	1/42	If no	(Grote *et al*., 2021)
	Rearing/rising new type animal	1/42	If no	(Pelling, 2010; Verlie, 2019)
	Weather forecasts/information availability	1/42	If no	(Stern and Stern, 2007; Grote *et al*., 2021)
	Warning information help	1/42	If no	(Mustafa *et al*., 2019; Grote *et al*., 2021)
	Prepare for future CC challenges	1/42	If no	(Mustafa *et al*., 2019; Verlie, 2019)

The MCCI is a complex mathematical model that combines multiple indicators and factors to measure the impact of CC. To calculate the MCCI, the first step is to identify the relevant indicators and assign weights to each indicator based on its relative importance. The data for each indicator is then collected and normalized to a common scale. Next, the sub-indices for each indicator are calculated by multiplying each normalized score by its corresponding weight. The sub-indices are aggregated to calculate the overall MCCI score. However, it is important to ensure that the weights assigned to each indicator are based on scientific evidence, and that the data used to calculate the sub-indices are accurate and reliable.

The mathematical formula for the MCCI can be expressed as:

$$MCCI = w_1I_1 + w_2I_2 + w_3I_3 + \ldots\ldots w_nI_n \quad \ldots(1)$$

Where, MCCI, multidimensional climate change index; $w_1, w_2, w_3, \ldots, w_n$: the weights assigned to each indicator; $I_1, I_2, I_3, \ldots, I_n$: the sub-indices for each indicator.

The MCCI vulnerability index then calculated by combining the weighted indicators to produce a composite score for each HH by multiplying the head count ratio and the intensity.

$$MCCI = H \times A \quad \ldots\ldots(2)$$

It considers various factors such as the intensity of CC, the head count ratio, and other socio-economic indicators. The head count ratio (H) is a measure, presents the percentage of the population living below the deprivation line. The intensity (A) represents the CC intensity. Arc-Geographic Information System (GIS) were used to map the spatial distribution of vulnerability indicators of the CC.

Results and Discussion

Climate change is a multifaceted issue impacting physical systems (temperature, precipitation, sea level, ice melt, leading to extreme weather, ecosystem changes, and affecting food and water), ecological systems (altering seasonal events and species distribution), social well-being (affecting food and water availability, health, displacement, and exacerbating inequalities), economic sectors (agriculture, tourism, increasing adaptation and disaster response costs), political relations (international cooperation on mitigation and adaptation), and cultural practices (traditions dependent on natural resources). Adaptation involves strategies to prepare for and cope with these impacts, such as infrastructure improvements and developing resilient crops. These dimensions can be measured through various indicators, including temperature changes, biodiversity loss, health impacts, economic costs, policy measures, cultural perceptions, and adoption of adaptation strategies.

Descriptive results of CC dimensions/indicators in Pakistan

The Table 2, data presents descriptive statistics for 12 indicators of physical CC vulnerability dimension in Pakistan. A high percentage of HHs (84.8%) reported observing rising temperatures, while 13.7% noted shifts in plant and animal species, with a substantial "don't know" response for the latter. Observations of floods/storms (37.8%), sea-level rise (71.5%), and glacier melt (48.3%) were also observed by the HHs. The variability in responses was highest for floods and storms (C.V. 87.8%). Chi-square tests were significant ($p<0.001$) for all indicators except species shifts, suggesting the observed responses were not due to chance. This pointed that the HHs in Pakistan are experiencing and perceiving physical impacts of CC, particularly rising temperatures and extreme weather, but awareness of ecological shifts may be lower.

The ecological dimension of HHs reported, observing changes in the timing of natural events (44.4%), shifts in species ranges (56.1%), impacts on crop production (50.1%), species decline (66.1%), changes in ecosystem services (51.9%), and alterations in marine ecosystems (50.9%). The statistical significance ($p<0.05$) of these observations across all six indicators suggests a widespread perception of ecological changes related to climate vulnerability.

In the social dimension, HHs reported effects on their health (22.3%), infrastructure (13.5%), displacement and migration (28.2%), and cultural practices (20.9%). Observations of coordinated responses to CC (28.2%) and the strengthening of community adaptation abilities (36.3%) were also noted. The high variability in responses and statistically significant differences ($p<0.05$) across all indicators indicate that CC is impacting various facets of social life in Pakistan.

The economic dimension showed that 23.3% of HHs agreed CC could cause economic damage requiring adaptation (significant at $p<0.0004$), and 26.6% agreed the energy sector is a major contributor to greenhouse gas emissions (significant at $p<0.0001$). However, agreement on greenhouse gas emissions

Table 2: *Climate change (CC) vulnerability measuring dimensions/ indicators descriptive statistics in Pakistan (n=5775).*

Dimensions	Indicators	Yes (%)	No (%)	DK (%)	S. Dev.	C.V	Chi^2	p value
Physical	HHs observing area rising temperatures	84.8	9.6	5.6	541.5	28.1	304.6	0.0003
	HHs looking the changes in precipitation patterns	15.0	51.7	33.2	1128.5	58.6	1323.2	0.0001
	HHs frequent and severe droughts	30.8	37.3	31.9	819.6	42.6	697.9	0.0009
	HHs observing floods, and storms	37.8	21.5	40.7	1690.7	87.8	2970.0	0.0000
	HHs observing expand and sea levels to rise	71.5	17.2	11.4	920.8	47.8	880.8	0.0001
	HHs observing the glaciers and ice sheets to melt	48.3	24.7	27.0	905.8	47.1	852.5	0.0002
	HHs observing frequent and severe heatwaves	36.3	34.0	29.8	559.4	29.1	325.1	0.0001
	HHs observing droughts, floods, hurricanes	23.3	43.1	33.7	1047.9	54.4	1140.8	0.0004
	HHs facing extreme weather events	32.2	41.8	26.0	1402.1	72.8	2042.4	0.0000
	HHs obverse shifts in the distribution and behaviour of plant and animal species	13.7	49.8	36.5	1047.9	54.4	5775.0	0.0000
	HHs observed biodiversity loss	24.7	60.8	14.5	1402.1	72.8	5775.0	0.0000
	HHs cultivated crop land use affected	44.8	44.4	10.9	1136.3	59.0	5775.0	0.0000
Ecological	CC affect timing of natural events, i.e. flowering, migration, and hibernation change	44.4	28.1	27.5	648.8	33.7	437.4	0.0004
	HHs observe shifts in the geographic range of plant and animal species	56.1	21.9	22.0	1387.4	72.1	2000.0	0.0000
	HHs looking CC effect on the production of crops and other plant-based resources	50.1	23.5	26.5	357.3	18.6	132.6	0.0001
	HHs observe that some species to decline in number or go extinct	66.1	23.0	11.0	629.9	32.7	412.3	0.0001
	HHs observing Changes in ecosystem services, such as clean water, pollination,	51.9	21.5	26.6	271.0	14.1	76.3	0.0002
	HHs observing the change can affect the productivity of marine ecosystems	50.9	19.9	29.2	296.1	15.4	91.1	0.0001
Social	CC effect HHs Health (through extreme weather events, changes in air and water quality, the spread of diseases)	22.3	44.1	33.7	587.0	30.5	358.0	0.0008
	CC affect infrastructure, loss of property and crops, and increased healthcare costs	13.5	60.2	26.3	435.1	22.6	196.7	0.0008
	CC cause displacement and migration, as people are forced to leave their homes due to sea level rise, droughts	28.2	32.2	39.6	1050.5	54.6	1146.6	0.2000
	CC affect cultural practices and traditions	20.9	41.9	37.2	1366.6	71.0	1940.3	0.0000
	HHs observing coordinated response at the local, national, and international levels for CC	28.2	40.8	31.0	1118.6	58.1	1300.1	0.0001
	HHs observing the strengthening communities' ability to adapt to changing conditions	36.3	34.0	29.8	559.4	29.1	325.1	0.0001
Economic	CC can cause economic damages that require adaptation measures	23.3	43.1	33.7	1047.9	54.4	1140.8	0.0004
	CC greenhouse gas emissions requires significant investments in low-carbon technologies and infrastructure	32.2	41.8	26.0	1402.1	72.8	2042.4	0.0000
	energy sector is a major contributor to greenhouse gas emissions	26.6	54.2	19.2	1136.3	59.0	1341.6	0.0001
	CC affect cultural practices and traditions	30.8	57.9	11.3	1366.6	71.0	5775.0	0.0000
	HHs have Investment in low-carbon technologies	25.9	55.3	18.9	1118.6	58.1	5775.0	0.0000
	CC affect economic growth through its impact on natural resources, infrastructure, and human health.	25.9	44.8	29.3	559.4	29.1	5775.0	0.0000
Political	HHs have knowledge of international cooperation and coordination of CC	15.0	51.7	33.2	1128.5	58.6	1323.2	0.0001

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Dimensions	Indicators	Yes (%)	No (%)	DK (%)	S. Dev.	C.V	Chi²	p value
	HHs know about the National climate policy	30.8	37.3	31.9	819.6	42.6	697.9	0.0009
	HHs know about the statements and actions of government officials and political candidates on CC	37.8	21.5	40.7	1690.7	87.8	2970.0	0.0000
	HHs consider that public opinion on CC can influence political decision-making	71.5	17.2	11.4	920.8	47.8	880.8	0.0001
	HHs have climate-related litigation, such as lawsuits against governments or corporations' knowledge	48.3	24.7	27.0	905.8	47.1	852.5	0.0002
	HHs know any say in advocacy groups and the level of public engagement in environmental issues	36.3	34.0	29.8	559.4	29.1	325.1	0.0001
Cultural	CC HHs cultural attitudes towards nature, such as the belief in the intrinsic value of the natural world	13.7	49.8	36.5	1047.9	54.4	5775.0	0.0000
	Cultural values, such as individualism or collectivism change	24.7	60.8	14.5	1402.1	72.8	5775.0	0.0000
	CC change HHs behaviours related to the environment	44.8	44.4	10.9	1136.3	59.0	5775.0	0.0000
	HHs consider that CC affect the cultural identity, such as national or regional identity	13.7	49.8	36.5	1047.9	54.4	5775.0	0.0000
	HHs Indigenous knowledge and practices related to the environment change due to CC	24.7	60.8	14.5	1402.1	72.8	5775.0	0.0000
	HHs religious beliefs can influence attitudes towards the natural world and the role of humans in caring for the environment	44.8	44.4	10.9	1136.3	59.0	5775.0	0.0000
Adaptation	Adaptation/mitigation strategies knowledge	15.0	51.7	33.2	1128.5	58.6	1323.2	0.0001
	Grow completely new crop variety	30.8	37.3	31.9	819.6	42.6	697.9	0.0009
	Rearing/rising new type animal	37.8	21.5	40.7	1690.7	87.8	2970.0	0.0000
	Weather forecasts/information availability	71.5	17.2	11.4	920.8	47.8	880.8	0.0001
	Warning information help	48.3	24.7	27.0	905.8	47.1	852.5	0.0002
	Prepare for future CC challenges	36.3	34.0	29.8	559.4	29.1	325.1	0.0001

requiring low-carbon investments was not statistically significant. These findings suggest a recognition of economic vulnerabilities and the role of the energy sector in CC among a segment of the population.

For the political dimension, knowledge levels among HHs varied: International cooperation (15%), national climate policy (30.8%), government actions (37.8%), public opinion influence (71.5%), climate litigation (48.3%), and advocacy groups (36.3%). The significant chi-square values ($p<0.0002$ to 0.0001) indicate a notable difference between observed and expected responses, suggesting generally low levels of knowledge and engagement in the political aspects of CC.

In the cultural dimension, few HHs believed in the intrinsic value of nature (13.7%) or that CC affects their cultural identity (13.7%). Around a quarter noted impacts on cultural values and indigenous knowledge (24.7% each), while 44.8% reported changing behaviors due to CC and believed religious beliefs influence attitudes towards nature. The data suggests varying levels of awareness regarding CC's impact on cultural aspects.

The adaptation dimension revealed low levels of knowledge regarding adaptation/mitigation strategies (15%), growing new crops (30.8%), and rearing new animals (37.8%). More HHs were aware of weather forecasts (71.5%) and the helpfulness of warning information (48.3%). The significant chi-square results across all adaptation indicators highlight a general lack of preparedness and knowledge concerning CC adaptation strategies among HHs in Pakistan.

Pakistan multi-dimensional Cc vulnerability index

The Figure 1 data pointed the measurement of vulnerability to CC among HHs across several provinces in Pakistan. The Figure 1 presents the head count ratio (H), intensity (A), and the overall MCCI score, offering insights into the extent and severity of CC vulnerability. The overall Pakistan average shows a head count ratio of 0.68, intensity of 0.58, and an MCCI of 0.38, reflecting a substantial nationwide vulnerability to CC of the farm HHs. The Khyber

Pakhtunkhwa province shows a moderate head count ratio (0.6) and intensity (0.64), resulting in an MCCI of 0.37. This suggests a considerable portion of HHs are vulnerable, with moderate to high intensity of impact. The province of Punjab, with a head count ratio of 0.8 and an intensity of 0.59, has a notable MCCI score of 0.48. This shows a high level of vulnerability, with many HHs affected, although perhaps less intensely than in Sindh. The province of Sindh also displays a high head count ratio (0.85) and intensity (0.6), leading to the highest MCCI score (0.51). This indicates a significant proportion of households are vulnerable, and those who are vulnerable experience severe impacts. Balochistan exhibits the highest head count ratio (0.99), indicating that nearly all HHs in the province are vulnerable to CC. While the intensity (0.44) is not the highest, the extremely high head count coupled with a significant MCCI score (0.44) signifies that CC poses a substantial threat to the region's population. Azad Jammu and Kashmir stands out with the lowest head count ratio (0.28) but a relatively high intensity (0.65), resulting in the lowest MCCI score (0.18). This suggests that while a smaller proportion of HHs are vulnerable, experience significant CC impacts. Gilgit-Baltistan has a head count ratio of 0.56 and an intensity of 0.57, leading to an MCCI of 0.32, indicates a moderate level of vulnerability. The results highlight the uneven distribution of CC vulnerability across Pakistan's provinces. Balochistan and Sindh emerge as regions with particularly high vulnerability. The high head count ratios in these provinces indicate that a large proportion of their HHs are at risk from CC impacts. The national average underscores the significant CC vulnerability facing Pakistan as a whole.

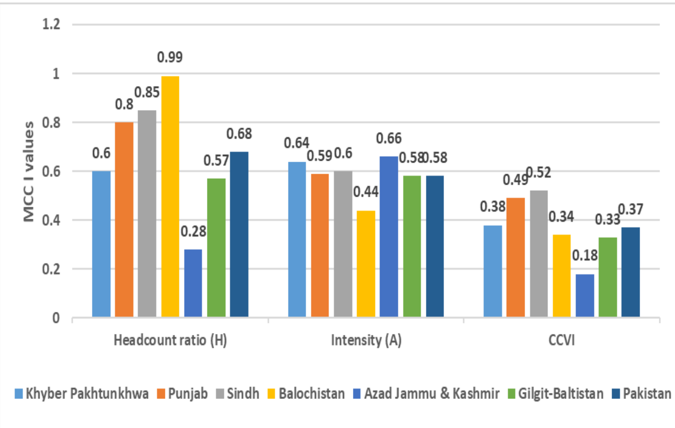

Figure 1: *Multidimensional climate change vulnerability index of the farm HHs in Pakistan.*

Multi-dimensional CC spatiotemporal vulnerability level in Pakistan

The Figures 2, 3 shows the vulnerability levels of HHs across Pakistani provinces, categorized from extremely high to very small, reveal significant regional disparities. The Khyber Pakhtunkhwa exhibits the most HHs in the small vulnerability category, while Punjab has the highest count in the medium category, and Sindh in the high category. Balochistan and Azad Jammu and Kashmir show minimal HHs in the small category, but Balochistan has a substantial number in the high category. Pakistan has a considerable number of HHs in the extremely high vulnerability category, with Khyber Pakhtunkhwa contributing the most. Gilgit-Baltistan is unique in having HHs in the very small vulnerability category, representing the least vulnerable group to CC.

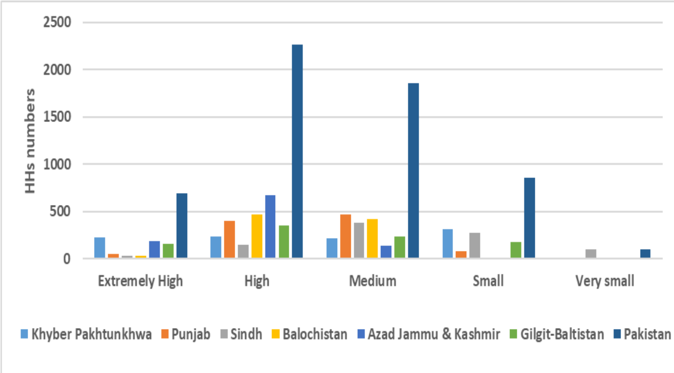

Figure 2: *Multidimensional CC vulnerability scale of farm HHs in Pakistan.*

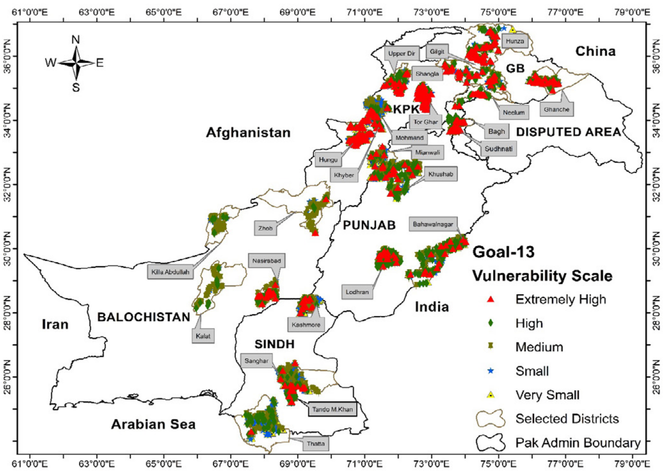

Figure 3: *ArcGIS Map of multidimensional CC vulnerability scale of HHs in Pakistan.*

MCCI and levels of CC vulnerability in Khyber Pakhtunkhwa

The data on HHs vulnerability to CC across different districts in Khyber Pakhtunkhwa (KP), Pakistan, presented in Figure 4. The data shows that the

Mohmand district stands out with a head count ratio of 1.0. This means that every household in the district is considered vulnerable to CC, combined with an intensity of 0.61, the MCCI is also 0.61, the highest. The district Torghar also shows a high level of vulnerability with a head count ratio of 0.67 and an intensity of 0.6, with an MCCI 0.4. The Upper Dir and Khyber districts have a head count ratio of 0.59, meaning a substantial portion of their households are vulnerable. Their intensity values are also relatively high (0.55 and 0.64, respectively), leading to MCCIs of 0.32 and 0.38. The Shangla and Hangu districts have lower head count ratios (0.41 and 0.31, respectively) compared to the other districts. However, their Intensity values are relatively high (0.67 and 0.76 respectively). This indicates that while fewer households are vulnerable, those who experience very severe impacts. The resulting MCCI values are 0.28 and 0.23, which are the lowest of the districts shown. There is significant variation in CC vulnerability across the districts of Khyber Pakhtunkhwa. Some districts (like Mohmand and Torghar) face widespread and intense vulnerability, while others (like Shangla and Hangu) have lower proportions of vulnerable households but higher severity of impacts. The head count ratio may be low, but the intensity may be very high, which means that a smaller portion of the population is experiencing very harsh effects of CC. It shows that while the region as a whole face's significant challenges, the specific nature and extent of vulnerability vary considerably across districts.

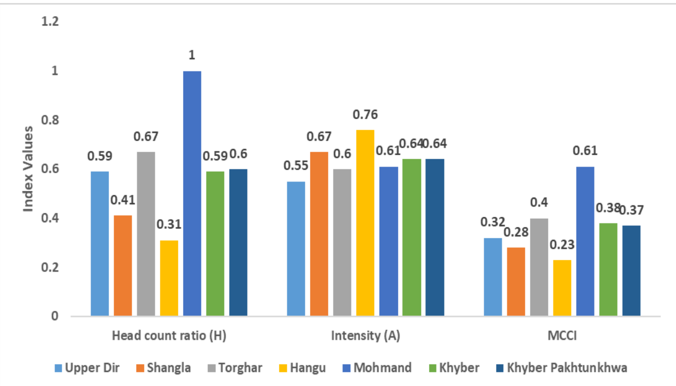

Figure 4: *Multidimensional MCCI of the farm HHs in Khyber Pakhtunkhwa.*

The Figure 5 presents the HHs vulnerability level/ status in six selected districts of KP towards the CC. Upper Dir, Shangla, Torghar, Hangu, Mohmand, and Khyber. The analysis reveals significant variations in vulnerability levels across these districts. Shangla and Torghar exhibit the highest proportions of households in the extremely high and high vulnerability categories. The districts of Upper Dir and Mohmand also show considerable levels of high CC vulnerability, while the Hangu and Khyber appear to have relatively lower in the most severe categories of CC. The overall vulnerability status for Khyber Pakhtunkhwa shows that the small vulnerability category has the highest representation with 315 HHs, followed by the high vulnerability category at 238, the extremely high vulnerability category at 227, and the medium vulnerability category at 220 HHs. Comparing this with the provincial distribution with the district-level data reveals that Hangu in the extremely high category is nearly double the provincial average. The Shangla in the extremely high category is also considerably higher than the provincial average. The district Mohmand shows a stark contrast with 0 in the extremely high category compared to the provincial. The districts in Khyber Pakhtunkhwa reveal significant vulnerabilities as Shangla, Torghar, and Hangu exhibit the highest levels of extreme vulnerability, while Upper Dir also shows high vulnerability.

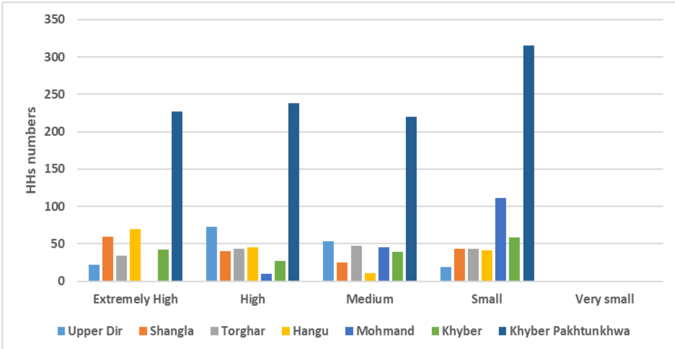

Figure 5: *Multidimensional CC vulnerability level/scale of farm HHs in Khyber Pakhtunkhwa.*

MCCI and levels of CC vulnerability in Punjab

The Figure 6 reveals the multidimensional CC vulnerability among farm HHs across the districts in Punjab. The MCCI (0.48), with the head count ratio of 0.8, indicates that a substantial portion of the region's farm HHs is vulnerable to CC. The head count ratio of Lodhran shows the highest vulnerability with a ratio of 1 and highest intensity (0.68), meaning all farm HHs in this district are classified as vulnerable while the district of Bahawalnagar (0.77), with intensity 0.59 and Khushab (0.75) with intensity 0.55 also show high vulnerability and most severe impacts. The Mianwali district has the lowest head count ratio (0.69) with the intensity of 0.55 among the listed districts but still reflects a significant portion of vulnerable households. The MCCI provide a comprehensive measure of CC vulnerability and shows that Lodhran exhibits the highest MCCI (0.68), indicating the greatest overall vulnerability while the Bahawalnagar (0.45), Punjab overall (0.48), Khushab (0.42) and Mianwali (0.38) follow, with Mianwali showing the lowest overall vulnerability among the districts. The data highlights significant regional variations in CC vulnerability across Punjab. The districts of Bahawalnagar and Khushab also showed high levels of vulnerability indicates that CC impacts are not uniform and are influenced by local environmental and socioeconomic factors. The lower MCCI of Mianwali compared to the other districts, does not mean that the district is not vulnerable, but rather that compared to the other districts, it is relatively less vulnerable.

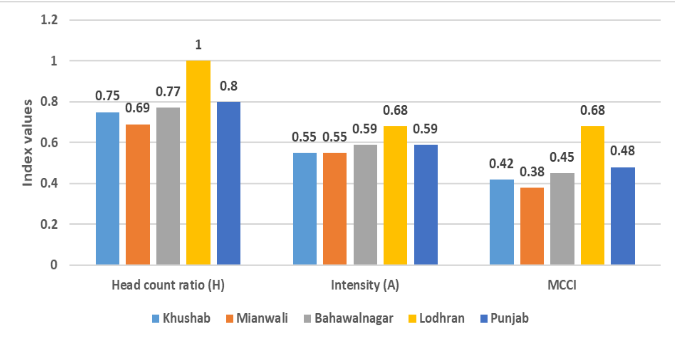

Figure 6: *Multidimensional CC vulnerability index of the farm HHs in Punjab.*

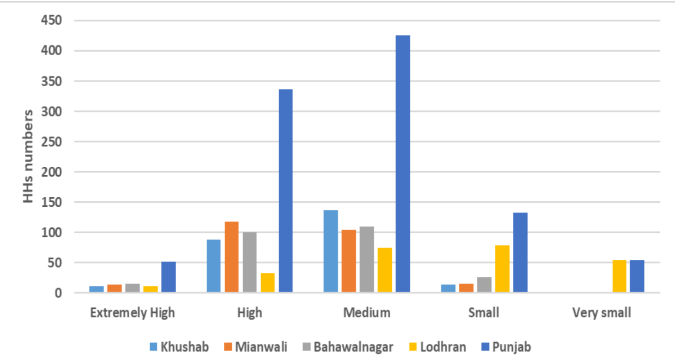

Figure 7: *Multidimensional CC vulnerability level/scale of farm HHs in Punjab.*

The Figure 7 presents the multidimensional CC vulnerability of farm HHs across different CC vulnerability levels: Extremely high, high, medium, small, and very small in Punjab. It demonstrates widespread vulnerability, with a substantial portion of households categorized as high or medium vulnerability, and pockets of extremely high vulnerability in all districts. The significant number of HHs across Khushab, Mianwali, Bahawalnagar, and Lodhran districts are vulnerable to CC, with the majority falling into the high and medium CC vulnerability categories. The district of Lodhran exhibits a unique distribution, showing households across all vulnerability levels, including a notable number in the small and very small categories. Across all districts, medium CC vulnerability consistently holds the highest number of HHs, suggesting it's the most prevalent vulnerability category. Extremely high and high CC vulnerability categories indicate a considerable number of HHs facing severe CC impacts. The dominance of the medium CC vulnerability category across all districts suggests that a substantial portion of Punjab's farm HHs are experiencing moderate CC impacts. The considerable number of HHs in the high and extremely high categories is a cause for concern. The similar CC vulnerability patterns observed in Khushab, Mianwali, and Bahawalnagar suggest that these districts may share common CC challenges.

MCCI and levels of CC vulnerability in Sindh

The Figure 8 data presents a MCCI for farm households (HHs) across four districts in Sindh, Pakistan, namely Kashmoor, Tando Muhammad Khan (T.M. Khan), Sanghar, and Thatta, along with the overall Sindh average. The Sindh MCCI is 0.51, with a head count ratio of 0.85 and an intensity of 0.60, highlighting the region's significant vulnerability to CC. The district of Kashmoor exhibits the lowest MCCI at 0.34, with a head count ratio of 0.69 and an intensity of 0.49, suggests that while a significant proportion of farm HHs in Kashmoor are vulnerable, the severity of their vulnerability is relatively lower compared to other districts. In contrast, T.M. Khan shows the highest MCCI at 0.64, accompanied by a high head count ratio of 0.88 and the highest intensity of 0.73, indicates that a large majority of farm HHs in T.M. Khan are not only vulnerable but also experience severe CC impacts. Sanghar follows with an MCCI of 0.52, a high head count ratio of 0.93, and an intensity of 0.56, signifying widespread vulnerability with moderate severity. The district of Thatta MCCI is 0.55, with a head count ratio of 0.89 and an intensity of 0.61, indicating a high proportion of vulnerable HHs facing substantial CC impacts. The results reveal a concerning level of CC vulnerability among farm HHs in Sindh. The high head count ratios across all districts, particularly in Sanghar and Thatta, underscore the widespread nature of this CC vulnerability. The variations in intensity across districts point to differences in the severity of CC impacts. T.M. Khan's high intensity suggests that farm HHs in this district are experiencing more severe consequences, potentially due to factors like water scarcity, extreme heat, or frequent flooding. The variations in vulnerability across districts suggest that adaptation strategies must be tailored to the specific needs and challenges of each area.

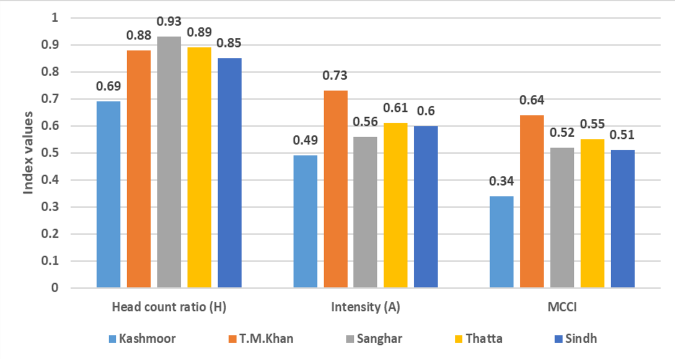

Figure 8: *Multidimensional CC vulnerability index of the farm HHs in Sindh.*

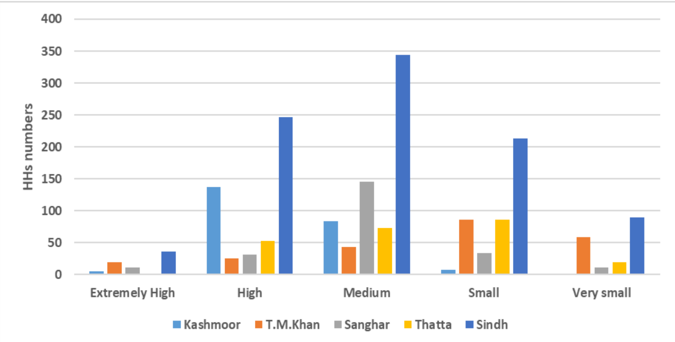

Figure 9: *Multidimensional CC vulnerability level/scale of farm HHs in Sindh.*

The Figure 9 presents the farm HHs across four distinct CC vulnerability levels i.e. extremely high, high, medium, and small for four districts in Sindh viz Kashmoor, T.M. Khan, Sanghar, and Thatta. The Sindh data reflects a broader distribution, with a high concentration in the medium category (344), followed by the high (246) and small (213) categories, and a significant number in the extremely high category (36). The data further depicts that the district of Kashmoor shows a concentration of HHs in the high vulnerability category (137), followed by the medium category (83), with a relatively small number in the extremely high (5) and small (7) categories. T.M. Khan presents a different distribution, with the highest number of HHs in the small vulnerability category (86), followed by the medium category (43), and in the extremely high category (19). Sanghar exhibits a concentration of HHs in the medium vulnerability category (145), followed by the small (34) and high (31) categories, with a smaller number in the extremely high category (11). The district of Thatta, shows a high number of HHs in the small vulnerability category (86), followed by the medium category (73) and a high category (53). The results highlight the heterogeneous nature of CC vulnerability across Sindh. The varying distributions across districts suggest that the factors contributing to vulnerability are complex and context specific. The data emphasizes the widespread nature of CC vulnerability, with a significant number of HHs experiencing medium and high levels of vulnerability.

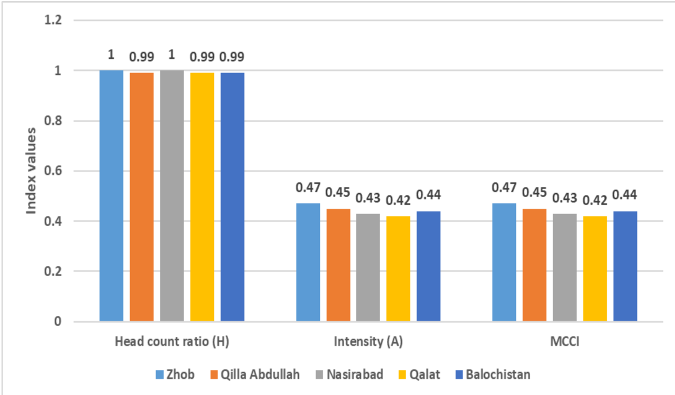

Figure 10: *Multidimensional CC vulnerability index of the farm HHs in Balochistan.*

MCCI and levels of CC vulnerability in Balochistan

The Figure 10 data presents the MCCI for farm HHs across four districts in Balochistan: Zhob, Qilla Abdullah, Nasirabad, and Qalat. The Balochistan CC head count ratio of 0.99, an intensity of 0.44, and an MCCI of 0.44, reflects the widespread vulnerability observed across the districts, with a moderate average intensity of impact. The Zhob district of Balochistan depicts a CC head count ratio of 1, indicating that all farm HH s within the district are classified as vulnerable. The intensity of vulnerability is 0.47, resulting in an MCCI of 0.47, suggests that while all HHs are vulnerable, the severity of impacts is moderately low compared to potential maximums. The district of Qilla Abdullah presents a CC head count ratio of 0.99, signifying that nearly all farm HHs are vulnerable with the intensity of 0.45, leading to an MCCI of 0.45. This shows a high proportion of CC vulnerable HHs with a slightly lower intensity of impact compared to Zhob. The district of Nasirabad shows a head count ratio of 1, meaning all farm HHs are vulnerable with the intensity is 0.43, resulting in an MCCI of 0.43. Qalat district also shows a head count ratio of 0.99, with intensity is 0.42 and an MCCI of 0.42. This district exhibits the lowest intensity and MCCI among the four districts examined. The CC head count ratios, consistently at 1 or 0.99 across all districts, highlight the pervasive nature of CC vulnerability in the region. This indicates that almost the entire agricultural population is exposed to significant climate-related risks. The intensity values, ranging from 0.42 to 0.47, suggest that while vulnerability is widespread, the severity of impacts is relatively moderate.

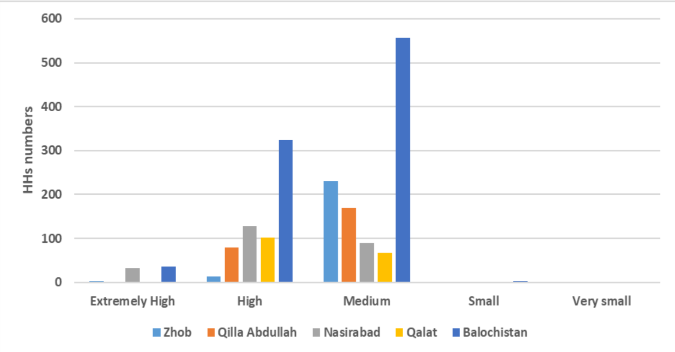

Figure 11: *Multidimensional CC vulnerability level/scale of farm HHs in Balochistan.*

The Figure 11 presents the farm HHs across five CC vulnerability levels, extremely high, high, medium, small, and very small for four districts in Balochistan. The data shows that in Balochistan the majority of HHs in the medium (557) and high (324) vulnerability categories, followed by the extremely high (36) category, underscores the widespread vulnerability of CC HHs farm in the region. The Zhob district shows a concentration of households in the medium vulnerability category (231), which indicates that while a significant number of HHs face moderate vulnerability, a small number are also in the extreme ends of the vulnerability spectrum. The district of Qilla Abdullah exhibits a similar pattern, with the majority of HHs in the medium vulnerability category (169), followed by the high category (80), suggests that the district's vulnerability is largely concentrated in the medium to high range. The Nasirabad district presents a different distribution, with a significant number of HHs in the high vulnerability category (128), followed by the medium (90) and extremely high (32) categories, indicates a higher prevalence of severe vulnerability in Nasirabad compared to other districts. The district of Qalat shows a concentration of HHs in the high vulnerability category (102), followed by the medium category (67), suggests that a substantial portion of Qalat farm HHs are experiencing high vulnerability. The results highlight the varying levels of CC vulnerability across Balochistan farm HHs. The districts of Zhob and Qilla Abdullah show a concentration of HHs in the medium vulnerability category, suggesting that while these districts face climate-related challenges, the impacts are generally moderate for a large portion of the population. The Nasirabad significant number of HHs in the extremely high and high categories indicates that a substantial segment of its farm HHs is facing severe CC impacts.

MCCI and levels of CC vulnerability in Azad Jammu and Kashmir

The Figure 12 data presents the MCCI for farm HHs across four districts in Azad Jammu and Kashmir (AJK). The index utilizes three key metrics: the Head Count Ratio (H), indicating the proportion of vulnerable households; the Intensity (A), representing the average severity of vulnerability; and the MCCI, a composite measure of both. The data shows that AJK CC head count ratio of 0.28, an intensity of 0.65, and an MCCI of 0.18, reflects the average vulnerability across the region, with a relatively low proportion of vulnerable HHs but a substantial average severity of impact. The Neelum district exhibits a head count ratio of 0.38, indicating that 38% of farm HHs are classified as vulnerable with the intensity of vulnerability is 0.51, resulting in an MCCI of 0.19. This suggests a relatively moderate proportion of vulnerable HHs with a moderate severity of impacts. Bagh district shows the lowest head count ratio at 0.24, meaning 24% of farm HHs are vulnerable with intensity is 0.53, leading to the lowest MCCI of 0.13. This indicates the smallest proportion of vulnerable HHs among the four districts, but with a relatively moderate severity of impact. The district of Muzaffarabad presents a head count ratio of 0.27, signifying that 27% of farm households are vulnerable. The Intensity is the highest at 0.79, resulting in an MCCI of 0.21, showing a slightly higher proportion of vulnerable HHs compared to Bagh, but with significantly higher intensity of impact. The Sudhnoti district has a head count ratio of 0.23, meaning 23% of farm HHs are vulnerable. The intensity is 0.77, resulting in an MCCI of 0.18. The results reveal a relatively low proportion of vulnerable farm HHs in AJK compared to other regions analysed, as indicated by the head count ratios ranging from 0.23 to 0.38. This suggests that while CC impacts are present, they do not affect the majority of farm HHs in these districts. However, the intensity values, particularly in Muzaffarabad and Sudhnoti, indicate that when HHs are vulnerable, they experience substantial severity of impacts. The MCCI values, ranging from 0.13 to 0.21, are relatively low, indicating a moderate overall vulnerability. The high intensity values in Muzaffarabad and Sudhnoti suggest that these districts might be experiencing specific climate-related challenges that exacerbate vulnerability.

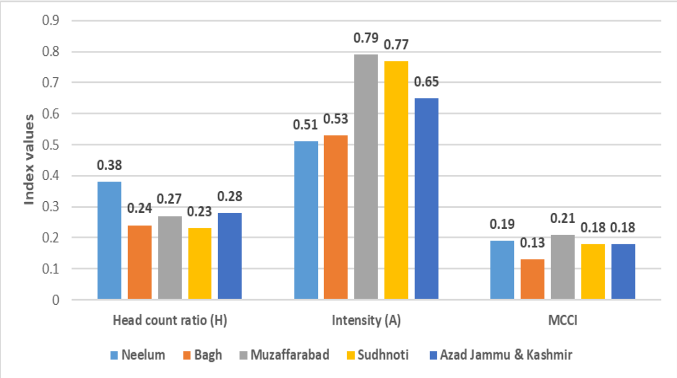

Figure 12: *Multidimensional CC vulnerability index of the farm HHs in Azad Jammu and Kashmir.*

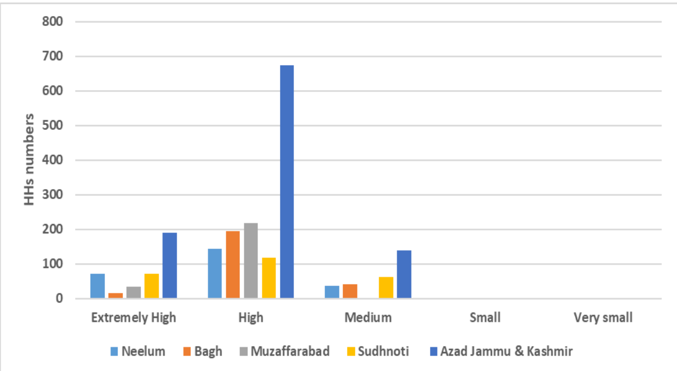

Figure 13: *Multidimensional CC vulnerability level/scale of farm HHs in Azad Jammu and Kashmir.*

Figure 13 data present the farm HHs across five CC vulnerability levels extremely high, high, medium, small, and very small for four districts in AJK. The data reflects the majority of HHs in the high vulnerability category (673), followed by the extremely high category (189), and a smaller number in the medium category (138). The district Neelum exhibits a significant number of HHs in the high vulnerability category (143), followed by the extremely high category (71), and a smaller number in the medium category (36), suggests that the majority of vulnerable farm HHs in Neelum are experiencing high to extremely high levels of CC impacts. Bagh district shows a similar pattern, with a high concentration of farm HHs in the high vulnerability category (195), followed by the medium category (40), indicates that Bagh's vulnerable farm HHs are predominantly facing high levels of CC impacts. The district of Muzaffarabad presents a more concentrated distribution, with the majority of HHs in the high vulnerability category (217), followed by the extremely high category (33), suggests that Muzaffarabad's vulnerable HHs are largely facing high to extremely high levels of climate-related challenges. The Sudhnoti district shows a more varied distribution, with a significant number of farms HHs in the high vulnerability category (118), followed by the extremely high category (70), and a notable number in the medium category (62). The results reveal a concerning trend of high to extremely high CC vulnerability among farm HHs in AJK indicates that the region is experiencing severe CC impacts, potentially due to factors like extreme weather events, landslides, or changes in precipitation patterns.

MCCI and levels of CC vulnerability in Gilgit-Baltistan

The Figure 14 shows the MCCI for farm HHs across four districts (Gilgit, Hunza, Diamer, and Ghanche) in Gilgit-Baltistan with a CC head count ratio (H), the intensity (A) and the MCCI. The overall Gilgit-Baltistan average head count ratio of 0.56, an intensity of 0.57, and an MCCI of 0.32, reflects the average CC vulnerability across the region, with a moderate proportion of CC vulnerable HHs and a moderate severity of impacts. The Gilgit district exhibits the lowest CC head count ratio at 0.23, indicating that 23% of farm HHs are classified as vulnerable with the intensity of vulnerability is 0.55, resulting in an MCCI of 0.13, suggesting a relatively small proportion of vulnerable HHs, but with a moderate severity of impacts when vulnerability occurs. The Hunza district shows a significantly higher CC head count ratio of 0.68, meaning 68% of farm HHs are CC vulnerable with the intensity is 0.59, leading to an MCCI of 0.4, indicates a substantial proportion of CC vulnerable HHs with a moderately high severity of impacts. Diamer district has a head count ratio of 0.67, signifying that 67% of farm HHs are CC vulnerable with the intensity is 0.58, resulting in an MCCI of 0.39, shows a similarly high proportion of vulnerable HHs as Hunza, with a slightly lower intensity of impact. The Ghanche district presents a head count ratio of 0.66, indicating that 66% of farm HHs are CC vulnerable. The Intensity is 0.58, yielding an MCCI of 0.38, exhibits a high proportion of vulnerable HHs with a moderate severity of impacts. The results reveal a significant variation in CC vulnerability across the districts of Gilgit-Baltistan. Gilgit district stands out with the lowest head count ratio, indicating a relatively low proportion of vulnerable farm HHs. However, even with this lower proportion, the intensity of vulnerability is still moderately high, suggesting that when HHs are vulnerable, they experience significant climate-related challenges.

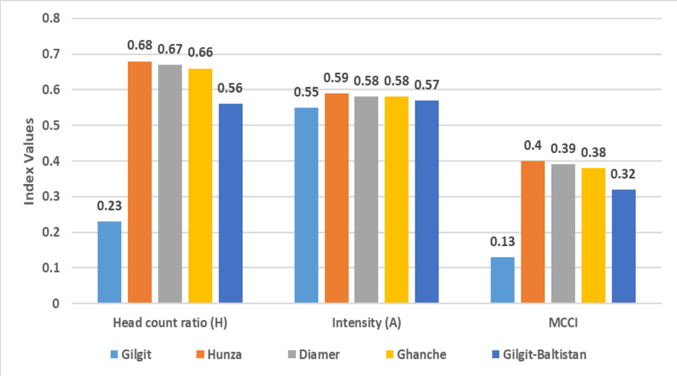

Figure 14: *Multidimensional CC vulnerability index of the farm HHs in Gilgit-Baltistan.*

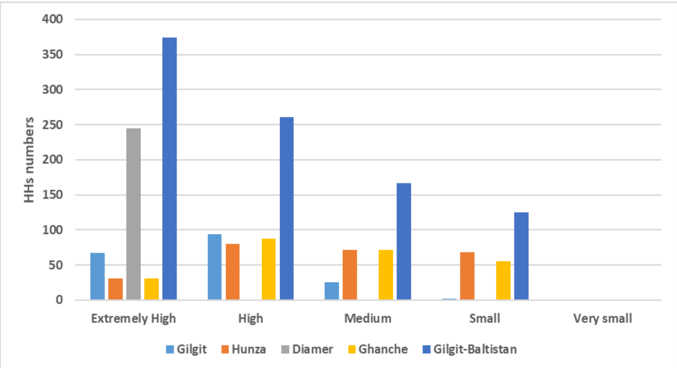

Figure 15: *Multidimensional CC vulnerability level/scale of farm HHs in Gilgit-Baltistan.*

Figure 15 data present the farm HHs across five CC vulnerability level for four districts in Gilgit-Baltistan. The data reflects a broader distribution, with the majority of HHs in the extremely high (374) and high (261) categories, followed by the medium (167) and small (125) categories. The Gilgit district shows a relatively balanced distribution, with a significant number of HHs in the high (94) and extremely high (67) CC vulnerability categories, indicates that while Gilgit has HHs across a range of CC vulnerability levels, a substantial portion is facing high to extremely high impacts. The Hunza district exhibits a more scattered distribution, with a significant number of HHs in the high (80), medium (71), and small (68) categories, along with an extremely high category (31), suggests a wider range of vulnerability levels in Hunza, with a significant portion of HHs experiencing moderate to high impacts. The district of Diamer presents an extreme case, with all vulnerable HHs concentrated in the extremely high category (245), indicates that Diamer's vulnerable HHs are facing exceptionally severe climate-related challenges. Ghanche district shows a distribution like Hunza, with a significant number of HHs in the high (87), medium (71), and small (55) categories, suggests a wide range of vulnerability levels in Ghanche, with a significant portion of HHs experiencing moderate to high impacts. The results highlight a significant variation in CC vulnerability across the districts of Gilgit-Baltistan. Diamer stands out with an exceptionally high concentration of HHs in the extremely high CC vulnerability category. Gilgit, Hunza, and Ghanche exhibit a wider range of vulnerability levels, with a significant portion of HHs experiencing moderate to high impacts.

This research provides a comprehensive analysis of CC vulnerability among farm HHs across Pakistan, using a multidimensional CC index approach encompassing physical, ecological, social, economic, political, and cultural dimensions. The findings reveal that Pakistani farm HHs are experiencing tangible CC impacts, including rising temperatures, altered precipitation, and increased extreme weather events, consistent with broader CC literature highlighting the challenges faced by developing nations. The MCCI effectively highlights regional disparities, with Balochistan exhibiting the highest headcount ratio, AJK the highest intensity, and Sindh the overall highest vulnerability. The varying levels of vulnerability across provinces reveal that while some regions exhibit high concentrations of extremely or highly vulnerable HHs, others show greater resilience. Regional disparities, such as Punjab's high medium vulnerability and Sindh/Balochistan high vulnerability. The MCCI and acknowledging the specific vulnerabilities of different population segments, this research provides a critical foundation for building a more resilient and sustainable future for Pakistan's agricultural sector and its vulnerable communities.

Conclusions and Recommendations

This research quantified the CC vulnerability of farm HHs across Pakistan, using MCCI and geospatial mapping of 5,775 surveyed HHs. The MCCI, encompassing physical, ecological, social, economic, political, and cultural dimensions, revealed significant regional disparities. Sindh emerged as the most vulnerable province, with the highest MCCI value

(0.52), followed closely by Punjab (0.49) and Khyber Pakhtunkhwa (0.48). The Balochistan exhibited the highest headcount ratio (0.99), indicating widespread impact, while Azad Jammu and Kashmir experienced the highest intensity of CC effects (0.66). The spatial analysis further highlighted the varying levels of vulnerability, with Punjab having the largest number of HHs in the medium vulnerability category, while Sindh and Khyber Pakhtunkhwa showed a concentration of HHs in the high and extremely high vulnerability categories respectively. The findings emphasize that CC is not a uniform phenomenon, with diverse regions facing distinct challenges requiring tailored strategies. The vulnerabilities identified are directly linked to the increased frequency and intensity of extreme weather events, shifts in ecosystems, and potential disruptions to food and water supplies. The research highlights the critical importance of moving beyond generalized approaches and implementing context-specific measures to safeguard the livelihoods of farming communities.

Based on the research findings, the following recommendations are proposed:

- There is a need for targeted interventions to focus on improving water management practices by promoting water-efficient irrigation techniques, developing water storage infrastructure, and implementing sustainable watershed management strategies with a specific focus to regions with high intensity scores, like Azad Jammu and Kashmir, to mitigate the impacts of water scarcity and erratic rainfall patterns.
- The protecting and restoring ecosystems are crucial for buffering against the adverse effects of CC by investing in reforestation, biodiversity conservation, and the promotion of sustainable land management practices particularly in Balochistan, to address widespread environmental degradation.
- To enhance preparedness and minimize the impact of extreme weather events, early warning systems, coupled with the promoting climate-resilient crop varieties, providing access to climate information services, and strengthening social safety nets with a special focus should be given to Sindh and Khyber Pakhtunkhwa, to the concentration of highly vulnerable farm HHs is significant.

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Novelty Statement

This study assesses the climate change vulnerability of Pakistani farm households through a MCCI, integrating ecological, social, economic, political, and cultural dimensions using survey data and geospatial mapping to quantify and spatially analyze climate-vulnerable households.

Author's Contribution

Dawood Jan: Conceptualization
Muhammad Israr: Data analysis/manuscript preparation
Shahzad Khan: Proofreading/data compilation
Shakeel Ahmad: GIS mapping/software/visualization/editing
Nafees Ahmad: Review/data compilation.

Conflict of interest
The authors have declared no conflict of interest.

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