# Flood Risk, Climate Adaptation and Rural Livelihood in Pakistan's Irrigated Agriculture: Statistical Analysis of Farmer Survey Data

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## Eidesstattliche Versicherung

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Declaration on Oath

I hereby declare upon oath that I have written the present dissertation independently and have not used further resources and aids than those stated.

Ort, den | Hamburg, 25.01.2024 Unterschrift | Muhammad Mobeen

***Dedicated to my late mother and father.***

# Abstract

Farming communities are increasingly susceptible to climate change due to their lower adaptive capacity and higher vulnerability. The rising frequency of climatic extremes in Pakistan challenges farmers' livelihoods and further lowers their adaptive capacity. This research, titled 'Flood Risk, Climate Adaptation, and Rural Livelihoods in Pakistan's Irrigated Agriculture: Statistical Analysis of Farmer Survey Data,' provides insights into flood risk, climate adaptation, and farmers' livelihoods in Pakistan's irrigated agricultural regions. The study aims to understand how farmers perceive, respond to, and adapt to the challenges presented by climate change and flood risks. The research begins by utilizing secondary remote sensing and meteorological datasets to discuss the 2022 flood in Pakistan. It then investigates farmers' immediate flood response and adaptation decisions in their cultivation practices. I conducted two separate field surveys of data collection to address the research question. Both surveys utilized a structured questionnaire with a five-point Likert scale. The first survey was conducted in flood-affected districts of Sindh province in July and August 2023. It involved interviews with 195 farmers, focusing on their experiences of displacement due to the 2022 flood. The second survey was conducted with 800 farmers in the irrigated agricultural areas of Punjab and Sindh from December 2021 to March 2022. This survey gathered insights on climate perceptions, livelihood capital, adaptation strategies, constraints, and decision-making factors. The central question of this work is how farmers perceive, respond to, and adapt to the challenges presented by climate change and flood risks. It is further subdivided into five individual questions. Each question is addressed in separate chapters.

The first chapter briefly introduces this project, its data, method, study area, and details of two field surveys conducted for this study. In 2022, Pakistan faced the worst flood of its history. I prepared an overview of the 2022 flood two months after its occurrence. The second chapter reports the extent and intensity of the 2022 flood in Pakistan. This chapter uses a secondary dataset of UNITAR's flood monitoring remote sensing datasets. In this chapter, I identified the highly affected districts in the highly flood-prone regions of the Indus plains. This short chapter affected districts in the Indus plains. This work reported that two-thirds of the country was under water, affecting 33 million people and causing 8 million to be displaced. Most of the displacement occurred in Sindh province, especially in the districts close to the Indus River.

Chapter 3 explored the dynamics of this displacement by employing the Protection Motivation Theory. This chapter uses survey data collected from 195 internally displaced farmers. I applied

a combination of partial least square structure equation modeling (PLS-SEM) and necessary condition analysis (NCA), which helped me identify the necessary drivers that motivate farmers to decide on displacement in flooding. This chapter highlights that "Fear" is the most significant predictor, with a coefficient of 0.489 accounting for 19%, while "Response Efficacy," with a coefficient of 0.324, contributed 14% to the displacement decisions of farmers. All other predictors are insignificant and unnecessary. Increased Fear and Response efficacy significantly boosts displacement motivation.

Chapters 4,5 and 6 deal with climate change perception, livelihood capital, climate adaptation, constraints, and factors of farmers' decisions. This section of three chapters uses data from a second survey collected from 800 farmers distributed across the irrigated agricultural area of Pakistan. In Chapter 4, I described how irrigated farmers in Pakistan perceive climate change and their adaptation strategies, constraints, and factors influencing their cultivation decisions. This chapter highlights a clear awareness of climate change and its impacts, including extended summers, contracted winters, and a decline in crop yield. I found that the farmers in Punjab primarily adapted crop and farm management, while farmers in Sindh focused on implementing irrigation measures. The study also identifies constraints impacting farming decisions, such as financial limitations, water scarcity, and soil fertility.

Chapter 5 deals with how the Values and Investments for Agent-Based Interaction and Learning in Environmental Systems (VIABLE) framework elaborates on the role of livelihood capital in climate adaptation, including investment pathways and factors influencing their adaptation strategies. This chapter also evaluates the moderating impact of climatic and non-climatic factors on their adaptation actions. This chapter used the partial least squares structural equation modeling (PLS-SEM) approach to the VIABLE framework. I used data collected from 800 farmers in the first survey. This part of the study found that livelihood capital is the most significant (beta = 0.57, effect size = 0.503) determinant of farmers' adaptation strategies, with other factors, such as investment options and farming constraints, having less impact. The VIABLE-SEM identified the viable action pathways for effective adaptation actions. In this analysis, I discovered that while non-climatic factors negatively affected the relationship between capital and adaptation, climatic factors positively influenced it, enhancing farmers' adaptive capacity.

In Chapter 5, the VIABLE-SEM highlighted that livelihood capital and climatic factors are two prominent determinants of adaptation. The results of Chapter 5 laid the foundation for the question: which component of livelihood capital and climatic factors are necessary for successful climate adaptation? This section employed the Sustainable Livelihood Framework (SLF) as its theoretical foundation. I applied the combination of PLS-SEM and NCA to analyze data from the first survey I collected from 800 farmers. The study found that both climatic factors and all forms of livelihood capital are necessary for successful adaptation. Natural and social capital emerged (beta values of 0.345 and 0.283) as significant. Interestingly, financial capital (beta coefficient -1.85) shows an inverse relationship with adaptation, suggesting complex interactions between economic constraints and adaptation strategies.

Chapter 7 summarizes the dissertation, highlighting its salient features, and presents an overall conclusion of this work. In conclusion, this study offers a valuable guide for policymakers, agricultural practitioners, and climate adaptation planners. This study contributes significantly to the discourse on climate change adaptation and rural livelihoods, paving the way for more effective and resilient agricultural practices in Pakistan's vulnerable irrigated agriculture.

## Zusammenfassung

Landwirtschaftliche Gemeinschaften sind aufgrund ihrer geringeren Anpassungsfähigkeit und höheren Anfälligkeit zunehmend vom Klimawandel betroffen. Die zunehmende Häufigkeit von klimatischen Extremeereignissen in Pakistan stellt die Lebensgrundlage der Landwirte in Frage und verringert ihre Anpassungsfähigkeit weiter. Diese Doktorarbeit mit dem Titel "Flood Risk, Climate Adaptation, and Rural Livelihoods in Pakistan's Irrigated Agriculture: Statistical Analysis of Farmer Survey Data" bietet Einblicke in das Hochwasserrisiko, die Klimaanpassung und den Lebensunterhalt der Landwirte in den bewässerten Agrarregionen Pakistans. Die Arbeit zielt darauf ab, zu verstehen, wie Landwirte die Herausforderungen des Klimawandels und des Hochwasserrisikos wahrnehmen, darauf reagieren und sich daran anpassen. Die Forschungsarbeit beginnt mit der Nutzung sekundärer Fernerkundungs- und meteorologischer Datensätze, um die Flut von 2022 in Pakistan zu diskutieren. Anschließend werden die unmittelbare Reaktion der Landwirte auf die Flut und ihre Anpassungsentscheidungen in Bezug auf ihre Anbaupraktiken untersucht. Zur Beantwortung der Forschungsfrage habe ich zwei getrennte Feldstudien zur Datenerhebung durchgeführt. Für beide Umfragen wurde ein strukturierter Fragebogen mit einer fünfstufigen Likert-Skala verwendet. Die erste Erhebung wurde im Zeitraum Juli-August 2023 in den vom Hochwasser betroffenen Bezirken der Provinz Sindh durchgeführt. Sie umfasste Interviews mit 195 Landwirten und konzentrierte sich auf deren Erfahrungen mit der durch das 2022 Hochwasser bedingten Evakuierung. Die zweite Umfrage wurde mit 800 Landwirten in den bewässerten landwirtschaftlichen Gebieten von Punjab und Sindh von Dezember 2021 bis März 2022 durchgeführt. In dieser Umfrage wurden Erkenntnisse über die Wahrnehmung des Klimas, das Kapital für den Lebensunterhalt, Anpassungsstrategien, Einschränkungen und Entscheidungsfaktoren gesammelt. Die zentrale Frage dieser Arbeit ist, wie Landwirte die Herausforderungen des Klimawandels und des Hochwasserrisikos wahrnehmen, darauf reagieren und sich daran anpassen. Sie ist weiter in fünf Einzelfragen unterteilt. Jede Frage wird in separaten Kapiteln behandelt.

Im ersten Kapitel werden das Projekt, die Daten, die Methode, das Untersuchungsgebiet und Details zu beiden durchgeführten Feldstudien kurz vorgestellt. Im Jahr 2022 erlebte Pakistan die schlimmste Flut seiner Geschichte. Ich habe einen Überblick über die Flut von 2022 zwei Monate nach ihrem Auftreten erstellt. Das zweite Kapitel berichtet über das Ausmaß und die Intensität des Hochwassers von 2022 in Pakistan. In diesem Kapitel wird ein sekundärer Datensatz der UNITAR-Fernerkundungsdatensätze zur Hochwasserüberwachung verwendet.

Die am stärksten betroffenen Bezirke in den hochwassergefährdeten Regionen der Indus-Ebene habe ich in diesem Kapitel identifiziert. Dieses kurze Kapitel befasst sich mit den betroffenen Distrikten in der Indus-Ebene. Darin wird berichtet, dass zwei Drittel des Landes unter Wasser standen, was 33 Millionen Menschen betraf und 8 Millionen Vertriebene zur Folge hatte. Die meisten Menschen wurden in der Provinz Sindh vertrieben, insbesondere in den Bezirken in der Nähe des Indus-Flusses.

In Kapitel 3 wird die Dynamik dieser Vertreibung mit Hilfe der Schutzmotivations-Theorie untersucht. Dieses Kapitel stützt sich auf Umfragedaten, die von 195 intern vertriebenen Landwirten erhoben wurden. Ich wende eine Kombination aus partieller Kleinstquadrat-Strukturgleichungsmodellierung (partial least square structure equation modeling, PLS-SEM) und Analyse der notwendigen Bedingungen (necessary condition analysis, NCA) an, mit deren Hilfe ich die notwendigen Faktoren identifizieren kann, die die Landwirte dazu motivieren, sich bei Überschwemmungen für eine Vertreibung zu entscheiden. In diesem Kapitel wird deutlich, dass „Angst" mit einem Koeffizienten von 0,489 (19%) der signifikanteste Prädiktor ist, während Reaktionsfähigkeit" mit einem Koeffizienten von 0,324 (14%) zu den Umsiedlungsentscheidungen der Landwirte beiträgt. Alle anderen Prädiktoren sind unbedeutend und unnötig. Erhöhte Furcht und Reaktionsfähigkeit steigern signifikant die Motivation der Vertreibung.

Die Kapitel 4, 5 und 6 befassen sich mit der Wahrnehmung des Klimawandels, dem Kapital für den Lebensunterhalt, der Klimaanpassung, den Zwängen und den Faktoren für die Entscheidungen der Landwirte. Dieser Abschnitt von drei Kapiteln verwendet Daten aus einer zweiten Erhebung, die bei 800 Landwirten in den bewässerten landwirtschaftlichen Gebieten Pakistans durchgeführt wurde. In Kapitel 4 habe ich beschrieben, wie die Bewässerungslandwirte in Pakistan den Klimawandel wahrnehmen und welche Anpassungsstrategien sie verfolgen, welche Zwänge bestehen und welche Faktoren ihre Anbauentscheidungen beeinflussen. In diesem Kapitel wird deutlich, dass sich die Landwirte des Klimawandels und seiner Auswirkungen bewusst sind, einschließlich längerer Sommer, kürzerer Winter und eines Rückgangs der Ernteerträge. Ich habe festgestellt, dass die Landwirte im Punjab in erster Linie ihre Anbaumethoden und ihr Betriebsmanagement angepasst haben, während sich die Landwirte im Sindh auf die Umsetzung von Bewässerungsmaßnahmen konzentrierten. In der Studie werden auch Sachzwänge genannt, die sich auf landwirtschaftliche Entscheidungen auswirken, wie finanzielle Beschränkungen, Wasserknappheit und Bodenfruchtbarkeit.

Kapitel 5 arbeitet mittels des konzeptionellen Rahmens für Werte und Investitionen für agentenbasierte Interaktion und Lernen in Umweltsystemen (Values and Investments for Agent-Based Interaction and Learning in Environmental Systems, VIABLE) die Rolle des Lebensunterhaltskapitals bei der Klimaanpassung heraus, einschließlich der Investitionspfade und der Faktoren, die ihre Anpassungsstrategien beeinflussen. In diesem Kapitel werden auch die moderierenden Auswirkungen klimatischer und nicht klimatischer Faktoren auf ihre Anpassungsmaßnahmen bewertet. In diesem Kapitel wird der Ansatz der partiellen Kleinstquadrate-Strukturgleichungsmodellierung (PLS-SEM) für den VIABLE-Rahmen verwendet. Ich verwende Daten, die in der ersten Erhebung von 800 Landwirten gesammelt wurden. Dieser Teil der Studie zeigt, dass das Existenzgrundlagenkapital die signifikanteste Determinante (Beta = 0,57, Effektgröße = 0,503) für die Anpassungsstrategien der Landwirte ist, während andere Faktoren, wie Investitionsmöglichkeiten und landwirtschaftliche Einschränkungen, weniger Einfluss haben. Mit der VIABLE-SEM werden die gangbaren Wege für wirksame Anpassungsmaßnahmen ermittelt. Bei dieser Analyse stellte ich fest, dass sich nichtklimatische Faktoren negativ auf die Beziehung zwischen Kapital und Anpassung auswirkten, während klimatische Faktoren diese positiv beeinflussten und die Anpassungsfähigkeit der Landwirte verbesserten.

In Kapitel 5 zeigt die VIABLE-SEM, dass das Lebensunterhaltskapital und die Klimafaktoren zwei wichtige Determinanten der Anpassung sind. Die Ergebnisse von Kapitel 5 legen den Grundstein für die Frage: Welche Komponenten des Lebensunterhaltskapitals und der klimatischen Faktoren sind für eine erfolgreiche Klimaanpassung notwendig? In diesem Abschnitt wird das Konzept des Nachhaltigen Lebensunterhalts (Sustainable Livelihood Framework, SLF) als theoretische Grundlage verwendet. Ich wende eine Kombination aus PLS-SEM und NCA an, um die Daten der ersten Umfrage zu analysieren, die ich bei 800 Landwirten durchgeführt hatte. Die Studie ergab, dass sowohl Klimafaktoren als auch alle Formen von Lebensunterhaltskapital für eine erfolgreiche Anpassung notwendig sind. Natur- und Sozialkapital erwiesen sich als signifikant (Betawerte von 0,345 und 0,283). Interessanterweise zeigt das Finanzkapital (Beta-Koeffizient -1,85) eine negative Korrelation zur Anpassung, was auf komplexe Wechselwirkungen zwischen wirtschaftlichen Zwängen und Anpassungsstrategien hindeutet.

Kapitel 7 fasst die Dissertation zusammen, hebt ihre wichtigsten Merkmale hervor und präsentiert eine allgemeine Schlussfolgerung dieser Arbeit. Zusammenfassend lässt sich sagen, dass die vorliegende Doktorarbeit einen wertvollen Leitfaden für politische Entscheidungsträger, landwirtschaftliche Praktiker und Planer der Klimaanpassung darstellt.

Die Studie leistet einen wichtigen Beitrag zum Diskurs über die Anpassung an den Klimawandel und die ländlichen Lebensgrundlagen und ebnet den Weg für effektivere und widerstandsfähigere landwirtschaftliche Praktiken in der anfälligen pakistanischen Bewässerungslandwirtschaft.

## List of publications

This dissertation is structured to include five research articles, each constituting an individual chapter. The author of this dissertation is the first author of all five research articles. The author has completed the five papers' content as the primary author. I will submit the manuscripts to peer-reviewed journals. The table below summarizes individual chapters' titles, authorship, and current status.

| Chapter | Title | Authors | Status |
|---|---|---|---|
| 2 | Assessing the 2022 Flood Disaster in Pakistan: Identifying the Worst-Affected Regions | Muhammad Mobeen, Uwe A. Schneider, Jürgen Scheffran, | First draft ready |
| 3 | Factors Affecting Farmers' Disaster Displacement Decisions: An Application of PLS-SEM and NCA in the Context of 2022 Floods in Sindh, Pakistan. | Muhammad Mobeen, Naz Memon, Juan Miguel Rodriguez Lopez, Uwe A. Schneider, Jürgen Scheffran. | The first draft is ready. |
| 4 | Climate change perception, adaptation, and constraints in irrigated agriculture in Punjab and Sindh, Pakistan. | Muhammad Mobeen, Khondokar H. Kabir, Uwe A. Schneider, Tauqeer Ahmed, Jürgen Scheffran. | Under revision with Mitigation and Adaptation Strategies for Global Change |
| 5 | Sustainable Livelihood Capital and Climate Change Adaptation in Pakistan's Agriculture: Structural Equation Modeling Analysis in the VIABLE framework. https://doi.org/10.1016/j.heliyon.2023.e20818 | Muhammad Mobeen, Khondokar H. Kabir, Uwe A. Schneider, Tauqeer Ahmed, Jürgen Scheffran. | Published in Heliyon |
| 6 | Investigating Various Facets of Livelihood Capitals as Necessary Predictors of Climate Adaptation in Pakistan's Irrigated Farmlands | Muhammad Mobeen, Naseem Ahmed, Khondokar H. Kabir, Uwe A. Schneider, Jürgen Scheffran. | The first draft is ready. |

## Declaration of Authorship

I solemnly declare my contribution to the authorship of the dissertation chapters, which comprise research articles either already submitted or anticipated to be submitted to peer-reviewed journals, as follows:

| Chapter | Title | Contribution of the first author | Contribution of co-authors |
|---|---|---|---|
| 2 | Assessing the 2022 Flood Disaster in Pakistan: Identifying the Worst-Affected Regions | Topic development, Data collection, Data analysis and drafting. | Data collection Naz Memon, Topic refining & draft editing. Juan Miguel Rodriguez Lopez, Uwe A. Schneider, Jürgen Scheffran. |
| 3 | Factors Affecting Farmers' Disaster Displacement Decisions: An Application of PLS-SEM and NCA in the Context of 2022 Floods in Sindh, Pakistan. | Topic development, Data collection, Data analysis, Software application, Model setup, Draft development. | Data collection Naz Memon, Topic refining & draft editing. Juan Miguel Rodriguez Lopez, Uwe A. Schneider, Jürgen Scheffran. |
| 4 | Climate change perception, adaptation, and constraints in irrigated agriculture in Punjab and Sindh, Pakistan. | Conceptualization, Data collection (predominantly) Methods, data analysis Review of results (thoroughly) Writing draft (predominantly) | Conceptualization & Draft editing: Uwe A. Schneider. Jürgen Scheffran, Khondokar H. Kabir, Data collection Tauqeer Ahmed |
| 5 | Sustainable Livelihood Capital and Climate Change Adaptation in Pakistan's Agriculture: Structural Equation Modeling Analysis in the VIABLE framework. | Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review & editing | Conceptualization & Draft editing, Data collection: Uwe A. Schneider. Jürgen Scheffran, Khondokar H. Kabir, Uwe A. Schneider Jürgen Scheffran, Tauqeer Ahmed |
| 6 | Investigating Various Facets of Livelihood Capitals as Necessary Predictors of Climate Adaptation in Pakistan's Irrigated Farmlands | | Conceptualization & Draft editing: Uwe A. Schneider. Jürgen Scheffran, Khondokar H. Kabir, Uwe A. Schneider Jürgen Scheffran, Naseem Ahmed |

Mr. Muhammad Mobeen
Born in Pakistan on 04.12.1981

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# Chapter 1: Introduction

## 1.1. Introduction

This dissertation offers an in-depth analysis of flood risk, climate adaptation, and livelihood in the irrigated agricultural regions of Pakistan, particularly in the wake of the 2022 floods in the area. In 2022, Pakistan was hit by the most severe flood of its history, which submerged one-third of its landmass, exposing the vulnerabilities of the livelihood of Pakistan's agricultural areas (Nanditha et al., 2023). The yearly monsoon cycle in Pakistan is a critical determinant of the country's climate, with four distinct seasons: the pre-monsoon season, the monsoon, the dry or post-monsoon season, and the winter season (Mues et al., 2017). The monsoon rain of 2022, characterized as 'extreme' based on its intensity and frequency surpassing the historical record, led to the catastrophic event of a flood (Malik et al., 2023a) and considerably affected the southernmost province of Sindh (Nanditha et al., 2023). The impact of this flood on Pakistan's agriculture was significant, leading to crop production losses and triggering a cascade of economic, political, and social crises (Kamal, 2023). Pakistan's agriculture mainly depends upon irrigation due to the arid and semi-arid climate, a critical aspect of its vulnerability. The irrigation is fed with surface water of the Indus Basin, which originates from the northern mountains. A complex canal network distributes the water throughout the agricultural regions in the Indus plains (Muzammil et al., 2021). However, the Indus Basin irrigation cannot cover the irrigation requirements, leading to reliance on groundwater for cultivation, causing its depletion (Usman et al., 2016). The threat of climate change further complicates this scenario, with studies indicating potential increases in irrigation requirements due to altered growing seasons, thereby intensifying pressure on water availability (Gul et al., 2021; Kirby et al., 2017; Saddique et al., 2022b). Studies show that the irrigation requirements for agriculture will increase due to changes in the length of the growing season, eventually putting pressure on water resources (Habib, 2004; Hussain et al., 2019). The increasing population in the region will further exacerbate this challenge (Kirby et al., 2017).

The present research landscape on flood risk, adaptation, and livelihood in Pakistan's agriculture highlights gaps in the current understanding and empirical evidence. Notably, the existing studies conducted by Abid et al. (2017); (Abid et al., 2015; Abid et al., 2019; Ali & Rose, 2021; Gorst et al., 2018; Hussain et al., 2019; Salam et al., 2021; Sargani et al., 2022; Syed et al., 2022) and Hasan et al. (2021), have predominantly focused on a single administrative unit or specific agro-ecological unit within a specific province. Moreover, no study focused on the irrigated farming region of Pakistan within these studies. The existing literature's findings are valuable but fail to capture the more diverse ecological, socio-economic, and cultural perspectives across Pakistan's vast irrigated agricultural landscape. The irrigated farming communities often face flood risk due to their proximity to irrigation channels. Their reliance on irrigated water makes them more vulnerable to extreme climatic events, which forces them to take immediate action to adapt and respond to climate change. However, a discernible gap exists in understanding the factors influencing farmers' decisions to displace during floods. Studies by Grothmann and Reusswig (2006), Liu et al. (2022), Hamilton et al. (2020), and Otto et al. (2023) have contributed to this area; however, the psychological drivers responsible for the displacement decisions of the farming community are still insufficiently understood.

Given the context above, the significance of this work is evident as it bridges the gap regarding the connections between flood risks, climate adaptation, and the livelihoods of farmers in irrigated agricultural areas of Pakistan. (Kirby et al., 2017). Zhu et al. (2013a) argue that future water availability will fluctuate depending on climate trajectories, and crop production and food security implications are negative. Studies suggest adaptation strategies can mitigate these adverse effects (Bekele et al., 2022; Kader et al., 2019). Research indicates water management and alternative cropping are effective against climate change (Frisvold & Bai, 2016; Myint et al., 2021). Therefore, this dissertation seeks to clarify these dynamics, offering valuable insights for developing sustainable agricultural practices and effective policy interventions to address the challenges faced by Pakistan's agriculture sector in the face of climate change.

## 1.2. Background of the study

This study's background is rooted in climate change, a prime concern for agrarian economies like Pakistan. The country’s geographical and climatic settings for being at the margins of monsoon render it susceptible to floods, frequently threatening its agricultural productivity. The 2022 floods in Pakistan, unprecedented in scale and severity, underscore the criticality of understanding and addressing the impacts of climate change on irrigated agriculture, a sector vital for the economy and the country's livelihood. Heureux et al. (2022) emphasize the importance of using climate impact assessments to develop targeted investments and efficient adaptation measures to ensure the resilience of agriculture in Pakistan. Janjua et al. (2021) highlight the threat of salinization to sustainable irrigated agriculture in Pakistan. Abid et al. (2015) give insights into farmers' perceptions of and adaptation strategies to climate change in the Punjab province of Pakistan, indicating the relevance of understanding farmers' choices of adaptation measures in the context of climate change impacts on agriculture, which aligns with the concerns of this study.

Moreover, irrigated agriculture in Pakistan faces multiple challenges posed by climate variability. These challenges include changing precipitation patterns (Mobeen et al., 2017), rising extreme weather events, and vulnerability to pest disease affecting yield and rural livelihood (Eckstein et al., 2019; Schilling et al., 2013b). These impacts have multifaceted ramifications ranging from social to environmental, food security, employment, and overall societal resilience. The recurrence of flood events in Pakistan, particularly the floods of 2010 and 2022, substantiates the need for this study. These disasters reveal physical and economic damage and long-term impacts on the livelihood of the farmers' communities in the irrigated areas. Moreover, the response to flood disasters regarding displacement choices and adaptation measures highlights the gaps in existing disaster management and climate adaptation policies in the region. This scenario urges to explore the farmers' climate change perception, their adaptation strategies, and the role of livelihood capital during climatic adversities including their decision-making processes during displacement due to recurring calamities in the study area. This context provides the foundation research problem and situating this study in the discourse of climate adaptation and sustainable rural development.

### 1.3. The Research Questions and Objectives

In exploring the flood risk, climate adaptation, and livelihood in the irrigated agricultural regions of Pakistan, the central research question of this work is,

'How do irrigated agricultural communities in the Indus Plains adapt to and respond to the impacts of climate change, including the specific challenges posed by flooding events such as the 2022 flood?

The discourse of this study is at the intersection of flood risks, climate adaptation, and rural livelihood in Pakistan’s irrigated agriculture. The primary issue arises from the vulnerability of Pakistan’s agricultural sector to recurring flooding events. The flood of 2022 is an exemplary case that further highlighted the fault lines of Pakistan’s agriculture system. Climatic extremes further compounded the climate-sensitive vulnerability of the region understudy. Therefore, this study aims to enhance the understanding of the complexities of flood risk, its impacts, and its implication for agriculture, adaptation strategies, and rural livelihood in Pakistan’s irrigated agricultural areas, focusing on the 2022 flood disaster.

To understand the impact of the 2022 flood, we ask: (Q1) What is the extent and impact of this flood on irrigated agricultural areas and the population in the lower Indus plains, as observed through UNITAR's flood monitoring remote sensing datasets?

To address this question, the research is guided by two primary objectives:

1. To analyze the impact of the 2022 flood on irrigated agricultural areas of the lower Indus plains, using the flood monitoring datasets from the United Nations Institute for Training and Research (UNITAR) based on Visible Infrared Imaging Radiometer Suite (NOAA-20/VIIRS) observations remote sensing of high flood weeks.
2. To assess the flood extent and affected population by identifying the worst affected areas in the lower Indus plains, Pakistan.

Focusing on the human impact of the flood, we inquire: (Q2) How does the 2022 flood in the lower Indus plains affect the displacement patterns of farming communities, and what are the underlying dynamics of these patterns when analyzed through Protection Motivation Theory?

To explore this aspect, the study is structured around the following two objectives:

3. To investigate the flood response regarding the immediate displacement of farming communities due to the 2022 flood by locating the hotspots of internal displacement areas in the lower Indus plains.
4. To explore the dynamics behind the affected population's uneven displacement and return patterns, utilize the Protection Motivation Theory (PMT) framework by examining the role of individual components of PMT.

In assessing the adaptive responses of the irrigated farming community, the research question posed is: (Q3) How do farmers in the Indus plains perceive the impact of climate change on their agricultural practices, and what constraints and factors influence their decisions regarding adaptation strategies? This question is dissected through two focused objectives:

5. To evaluate the climate change impact perception and their adaptation strategies on their agricultural practices.
6. To highlight the perceived constraints and factors affecting farmers' decisions based on survey-based data.

To analyze the economic aspects of adaptation, we ask: Employing the VIABLE framework (Q4), how does livelihood capital influence climate adaptation in farming, and what roles do climate and non-climatic factors play in moderating these actions?

This inquiry is pursued through two related objectives:

7. Employ the VIABLE framework to evaluate the role of livelihood capital for climate adaptation and identify viable pathways of investment, farming purposes, factors, and constraints on adopting adaptation measures.
8. To assess the moderating role of climate and non-climatic factors on the adaptation action of the farmers.

Lastly, to integrate the socio-economic factors with climate adaptation, the research question is: (Q5) What roles do livelihood capital and climatic factors play in climate adaptation for agricultural communities, as analyzed through the Sustainable Livelihood Framework and Necessary Condition Analysis? The completion of this question is sought through the following objectives:

9. To further explore the role of livelihood capital and climatic factors using the Sustainable Livelihood Framework (SLF) on survey data.
10. To explore the necessary components of livelihood capital and climatic factors for climate adaptation using Necessary Condition Analysis on survey-based data.

### 1.4. Study area

The region in question makes up roughly 40% of Pakistan's landmass, and 74% of the country's population resides there (Figure 1.1). This area encompasses the Indus Basin Irrigation system of Punjab and Sindh, which are located in Pakistan (Mobeen et al., 2023). Glacial and snowmelt waters from the Himalayas, Karakoram, and Hindu Kush ranges feed the drainage channels of this irrigation system. It is pivotal in the region's hydrology (Immerzeel et al., 2010). The system, characterized by its arid climate and monsoonal precipitation system, supports an extensive agricultural area over an irrigable area of more than 16 million hectares (Steenbergen et al., 2015). A network of barrages, headworks, and canals control water distribution in the area (Qureshi, 2011). This extensive water management system not only sustains the agricultural demands but also preserves the ecological balance of the Indus basin. Environmental flow requirements are meticulously maintained to prevent adverse effects like coastal erosion. However, challenges persist, notably in groundwater management. The Indus Basin Irrigation System (IBIS) faces a significant discrepancy between water supply and demand (Archer et al., 2010), with tail-end farmers receiving considerably less water than head-end farmers (Qureshi et al., 2010). I selected irrigated agricultural areas as the study's focus for exploring flood risks, impacts, and farmers' adaptation strategies for the following reasons. Primarily, these regions are pivotal to Pakistan's agricultural production, playing a significant role in the national economy and ensuring food security. Their extensive irrigation systems, primarily sourced from the Indus River, support a substantial portion of agricultural activities, making them ideal for exploring climate change adaptation in Pakistan's agriculture. Additionally, these areas face significant threats from climate extremes and floods. This vulnerability emphasizes the importance of investigating adaptive measures in response to climatic alterations, especially in areas dependent on irrigated water supply.

Furthermore, the diverse local climate variations and varied soil types within these irrigated regions offer a comprehensive perspective on how these factors affect agricultural practices. Lastly, the agricultural-dependent socio-economic structure of irrigated farmers provides a unique lens to assess the socio-economic consequences of climate change and the success of various adaptation strategies. The study aims to significantly enhance the understanding of sustainable agricultural practices in climate change, providing vital insights for policymaking and bolstering the future resilience of Pakistan's agricultural sector.

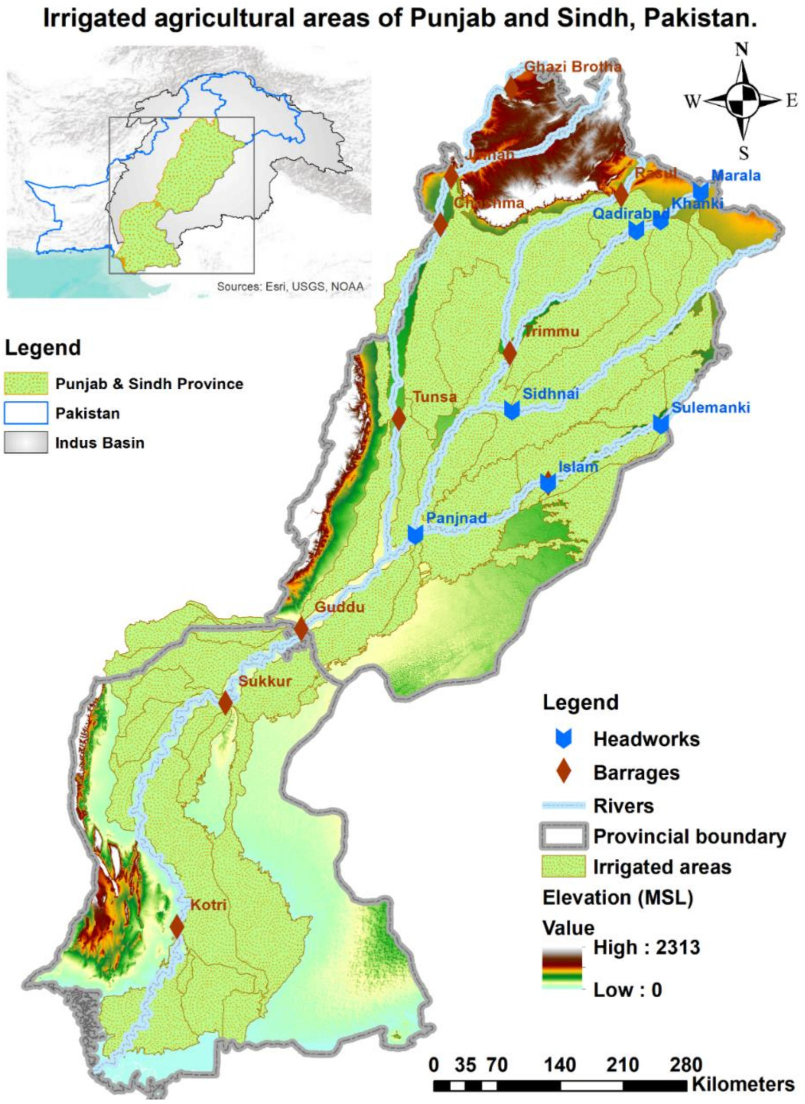


**Figure 1.1 Study area map**

The soil in the study region comprises alluvium deposits accumulated by the Indus River and its tributaries in the geological past, making the area fertile for agricultural purposes. Pakistan is among the world's top ten producers of cotton, sugarcane, wheat, mango, dates, and Kinnow (citrus). The four dominant crops (rice, cotton, wheat, and sugarcane) contribute 4.9% to Pakistan's gross domestic product. The average temperature in upper irrigated areas ranges from 21°C to 45°C and exceptionally reaches 50°C in summer and falls to 8°C in winter. In lower irrigated regions of Sindh, temperatures rise above 46°C from May to August and drop to 2°C in winter. The interior of lower Sindh recorded as high as 53.5°C in 2010, the fourth highest ever recorded in Asia (Abbas et al., 2018; DG Huber & J Gulledge, 2011). Most regions in the Punjab receive moderate to high rainfall ranging from 270 to 830 mm/year, while Sindh province receives 150 to 180 mm/year. The region is experiencing a decrease in precipitation from north to south. Recent calculations in 2021 estimate a decreasing precipitation trend across Pakistan with 1.11 mm/year (Ali et al., 2021; Mobeen et al., 2017). The elevation of the Indus Plain varies from 300 m in northern Punjab to 75 m near the southern border of Punjab to the Arabian Sea. The slope decline rate in plains is 0.3 m per 1.6 km (Khan, 2016).

## 1.5. Data collection

### 1.5.1. Primary data

This dissertation uses both primary and secondary datasets. For primary data, I conducted two extensive field surveys in the irrigated agricultural farms in Punjab and Sindh, Pakistan. Figure 2 shows the location visited during two extensive fieldwork.

#### 1.5.1.1. First Fieldwork

To address the adaptation and livelihood part of this thesis, I performed a field survey from December 2021 to March 2022. Farmers cultivating irrigated areas of Punjab and Sindh province, Pakistan, were the population under study. In Pakistan, 80% of farmers own 28% of cultivable land. There are 7.4 million small farmers in Pakistan who hold less than 12 acres of land (5 hectares) (Naseer et al., 2016). I chose small farmers because they are essential to Pakistan's agriculture for several reasons. Firstly, most of them live in rural areas and make their living through agriculture. Secondly, small landholdings are common throughout the country. Therefore, they are crucial for a country’s food security. Thirdly, small farmers are often more vulnerable and less resilient to economic shocks and natural disasters.

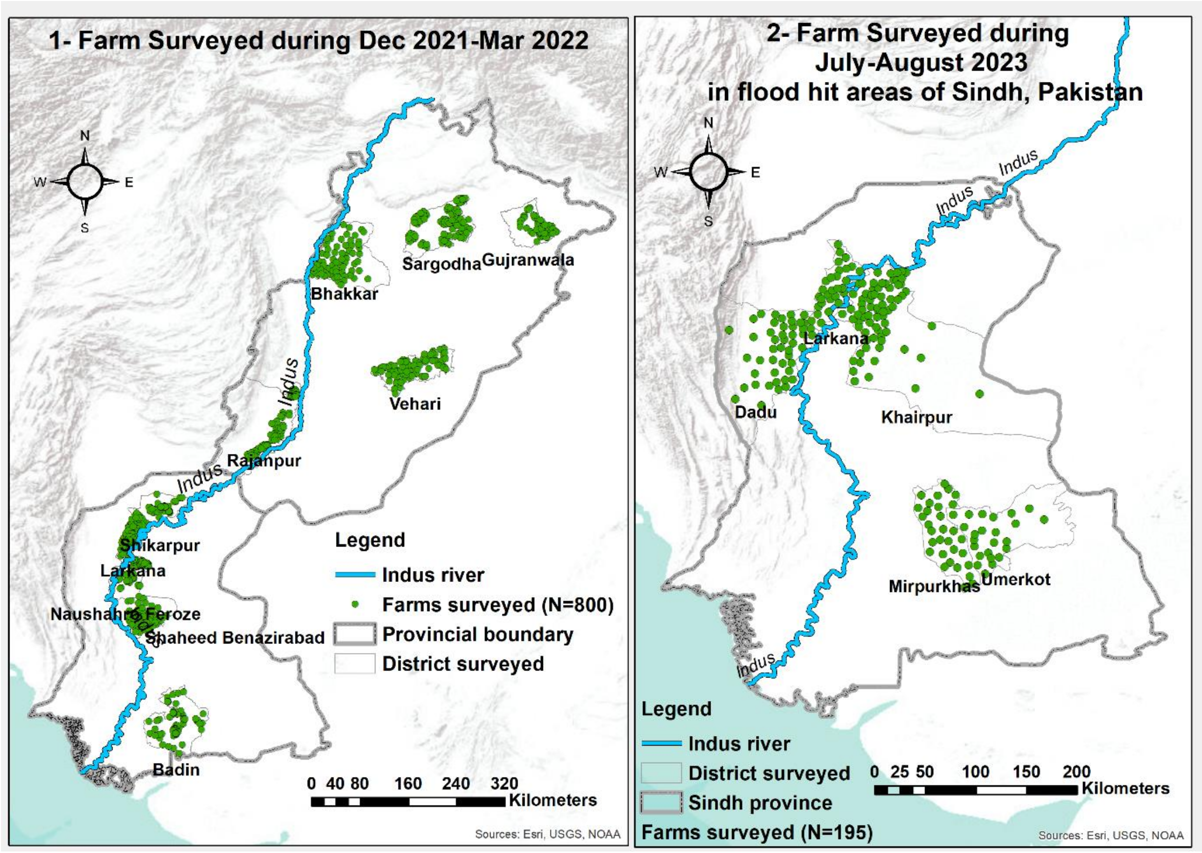


**Figure 1.2 Location of farm surveyed during fieldwork**

Small farmers are dispersed throughout the irrigated plains of the Punjab and Sindh provinces. I used a multistage spatial cluster sampling strategy to select respondents from the study area. In the first stage, five districts were selected from Punjab and five from Sindh, based on their physiographic and irrigation network. Punjab plains are divided into four interfluves, while Sindh has relatively uniform physiography. In Punjab, the Terbela and Mangal reservoirs provide water for irrigation, while Guddu, Sukkur, and Kotri Barrage irrigate agricultural land in Sindh.

In Punjab, a district was randomly selected from each interfluve, including Bhakkar from Sagar Doab, Vehari from Bari Doab, Sargodha from Chaj Doab, Gujranwala from Rachna Doab, and Rajanpur from the lowermost part of Punjab. Terbela Reservoir provides irrigation water to Bhakkar, Vehari, and Rajanpur, while Mangal Reservoir provides irrigation to Sargodha district. In Sindh, districts were selected based on irrigation-controlling infrastructures, including Shikarpur, irrigated from the Guddu Barrage; Badin from the Kotri Barrage; and Larkana, Naushahro Feroze, and Shaheed Benazirabad from the Sukkur Barrage.

Tehsils and Talukas (district sub-units) were selected in the second stage. Thus, I and the enumerators surveyed 39 tehsils in total. In stage three, the survey team randomly visited the mauzas (the smallest revenue-collecting unit in Pakistan) to ensure the best spatial coverage of a tehsil. In the last stage, farmland and respondents were selected for the interview based on road connectivity to reach the farmers and their farmlands. A total of 800 and precisely 80 farmers from each district were interviewed.

#### 1.5.1.2. Second Fieldwork

To evaluate farmers' flood risks and displacement, I conducted the second fieldwork in July and August 2023 in Sindh province. Sindh province became the focus of our study due to its high susceptibility to flooding, especially during the 2022 floods that inflicted remarkable damage on the region (Roth et al., 2022). The flood caused substantial displacement in Sindh province. The displacement reports published by (IOM, 2022) identified districts witnessing significant population displacement.

I identified the five highly flood-affected regions of Sindh province (shown in Figure 1.2) based on (IDMC, 2023 ; IOM, 2022) reports and our geospatial analysis of the 2022 flood given in Chapter 2. I adopted the purposeful sampling technique guidelines, a non-probability sampling method used to identify and select information-rich cases relevant to the study's purpose (Palinkas et al., 2015). I utilized accessibility considerations and his pre-existing social networks to choose the union councils for site visits. I employed a random sampling method to select farmers willing to participate in the study, often facilitated by pre-arranged agreements with local leaders. According to the Provincial Disaster Management Authority PDMA (2022) and the Government of Sindh, 1.5 million people were displaced in these five districts, serving as our target population. This group drew a sample of 195 farmers based on specified criteria.

### 1.5.2. Secondary data

The secondary data consists of in situ meteorological observations of rain from the Pakistan Meteorological Department. This study used flood inundation datasets from the United Nations Institute for Training and Research (UNITAR) based on Visible Infrared Imaging Radiometer Suite (NOAA-20/VIIRS) observations.

## 1.6. Methodology

This project used multiple methods using primary and secondary datasets. In Chapter 2, I used remotely sensed satellite imagery for flood risk investigation, the Visible Infrared Imaging Radiometer Suite (NOAA-20/VIIRS) from UNITAR. The flood investigation also used meteorological observation from the Pakistan Meteorological Department. I used ArcMap 10.8

with Python's Geopandas package to produce temporal flood extent maps in this chapter. In the third chapter, the study used an integrated statistical methodology to investigate the displacement in flooded areas. Partial Least Square Structural Equation Modeling (PLS-SEM) and Necessary Condition Analysis (NCA) in the SmartPLS 4.0. was used to evaluate the PLS-SEM and NCA models. With this technique, the individual component of the Protection Motivation Theory was assessed. This section also used Seaborn Python libraries for better results visualizations. The result of this section produces the significant and necessary components for flood displacement decisions.

In Chapter 4, the study deals with climate change perception, adaptation, factors, and constraint dynamics across both provinces. IBM SPSS Statistics (Version 28.0.1.1) and RStudio were employed for data analysis and visualization. This chapter used Likert data visualization libraries to visualize the five-point Likert scale data. In Chapter 5, I applied PLS-SEM to the survey data collected from the first fieldwork. This section used the VIABLE framework as a structural model in which I identified the significant pathways and moderating factors. This study also applied mediation and moderation analysis on the relationship between livelihood capital and climate adaptation in this section. The results of this section led me further to test the necessity of individual components of livelihood capital. In Chapter 5, I identified livelihood capital and climatic factors as significant components for adaptation, which led to the question of which type of capital is necessary. Then, NCA is applied to the individual components of capital. In Chapter 5, I used SmartPLS 4.0 to integrate PLS-SEM and NCA. For data visualization, the Seaborn library of Python was employed. These outputs facilitated a comprehensive understanding of the research questions. This integrative method not only effectively explains the underlying processes but also cross-validates the findings of this project.

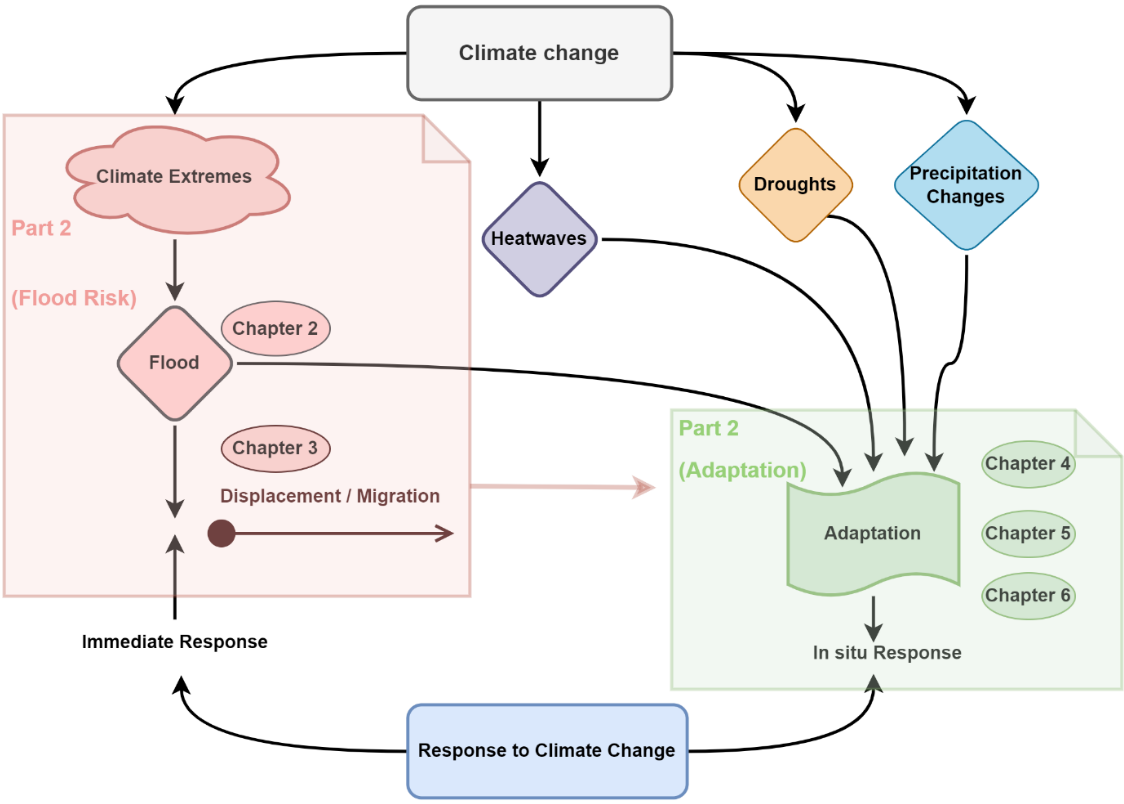


**Figure 1.3 Thematic structure of thesis exploring climate change, extreme weather events, and human responses.**

Figure 1.3 illustrates the thematic focus of this study, exploring the multifaceted relationship between climate change, climatic extremes like floods, and human responses like displacement and adaptation. It posits that climate change is a catalyst triggering the frequency and intensity of heat waves, droughts, and precipitation changes, leading to flood risks (in Chapter 2) and people displacement. The thesis examines the immediate response to floods, detailed in Chapter 3, and long-term response-like adaptation across Chapters 4, 5, and 6.

## 1.7. Structure of a thesis

The thesis comprises seven chapters: one is published, three are submitted and currently under review, and one is in preparation as a journal article. The chapters that are likely to be published, the author of this thesis is the first author and responsible for most of the chapter's content. The approach of the thesis is interdisciplinary. The data and methods used in this project involve primary and secondary data, but most of the analysis was applied to the field survey data produced from the fieldwork conducted in the study area. This content represents disciplines like geography, natural disasters, decision sciences, sociology, and statistics. Thematically, the thesis comprises two main parts;

The first part (Chapters 2 &3) is about flood risks and implications, and the second part (Chapters 4,5 and 6) is about climate change adaptation and livelihood capital. Here are the individual details of the characterization.

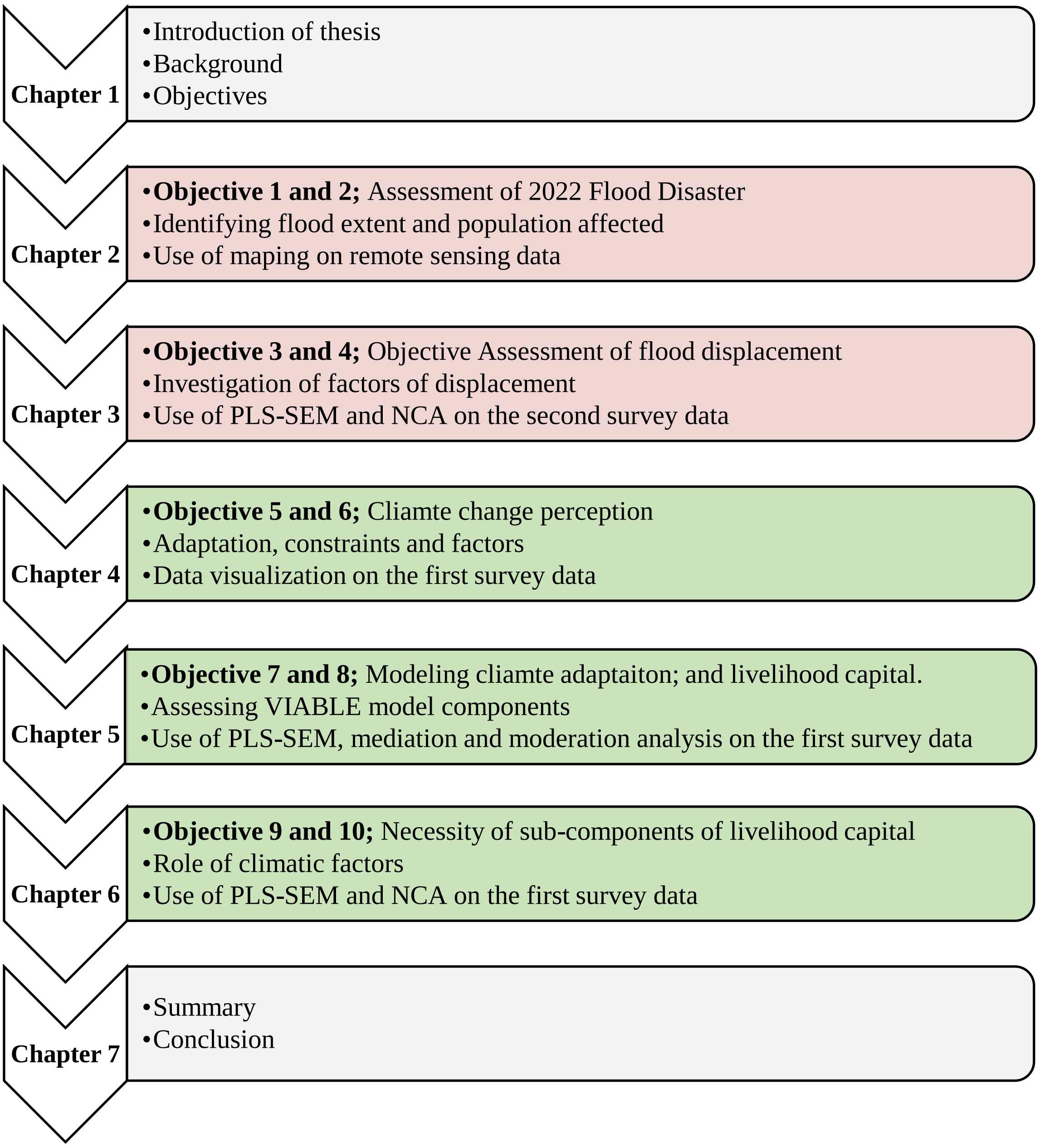


**Figure 1.4 Chapterization of thesis**

# Chapter 2: Assessing the 2022 Flood Disaster in Pakistan: Identifying the Worst-Affected Regions


## Abstract

In the summer of 2022, Pakistan experienced the worst flood of this decade. One-third of its land was underwater, affecting 33 million people, while 8 million were displaced and 1,730 lost their lives. Total damage and economic losses exceeded USD 30 billion, while recovery requires another USD 16 billion. This damage exceeds that of the 2010 flood. We examine the flooding period from August 25 to November 20, using the flood monitoring datasets from the United Nations Institute for Training and Research (UNITAR) based on Visible Infrared Imaging Radiometer Suite (NOAA-20/VIIRS) observations. Through our geostatistical analysis, we found that Khairpur, Jacobabad, Larkana, Dadu, Naushahro Feroze, Shaheed Benazirabad, Badin, and Thatta were the worst affected districts and had the highest number of people exposed to flood. The results of this study can help design post-flood policies and actions in the affected areas. We indicate that further empirical and field research is needed in the affected areas to establish post-disaster damage assessments.


## 2.1 Introduction

The monsoon climate and an uneven underlying topography make Pakistan vulnerable to floods in a world of increasing extreme climate events (Sajjad et al., 2020; Sayama et al., 2012). In 2022, Pakistan faced multiple climatic disasters, ranging from heat waves to torrential rainfall spells that led to a country-wide flood. In June 2022, a heat wave triggered rapid glacial melting, which added a deluge of water to the Indus River system. Pakistan received more than eight monsoon cycles, compared to the annual average of three to four (Abbas, 2022). Pakistan was hit by the worst flooding in a decade, which left one-third of its land underwater (Earth Observatory, 2022; Rowe, 2022). Sindh province received 784% more rain than its average for August, while Balochistan province received 496% more than its average in August. This torrential downpour caused flash floods that devastated 23 districts of Sindh and were declared calamity-hit. The plains along the right and left banks of the Indus River were submerged. Padidan (in the Naushahro Feroze district) meteorological observatory recorded 1187 mm of rain in August, the highest amount of rain ever recorded at this station. The south of Pakistan was completely inundated due to the unprecedented frequency and magnitude of the flood. In Sindh, the floods wreaked havoc on the "Kharif" season's food and cash crops, including rice, maize, cotton, sugarcane, vegetables, and orchards. Acute food shortages and price hikes on food items are expected by the middle of 2023 (FAO, 2022; Iqbal et al., 2022).

To better understand the extent of damage, we evaluate the uneven impacts of flooding in the Indus plains from August 25 to November 20, 2022, and identify the worst affected areas in the Sindh province based on flood water extent and population exposure. This timely insight can inform post-flood policies and actions in the affected areas.

### 2.2 Causes of flood

The Indus River basin in Pakistan is recurrently affected by flooding (Nazeer & Bork, 2021). Flooding affected the southern Indus basin in 2003, 2005, 2006, 2010, 2011, 2012, 2015, and 2016 (Atif et al., 2021). In 2022, Pakistan experienced an unprecedented flood during the monsoon season. During the three months of monsoon (i.e., July to September), Pakistan as a whole received significantly above-average rainfall (+175%) while Sindh province received excessively above average (+426%) (PMD, 2022a, 2022b). This unusual rain was caused by multiple hydrometeorological events that followed a cascading pattern.

Firstly, the existence of a persistent triple-dip La Nina and Negative IOD (Indian Ocean Dipole) is usually followed by excessive rain witnessed during 2010-2012 (PMD, 2022a). Secondly, the land experienced abnormally high temperatures over Sindh province from April to June. This temperature persisted and triggered heat waves within the interior of Sindh, resulting in a drop-in air pressure. This low-pressure system attracted the monsoon moisture with greater force than usual (Mallapaty, 2022). It tilted it towards the south (Lat. 22-24°N) as compared to its normal position (Lat. 28°N or above) (PMD, 2022a). The monsoon system developed over the Bay of Bengal moved towards the Sindh-Balochistan province of Pakistan due to northeast-southwest sub-tropical high pressure.

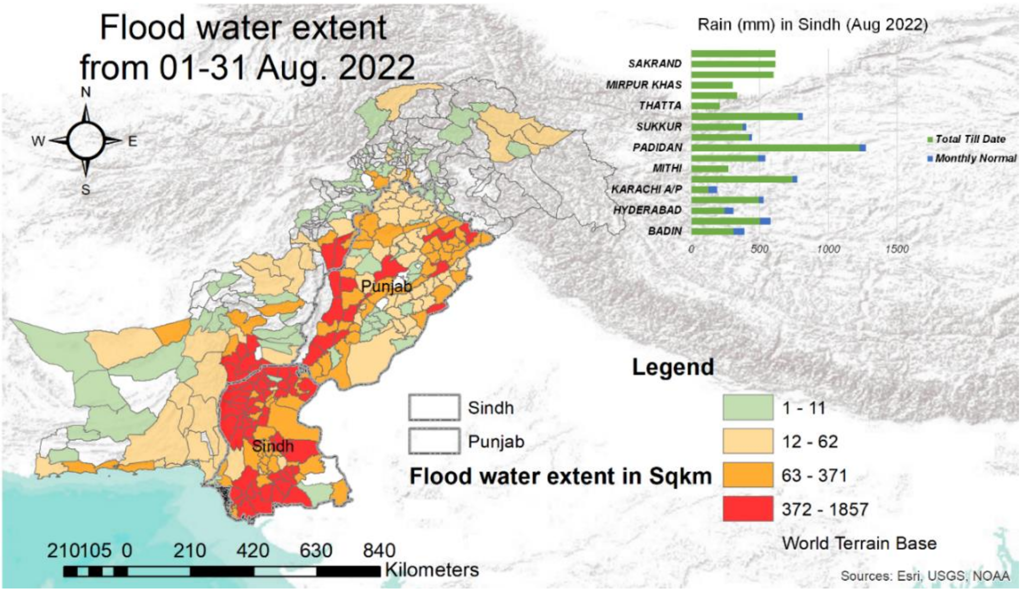


**Figure 2. 1 Flood extent and rainfall in August 2022 Source: Authors, based on (PMD, 2022b; UNITAR, 2022a)**

These meteorological conditions have led to more frequent and intense spells of monsoonal precipitation since the middle of June 2022, amplified by the looming low-pressure system over the lower Indus (Mallapaty, 2022). These monsoon spells pored 355.0 mm daily and up to 1228.5 mm monthly in Sindh interior (PMD, 2022b).

Additionally, 16 Glacial Lake Outburst Flood (GLOF) events occurred in the mountainous north against normal 5/6 events yearly (Jones, 2022; PMD, 2022a; UNDP, 2022). A tremendous amount of water entered the river system before the start of the monsoon spell. Figure 2.1 shows rain and inundated areas of Pakistan during August 2022. During 2022, the number of rainy days was considerably higher than normal over the country, particularly in Sindh and Balochistan regions. The rain spells in August 2022 were the highest ever recorded in the last hundred years, both monthly (in 21 locations) and daily (in 13 locations) (PMD, 2022b). The 2022 flood reportedly surpassed the peak flow rate of the devastating floods in 2010 over Pakistan (Bhuto, 2022). Moreover, the 2022 event is similar to the 2010 one in the existence of La-Niña and Rossby formations in the high-altitude jet streams (Aziz, 2022). The 2010 flood event was intensified by anthropogenic forcing (Hong et al., 2011). Other than this, intense water pours from the underlying drainage and flawed irrigation networks at the lower Indus also cause flooding and water breach from the Indus River banks. Between 2000 and 2014, the so-called embankment, diversions, and protection features were breached 54 times by the Indus water (Syvitski & Brakenridge, 2013). The flawed irrigation structure in the lower Indus is constantly exposed in case of rain above normal. Almost all water accumulated in the north is released in one channel of the lower Indus (Atif et al., 2021).

## 2.3 Material and methods

### 2.3.1 Data

We used a secondary dataset provided by UNITAR. The data consists of excel sheets produced by their deep learning algorithm of post-flood analysis using remotely sensed satellite imagery. The UNITAR analyses the remote sensing satellite datasets of the Visible Infrared Imaging Radiometer Suite (NOAA-20/VIIRS) for preliminary flood assessment (UNITAR, 2022a). We used these Excel sheets to develop our maps. We also used meteorological datasets from the Pakistan Meteorological Department (PMD, 2022b) and disaster updates and press releases from the National Disaster Management Authority of Pakistan (NDMA, 2022).

### 2.3.2 Methods

We applied the geostatistical method of data visualization in our analysis. The analyses are based on the statistical and geospatial datasets, which were further processed in ArcMap 10.8. The flood extent maps are generated by using graduated colors from the symbology of spatial quantities in ArcMap 10.8. The shapefiles shown in the maps are classified into five categories based on the quantile classification method. The spatiotemporal trend analyses of flood extent and population exposure are plotted in the Geopandas package used in a Python environment

## 2.4 Results

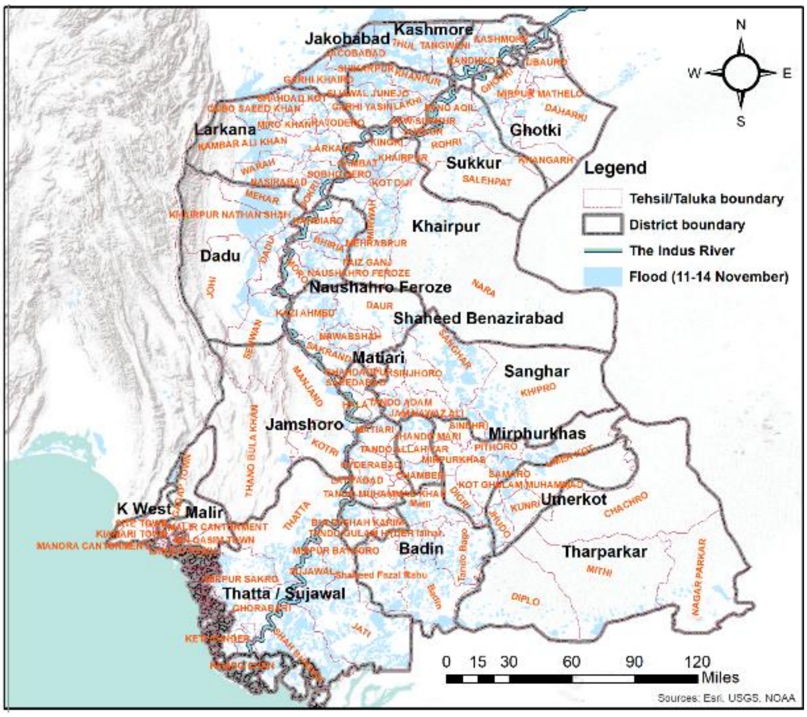


**Figure 2. 2 Administrative divisions of Sindh province**

### 2.4.1 August 2022

In August 2022, the country's entire month was wetter (PMD, 2022a). Pakistan witnessed August 2022 as the peak of the flood (Figure 2.3), when 18% of Pakistan's population was potentially exposed to flood risk. The south of Pakistan was the most affected, where most of Sindh's land (Figure 2.1) was inundated, and 37% of the population of Sindh was exposed to flood. This percentage in Sindh gradually decreased to 34% by the end of August 2022 (Unitar, 2022c). On August 15, 2022, a 30,000 $km^2$ area of Pakistan was analyzed, and 1,550 $km^2$ of land was under water. The water receded (325 $Km^2$) its channels in the last week of August (Unitar, 2022d). In another monitoring conducted from 03 to August 23, 2022, out of 780,000 $km^2$ of cloud-free area, 55,000 $km^2$ of land appeared to be affected, where almost 19,368,000 people were potentially exposed to flood. It is estimated that up to 48,530 $Km^2$ of cropland was affected. Figures 3 and 4 show the weekly status of the area under water and the number of people exposed to flood in Pakistan and in Punjab and Sindh provinces. During 25-31 August, Badin, Khairpur, and Sangar districts (Figures 2.2 and 2.4) had the most significant area under flood. Khairpur, Larkana, and Dadu had the highest number of people exposed to flood water.

### 2.4.2 September 2022

In September 2022, the flood extent and exposed population were monitored four times. Badin, Khairpur, Sangar, and Dadu had the largest area under water throughout September 2022. Flood water started receding throughout the country at the start of the month. However, Sindh province was still under water. During 01-07 September, many districts in the southern province of Sindh still appeared to be heavily inundated. Guddu and Sakhar Barrage were under threat due to high flooding. The floodwater further inundated Khairpur, Jamshoro, Shaheed Benazirabad, and Thatta districts. Out of 880,000 $km^2$, about 60,000 $km^2$ of land appears to be affected by the flood. However, the area under flood has decreased by about 25,000 $km^2$ since August 2022. Approximately 19 million people were potentially exposed to flood in the second week of September. In the second week of September, the overall flood situation (Figure 2.3) was further aggravated when approximately 1,700 $km^2$ of Balochistan, 3,900 $km^2$ of Punjab, and 850 $km^2$ of Sindh were underwater (Unitar, 2022b). In the third week of September (15 to September 21), approximately 17 million people were still potentially exposed to flood waters. The overall floodwater extent continues to recede, while 28% of Sindh's total population was still exposed to flooding. This percentage of exposure was reduced by 25% by the end of

September 2022 (UNITAR, 2022a). Khairpur, Dadu, Larkana, and Naushahro Feroze (Figures 2.2 and 2.4) had the largest number of people exposed to flood water.

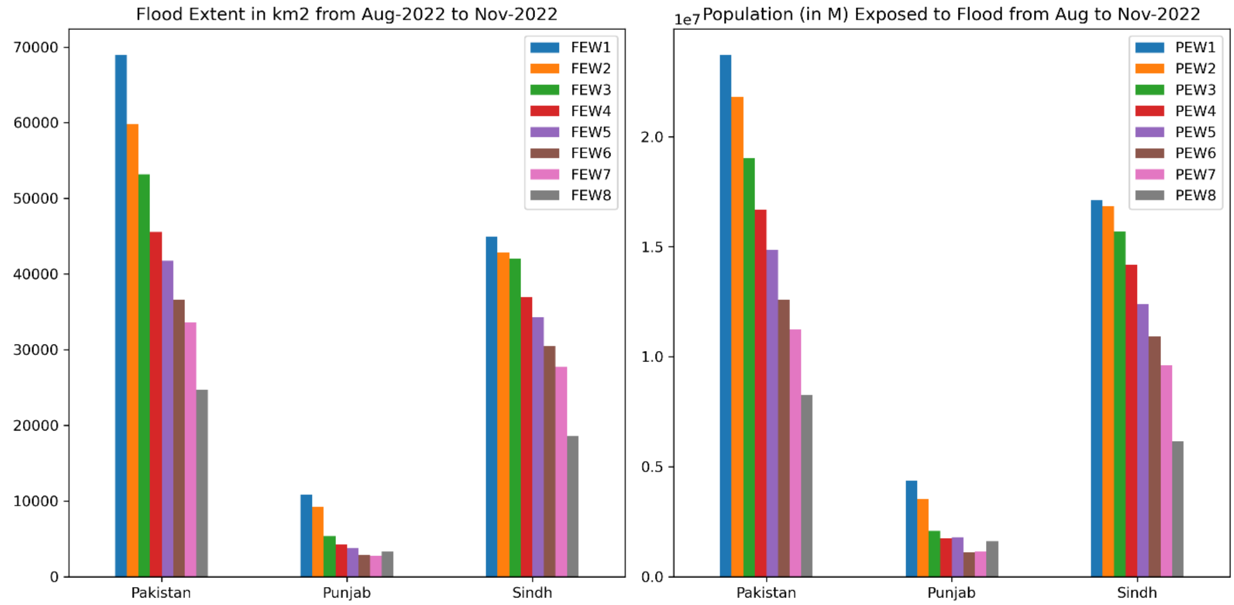


**Figure 2. 3 Weekly status of flood extent and population exposed from August to November 2022, FEW stands for Flood Extent in Week & PEW Population Exposed in Week (UNITAR, 2022a)**

### 2.4.3 October 2022

At the start of October 2022, approximately 15 million people remained potentially exposed to flood, but this number continued to decrease when 25% of the population of Sindh (Figure 2.3) was found exposed with approximately 2,600 km² area under water. By the third week of October, 11 million people remain potentially exposed or living close to flooded areas. Based on observations made between October 3 and 9, 2022, and October 11 to 17, 2022, the overall size of the flood water is decreasing. There is approximately 200 km$^2$ of floodwater in Balochistan, 100 km$^2$ in Punjab, and 2,700 km$^2$ in Sindh. In the first and second week of October, Badin, Jacobabad, Sangar, and Khairpur (Figures 2.2 and 2.4) were highly inundated and had a larger number of people exposed to flood.

### 2.4.4 November 2022

By the end of November, water was receding to its channels, but eight million people were still exposed to flood. The satellite detected approximately 9,000 km² of Sindh, 400 km² of Balochistan, and 500 km² of Punjab underwater (Figure 2.3). But until the last observation on November 20, 12% of the population of Sindh was exposed to flood. Figure 2.4 shows

Jacobabad, Dadu, Khairpur, and Badin has still stagnant floodwater in their areas, with a larger number of people exposed to this flood.

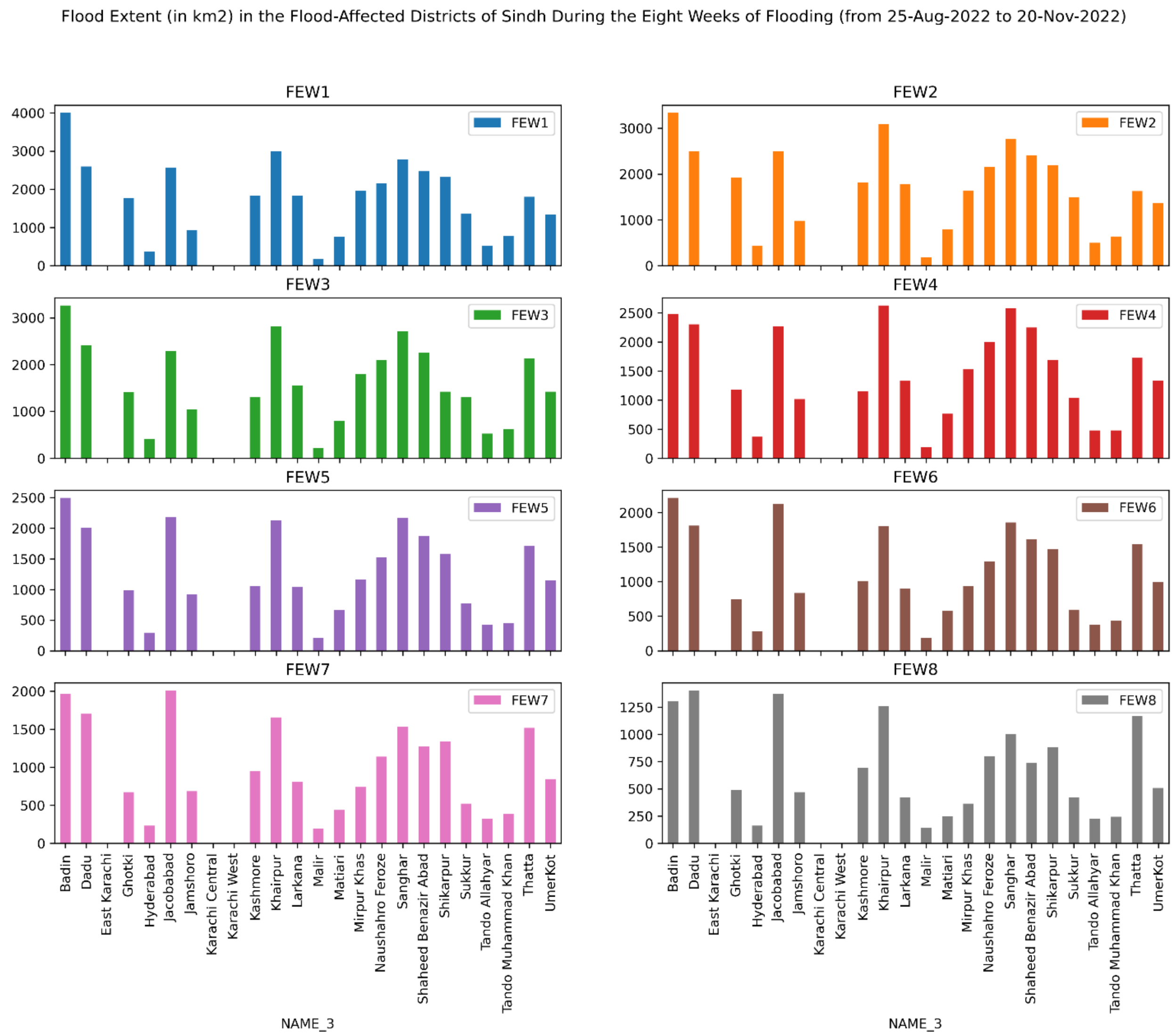


**Figure 2. 4 Flood extent (in km2) in different districts of Sindh province from August to November 2022 (UNITAR, 2022a, 2022b) * FEW stands for Flood Extent in Week & PEW Population Exposed in Week (UNITAR, 2022a, 2022b)**

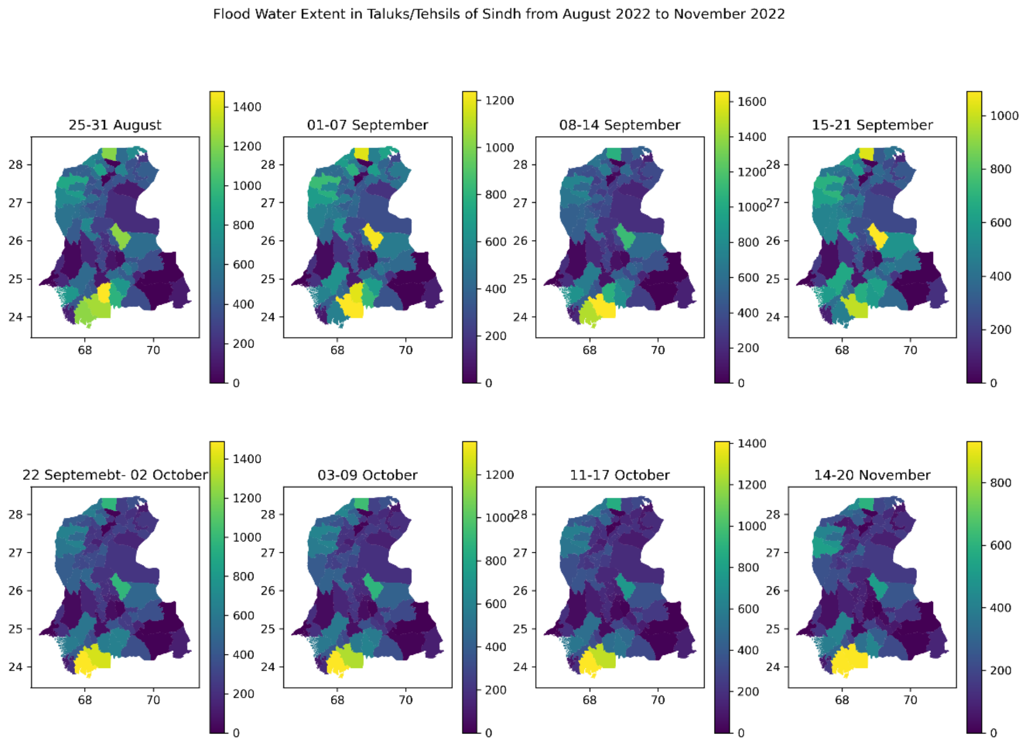


**Figure 2. 5 Spatio-temporal distribution of flood in Sindh from August to November 2022 (Unitar, 2022b)**

Figures 2.4 and 2.5 show the spatial extent of water since August 2022 in Sindh province. The figure highlights districts Shikarpur, Larkana, Dadu, Khairpur, and Naushahro Feroze (Northwestern part of Sindh) that remained under high flooding, up to 4000 $km^2$ of their area affected in August 2022. By November, this was reduced to 1000 $km^2$. Floods highly impacted this cluster of districts due to their comparatively higher population. The second flooding hot spot was the coastal areas or delta of the Indus River, where approximately 4000 $km^2$ of District Badin and Thatta/Sajawal were affected (Figures 2.2 and 2.5). It also gradually reduced to 1000 in November 2022. These districts have a larger area with a relatively smaller population. The cities of Khairpur Nathan Shah, Sukkur, Larkana, and Sehwan (Figure 2.2) were also surrounded by water for miles (Unitar, 2022b).

In 2022, most of Sindh's agricultural areas were affected by floods. Sindh has a total area of 14 million hectares, of which 4.9 million hectares is cropland. The flood is estimated to affect 2.8 million hectares of cropland. The flood devastated Sindh's rice-growing region, where 80% of the crop was destroyed. Sugarcane is primarily grown in the northeastern districts, where 61% of expected sugarcane production was lost due to flooding (Qamer et al., 2022).

### 2.4.5 Impact on people

Exposure of the population followed a similar pattern as of flood extent. Figure 2.6 shows Khairpur, Kambar Shahdad Kot, Larkana, Dadu, and Jacobabad, where most people were threatened. Approximately 1.5 million people from every district were exposed to floods in these districts. In Shikarpur, Naushahro Feroze, Jacobabad, Shaheed Benazir Abad, and Badin (Figure 2.2), almost 1 million people from every district were exposed to flood. This intensity of exposure was gradually reduced to 50,000 exposed persons by the end of November 2022 (Figure 2.3).

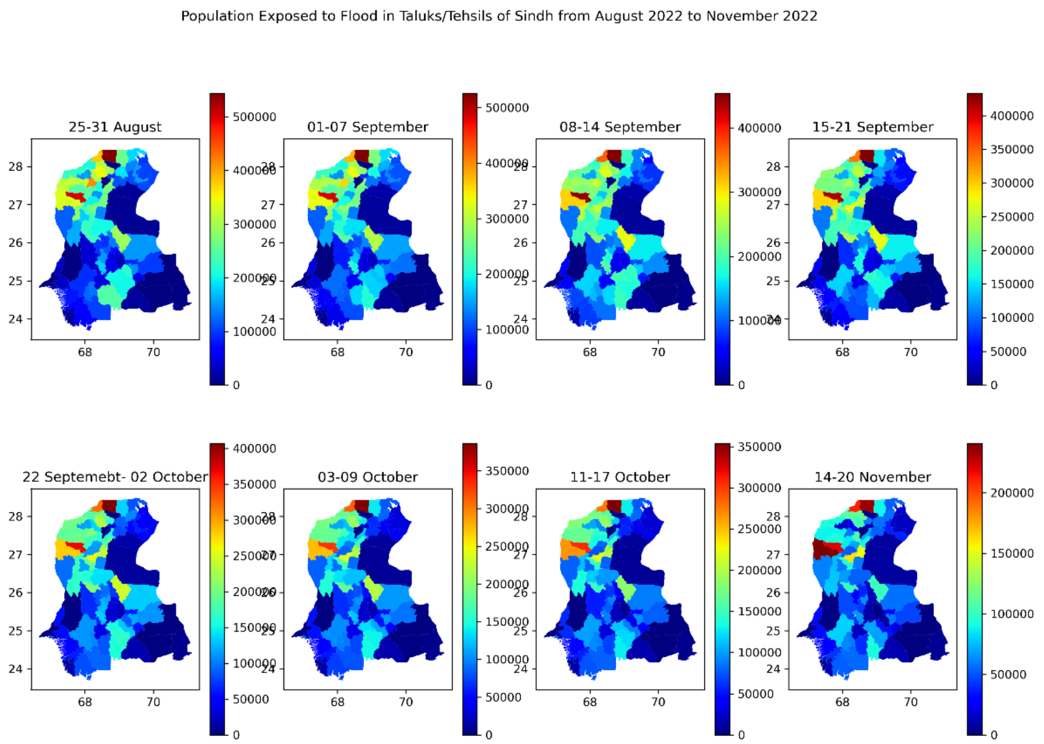


**Figure 2. 6 Number of people exposed to flood in Talukas of Sindh (UNITAR, 2022a, 2022b)**

### 2.5 Discussion and conclusion

Sindh is 23% of Pakistan's total population and contributes 27% of Pakistan's GDP. Nearly half of Sindh's population lives in rural areas with high poverty rates (Guriro et al., 2019; Ram, 2010), especially in flood-affected districts, resulting in food insecurity, malnutrition, and limited access to healthcare and education (Haque et al., 2021). The institutional arrangement for disaster response in this region is weak. Unpreparedness on the part of institutions contributes to vulnerability to the effects of climate change. In Sindh, most flooding occurred near the Indus embankments, flood protection walls, spurs, and dispersion structures. These structures run alongside the river. Between 2000 and 2014, 54 breaches occurred, killing 954 people and injuring 92,767 others. These flood-protection structures require upgrades. Heatwave frequency has increased significantly over the last 30 years, resulting in longer, hotter summers and accelerated evaporation and transpiration. Monsoon seasons become more intense with every one °C increase in temperature(Endo et al., 2012). If global emissions continue to rise, Pakistan's average annual temperature may rise by 3° to 6° Celsius by the end of the century, resulting in even more devastation.

The combination of a preceding heat wave and intense monsoon-induced flooding is a reason for increased concern. Increased weather variability in a warming climate may lead to more intense impacts that interact over time, coupling effects and decreasing response capacity among different population sectors. The high-intensity flooding and extensive damage to the exposed population demonstrate the degree to which Pakistan is exposed and vulnerable. It is crucial to understand exposure determinants and implement adaptation measures, making the most efficient use of available resources.

Politicians, scientists, and the United Nations have criticized Pakistan's reliance on foreign grants for climate mitigation and adaptation. In recent United Nations climate change conferences, there have been increasing demands for historical GHG-emitting nations to contribute to mitigation funding (Walsh & Ormond-Skeaping., 2022). Climate change will have long-term consequences for vulnerable countries. With collaboration and climate-resilient infrastructure, developing countries like Pakistan will be better prepared for cascading effects such as natural disasters.

**Conflicts of interest**: The authors declare that they have no conflict of interest.

**Data availability statement**: This paper is based on secondary datasets, which are attached in the Supplementary material

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## Chapter 3 Factors Affecting Farmers' Disaster Displacement Decisions: An Application of PLS-SEM and NCA in the Context of 2022 Floods in Sindh, Pakistan.

### Abstract

The decision for displacement during floods is critical for the safety of individuals. This study examines the key factors that motivate farmers to displace as a protective measure in the flood-prone districts of Sindh, Pakistan. Guided by the Protection Motivation Theory (PMT), we explored the necessity and sufficiency of six predictors: Severity, Vulnerability, Response efficacy, Self-efficacy, Reward, and Fear toward the motivation for displacement decisions during floods. We employed Partial Least Square Structural Equation Modeling (PLS-SEM) and Necessary Condition Analysis (NCA) to analyze responses from 195 farmers impacted by the 2022 floods. We conducted field visits in the flood-hit area of Sindh in July and August 2023 and collected empirical data using a structured questionnaire based on a five-point Likert scale. Our analysis identified Fear and Response efficacy as necessary and influential factors in the farmers' decisions to displace during flood events. A minimum level of Fear quantified at 3.11 and Response efficacy at 2.32 are critical for activating sufficient protection motivation to decide on displacement. Notably, Fear proved to be the most significant predictor, with a coefficient of 0.489 accounting for 19%, while Response efficacy, with a coefficient of 0.324, contributed 14% in displacement decisions. The study also found that the increase in Fear and Response efficacy significantly boosts displacement motivation, whereas other predictors are insignificant and unnecessary. These findings can help design interventions and policies for disaster risk reduction in flood-prone areas.

**Keywords:** Displacement, Farmer, Flood, Necessary Condition Analysis, Pakistan.

### 3.1. Introduction

Water has frequently become a problem, producing droughts and floods increasingly intensified by climate change (Trenberth, 2011). Extreme weather events have become more frequent, posing grave threats to many societies worldwide (Cann et al., 2012; Pałczyński et al., 2018; Pan et al., 2023). We analyze the 2022 flood in Pakistan that caused 10.25 million internally displaced, making it the world's largest disaster displacement event in the last ten years (IDMC, 2023 ). However, some farmers still preferred to stay at their homes even though the water touched the roofs of their houses. This situation presents contrasting signals of people's displacement decisions during floods. Farming communities, with their inherent vulnerabilities, are particularly at risk of flooding (C. C. I. IPCC, 2014; Posthumus et al., 2009). Flooding worldwide has recently surged, impacting agricultural communities (Jongman et al., 2015). Pakistan, especially its Sindh province, exemplifies the acute impact of flooding. (Otto et al., 2023; Shehzad, 2023).

The economic fallout was also immense, with losses surpassing USD 30 billion and recovery costs estimated at an additional USD 16 billion (Malik et al., 2023b). These figures are even more significant than the 2010 flood, highlighting the increasing severity of climate change-induced disasters (IDMC, 2023 ; Malik et al., 2023b; Salik et al., 2015). The immediate human response to such a disaster is to leave the areas hit by floods. Therefore, understanding the factors influencing displacement decisions of flood-affected populations is crucial to mitigating flood damages (Grothmann & Reusswig, 2006; Liu et al., 2022). However, individual choices regarding evacuation during flood risks remain varied and are not universally consistent (Hamilton et al., 2020). This variation in displacement decisions leaves a gap in understanding the necessary conditions for motivating the farmers to be displaced, especially in Sindh province, where most disaster displacement occurred in 2022 (Malik et al., 2023b; PDMA, 2022). A substantial body of literature exists exploring the reasons behind such decisions, and the focus has been predominantly on sufficiency conditions (Grothmann & Patt, 2005). Hamilton et al. (2020) identified a limited understanding of the social psychological mechanisms guiding behavioral responses during floods. This further highlights the gap in understanding the necessary conditions for these decisions, particularly in highly vulnerable regions like Sindh (Heureux et al., 2022; Otto et al., 2023).

The Protection Motivation Theory (PMT) offers a potential framework for these behavioral decisions (Rogers, 1975). It has been used in various contexts, including risk-reducing behavior against natural hazards (Bubeck et al., 2017). However, the complexity of decision-making requires a sophisticated approach beyond traditional methods. To address this knowledge gap, we employ the Protection Motivation Theory (PMT) to identify the necessary conditions influencing farmers' decisions to migrate or evacuate during floods. Using empirical data from the interview responses of 195 farmers located in the flood-hit districts of Sindh, we critically assess PMT elements, including critical factors such as Severity, Vulnerability, Response efficacy, Self-efficacy, Response costs, Fear, Rewards, and Protection motivation (Rogers, 1975). We applied Necessary Condition Analysis on PMT to test that specific conditions within these elements are crucial for farmers' evacuation or migration decisions in the face of flood risks (Dul, 2016).

Specifically, this research aims to investigate the farmers' decision of displacement during floods, utilizing the PMT by examining the role of Severity, Vulnerability, Protective Cost, Response efficacy, Self-efficacy, Fear, and Reward, with a particular focus on the affected farmers during 2022 floods in Sindh, Pakistan. Furthermore, this study combines PLS-SEM NCA to pinpoint those predictors necessary for farmers to evacuate in response to flooding.

### 3.1.1. Internal Displacement and 2022 Flood in Sindh Pakistan

In 2022, Pakistan experienced the worst floods of its history. Preceded by countrywide heat waves, in the summer of 2022, Pakistan received extreme rainfall throughout its landmass. Sindh province received 508% above-average rain, triggering flash floods (PMD, 2022a). Irregular topography in the lower Indus basin further exacerbated the situation (Sajjad et al., 2020; Sayama et al., 2012). One-third of the country's territory was underwater by August 2022. The government of Sindh declared an emergency in 23 districts in Sindh. By the end of August 2022, there was an exceptional 784% increase in the month’s rainfall (Abbas, 2022; Earth Observatory, 2022; Rowe, 2022). Padidan, a meteorological observatory in Naushahro Feroze district, witnessed a record-breaking 1187 mm of rain (PMD, 2022a). The scale of this disaster caused the people to leave their homes to save their lives and cattle.

The districts of Khairpur, Larkana, Dadu, Umer Kot, and Mirpur Khas experienced the most severe flooding, causing widespread inundation and displacement of a large number of people. Among these districts, Khairpur in the Sindh province was the hardest hit, accounting for 41% of the total displacement, followed by Dadu and Mirpur Khas. Approximately 1.5 million people in each of these five districts were affected by the floods. As shown in Figure 2.1, most of the displacement occurred in these five districts of Sindh province, making them suitable for investigating factors contributing to displacement using the Protection Motivation Theory as a theoretical framework (IOM, 2022). Figure 2.1 shows most of the displacement was caused in Khairpur, Larkana, Dadu, Umer Kot, and Mirpur Khas, districts of Sindh province, substantiating their selection as a case for investigating factors of displacement in light of the Protection Motivation Theory as a theoretical framework (IOM, 2022). This research examines the five districts that have experienced the highest level of displacement: Khairpur, Larkana, Dadu, Umer Kot, and Mirpur Khas. These districts represent the extent of population displacement at the union council level (IOM, 2022).

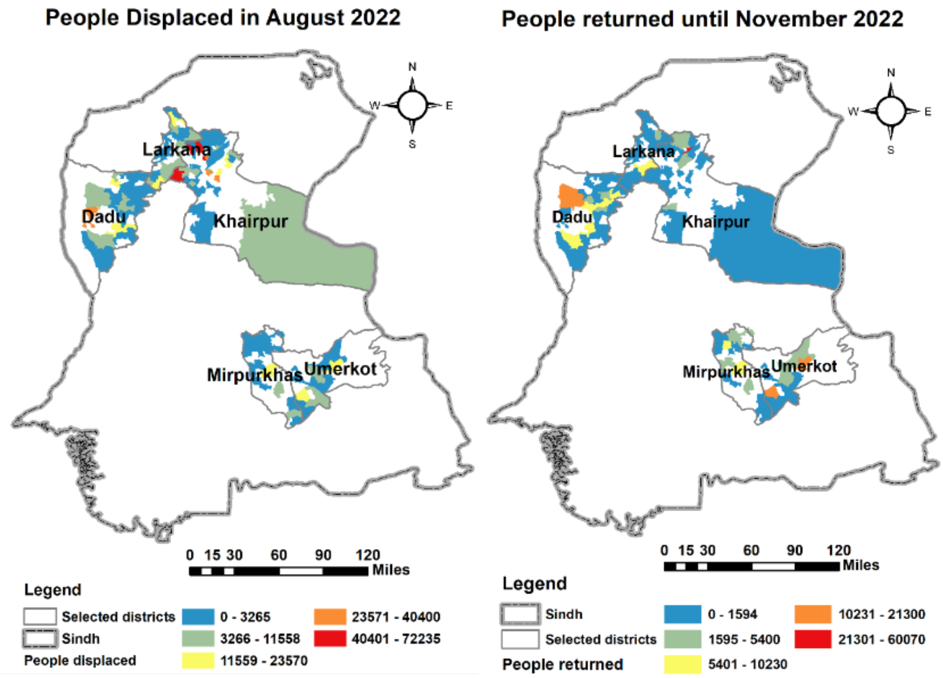


**Figure 3. 1 People displaced and returned in flood 2022 (Own figure based on data DTM on Oct 2022)**

The study's focus on these five districts is timely and crucial to understanding the displacement factors. Drawing from IOM (2022) data, the study analyzes displacement and return dynamics in flood-affected areas, revealing significant effects on the farming community. The study provides insight into post-flood displacement and return, emphasizing disparities in individuals displaced and those who returned by November 2022.

### 3.2. Theoretical background

This study operationalizes the Protection Motivation Theory and then integrates PLS-SEM and NCA to understand disaster displacements of flood affectees in Pakistan. The objectives of this study require a comprehensive methodology covering quantitative and qualitative approaches. Quantitative methods, including statistical analysis of data from surveys, remote sensing data (Sadek et al., 2020; Schumann et al., 2009), and historical archives, are used to understand the trends and patterns of displacement (Hunter, 2005). Techniques such as regression and spatial auto-correlations are commonly employed (Ansari et al., 2022; Babcicky & Seebauer, 2019). Conversely, qualitative methods, covering interviews and ethnographic investigations, explore the affected farmers' subjective experiences and perceptions, explaining the social, cultural, and psychological factors influencing their displacement decisions (Dun, 2011; Lindvall et al., 2020; López-Carr & Marter-Kenyon, 2015). The mixed method integrates both approaches.

Newly introduced methodologies like PLS-SEM and NCA are used for their efficacy in explaining the complex dynamics of disaster displacement. PLS-SEM helps to test theoretical models and understand the interdependence of variables, while NCA identifies the necessary predictors for outcomes, which is crucial for comprehending the farmers' displacement decisions. Therefore, this multifaceted approach, aligning with the research objectives, justifies its application to understand the factors influencing farmers' decisions during the 2022 floods in Sindh, Pakistan.

#### 3.2.1. Necessary Condition Analysis and Partial Least Square Structure Equation Modeling

The Necessary Condition Analysis (NCA), as developed by Dul in 2016, emerges as a sophisticated data analysis approach to discern necessary conditions within data sets, a task it performs with noteworthy efficiency (Dul, 2016; Richter et al., 2020). This technique is distinctive, not in determining sufficiency, but in identifying conditions for attaining a particular outcome. Expressed in terms such as "X is a precondition for Y," it emphasizes the necessity of certain factors, highlighting that their absence cannot be compensated by other variables (Dul et al., 2020). In essence, the necessary condition becomes a bottleneck, constraining the possible achievement of the desired outcome if not adequately met.

NCA plays a pivotal role in research, offering a two-pronged utility: it visualizes relationships between variables through ceiling lines and bottleneck tables, and it quantifies the strength of these necessary conditions through parameters like accuracy, effect size, and significance testing, thus ensuring methodological robustness and mitigating calculation errors (Dul, 2016; Dul et al., 2020). The technique synergistically complements other regression-based methods, such as PLS-SEM, providing a holistic view of data relationships (Sukhov et al., 2023; Sukhov et al., 2022). It is potent in its capability to predict the required intensity of a condition to achieve a specific outcome, proving instrumental in diverse fields ranging from information systems to organizational success.

The ascension of NCA in various academic disciplines has prompted a rigorous examination of its statistical underpinnings and application methodologies. Researchers like Thiem (2021), Richter et al. (2020), and Lankoski et al. (2023) have explored its versatility, while Dul et al. (2023); (Dul et al., 2020; Dul et al., 2019; Dul et al., 2021) and Sukhov et al. (2023); (Sukhov et al., 2022) have scrutinized its statistical components, addressed misconceptions, and proposed best practices. These studies underscore the method's prominence and call for careful implementation to avoid misinterpretation.

However, despite its strengths, NCA is not without its limitations. It does not incorporate sampling errors or confidence intervals into its calculations or measure the triviality of the necessary conditions. Therefore, researchers must not solely rely on NCA outputs but also critically evaluate their theoretical frameworks, measurement quality, and overall research design (Dul, 2016). In sum, NCA is a valuable addition to the researcher's arsenal, complementing existing statistical methods and providing unique insights. Still, its utility is maximized when used judiciously and in conjunction with robust theoretical and methodological considerations.

Ceiling accuracy, a critical metric in Necessary Condition Analysis (NCA), is calculated as the percentage of observations on or below the ceiling line, providing insights into the solution's precision. Dul (2016) highlights that while there is no explicit standard for acceptable accuracy levels, comparing the estimated accuracy to a benchmark, such as 95%, facilitates an assessment of the solution's quality. Concurrently, the necessity effect size (d) indicates whether a variable is imperative for an outcome. The calculation of d involves the ratio of the ceiling zone, an area devoid of observations, to the scope, which can contain all potential observations, resulting in values ranging between 0 and 1. Dul (2016) provides a classification for interpreting d, where values less than 0.1 signify a small effect, between 0.1 and 0.3 a medium effect, between 0.3 and 0.5 a large effect, and values above 0.5 a very large effect.

Leveraging NCA and PLS-SEM together empowers researchers to pinpoint essential conditions for specific outcomes, adhering to the principles of necessity logic. This synergy facilitates the identification of indispensable factors and quantifies the extent to which these conditions must be fulfilled to achieve a desired outcome level. Practical applications range from predicting the degree of usefulness of an information system to ensure substantial system use to determining the necessary level of usage within an organization for information systems to contribute to success significantly. Thus, crafting a seamless and concise narrative makes it evident that ceiling accuracy and effect size in NCA are instrumental in delineating the boundaries of necessity. At the same time, their integration with PLS-SEM offers a comprehensive toolkit for researchers striving to unravel the complexities of necessity in various domains.

### 3.2.2. Protection Motivation Theory (PMT)

The Protection Motivation Theory (PMT) outlines that an individual's decision to safeguard themselves by their perceived intensity and susceptibility to a threat, confidence in a protective action, capability to perform such an action, anticipated costs, Fear, perceived rewards of avoiding protection, and overall motivation to defend themselves (Rogers, 1975, 1983). Following this rationale, we leverage necessity logic to understand the evacuation decision in flood scenarios. A similar approach to exploring the protective behavior of humans has been used by different studies (Ansari et al., 2022; Babcicky & Seebauer, 2019; Grothmann & Reusswig, 2006; Gumasing et al., 2022; Kurata et al., 2022). Health, environment, and privacy studies extensively employed PMT as their foundation (Chen et al., 2023; Kim & Choi, 2021; Plotnikoff et al., 2009).

Our study employed the Protection Motivation Theory (PMT) to investigate farmers' risk assessment behaviors and subsequent decisions concerning displacement due to flood risk. Because 'Flood Severity' acknowledges the flood's intensity as a prerequisite for evacuation decisions. 'Vulnerability' refers to an individual's sensed susceptibility to flood hazards, which often acts as a catalyst for opting to evacuate. 'Response Efficacy' and 'Self-Efficacy' encapsulate the beliefs in the effectiveness of evacuation and in one's capacity to undertake it, respectively.

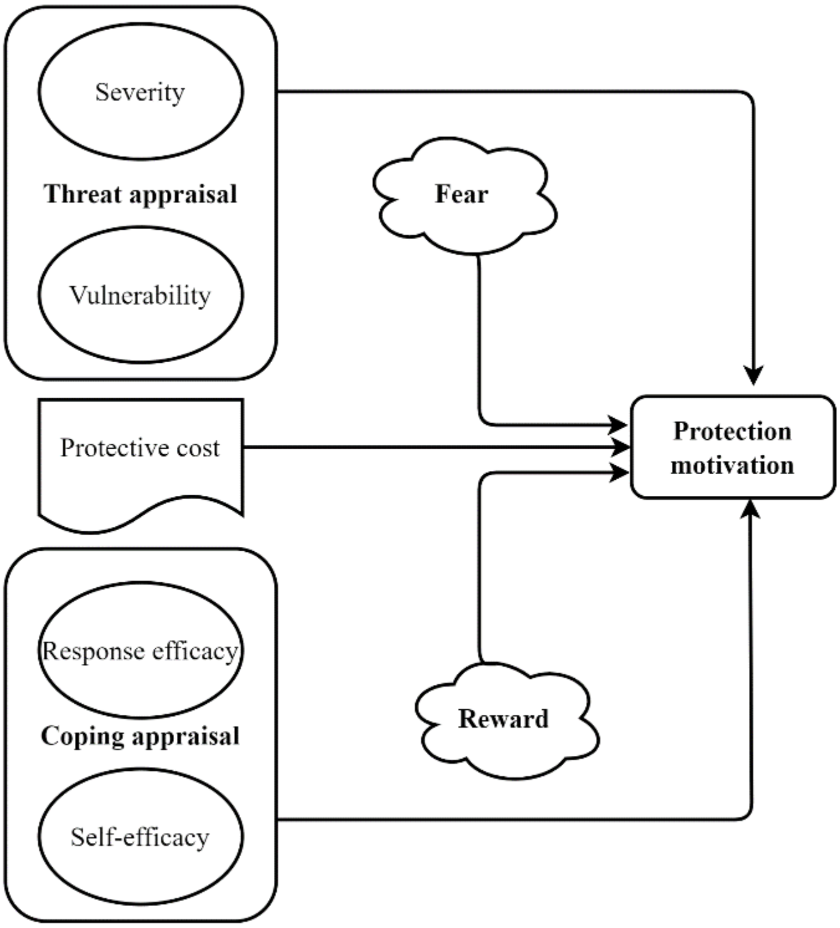


**Figure 3. 2 Schematic diagram of Protection Motivation Theory**

The absence of these beliefs generally leads to a reluctance to evacuate. 'Response Costs' evaluates the financial burden of evacuation, wherein prohibitive costs can deter individuals from leaving. The construct of 'Fear' accentuates that a substantial level of Fear concerning the flood is integral to an evacuation decision. Additionally, 'Rewards' gauge the benefits or drawbacks of displacement actions. Applying a 'Sufficiency Logic,' we posit that a holistic perception of severe flooding, Vulnerability, efficacy in response measures, manageable costs, and significant Fear can collectively lead to a decision to evacuate. However, these conditions do not negate other potential routes to the same decision, thus giving rise to 'Necessity Logic,' which outlines indispensable predictors for displacement, the absence of which makes evacuation highly unlikely.

## 3.3. Methodology

### 3.3.1. Study area

The study's focus on these five districts is both timely and crucial. It brings the immediate need for upgraded flood-protection infrastructure, policy reform, and a proactive approach to disaster management, all while challenging the country's reliance on foreign grants for climate adaptation (Walsh & Ormond-Skeaping., 2022). The spatial displacement pattern in our study area (see Figure 3.1) lays a robust foundation for displacement and migration research. The geographical focus of our research is on the five districts reporting the highest displacement, namely Khairpur, Larkana, Dadu, Umer Kot, and Mirpur Khas. These districts emerged as key regions representing the magnitude of population displacement at the union council level (IOM, 2022).

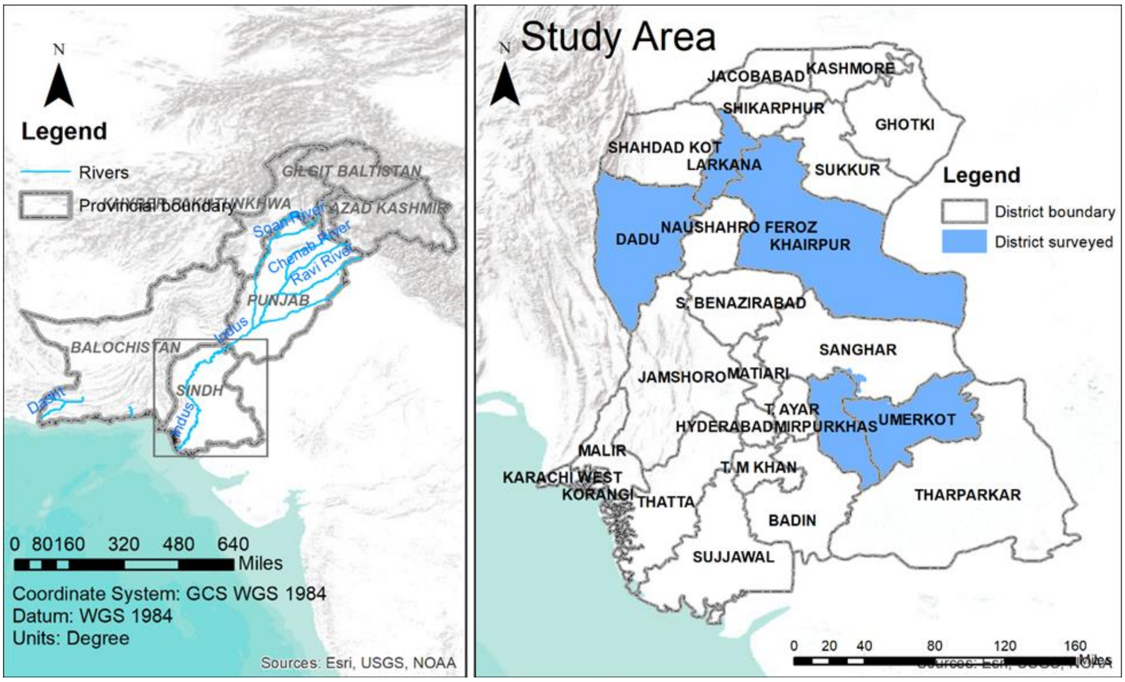


**Figure 3. 3 Geographical focus of field survey**

### 3.3.2. Population and sampling

Sindh province emerged as the focus of our study due to its high susceptibility to flooding, notably the 2022 floods that inflicted remarkable damage on the region (Roth et al., 2022). The flood caused substantial displacement in the reports published by IDMC (2023 ) and IOM (2022), which specified districts witnessing significant population displacement (See Figure 3.1). Guided by the post-flood reports and maps, we selected five districts that experienced the most population displacement (Figure 3.1). We adopted the purposeful sampling technique guidelines, a non-probability sampling method used to identify and select information-rich cases relevant to the study's purpose (Palinkas et al., 2015). To select union councils for site visits, we utilized accessibility considerations and pre-existing social networks within these communities. We adhered to the guidelines of judgmental purposive sampling, where the enumerators used their judgment and knowledge of the communities to select the areas that were most relevant or accessible for their research (Ames et al., 2019). We had a fruitful experience executing this multicriteria-based sample selection strategy in our previous study with the farmers (Mobeen et al., 2023). We conducted the field surveys during July and August 2023. Upon arrival at each village or union council, we employed a random sampling method to select farmers willing to participate in the study, often facilitated by pre-arranged agreements with local leaders. Ahmed et al. (2017) used a similar sampling strategy. According to data released by the Provincial Disaster Management Authority PDMA (2022) and the Government of Sindh, 1.5 million people were displaced in these five districts, serving as our target population. This group drew a sample of 195 farmers based on specified criteria. As of November 2023, over half a million displaced individuals had returned to their homes, as reported by IOM (2022). This sampling approach lends robustness to our subsequent analyses.

### 3.3.3. Development of scale and data collection

We deconstructed the Protection Motivation Theory (PMT) elements: Severity, Vulnerability, Protective Cost, Response Efficacy, Self-Efficacy, Fear, Reward, and Protection Motivation. We developed a five-point Likert scale questionnaire based on the guidelines (Robinson, 2014). Each construct was represented by four items, with response options ranging from 'Not at All' to 'Very High,' a methodology consistent with prior PMT-based research in various fields (Ansari et al., 2022; Babcicky & Seebauer, 2019; Grothmann & Reusswig, 2006). Data collection commenced in July 2023 and concluded in August 2023, facilitated by trained enumerators. The first author and the enumerators conducted field interviews with the farmers. The enumerators were given off-site and on-site training sessions before entering the field. A preliminary round of interviews was conducted with farmers in Khairpur district to validate the instrument. This pretesting led us to reduce the number of items per construct, as we observed a lack of interest from respondents after 25 minutes of dialogue. The refined instrument thus balanced comprehensiveness and participant fatigue, ensuring quality data for subsequent analyses.

### 3.3.4. Data analysis

We integrate PLS-SEM and NCA by using SmartPLS 4.0.9.6 (Ringle et al., 2022). Grounded in the most recent advancements in structural equation modeling research (Richter et al., 2020) and solidly following the proven methodologies for conducting PLS-SEM analyses (Hair et al., 2022; Richter et al., 2022; Ringle et al., 2020; Sarstedt & Cheah, 2019). In choosing PLS-SEM, we align with the guidance Ringle et al. (2020) provided, who advocate using composite-based approaches when dealing with intricate constructs. This strategic decision underscores our commitment to robust and precise modeling, ensuring the integrity and validity of our analytical processes. Through PLS-SEM, we derive composite scores for latent variables by accurately estimating individual indicator weights, accounting for measurement errors (Hair Jr et al., 2017), and subsequently integrating these findings into the NCA framework. This dual-methodological approach illuminates the essential and sufficient factors that dictate overall travel satisfaction, providing a holistic understanding vital for dissecting the intricacies of farmers' displacement choices under the Protection Motivation Theory. Our analysis uniquely positions us to uncover the nuanced dimensions of service quality attributes within the specific socio-environmental context of the 2022 floods, ensuring a robust and contextually grounded investigation. For further evaluation of the construct that we used in the model, we also used Importance-Performance Matrix Analysis (IPMA), which serves as an extension to the PLS-SEM and NCA results, providing nuanced insights into the performance of individual constructs (Hair et al., 2014; Hock et al., 2010; Völckner et al., 2010).

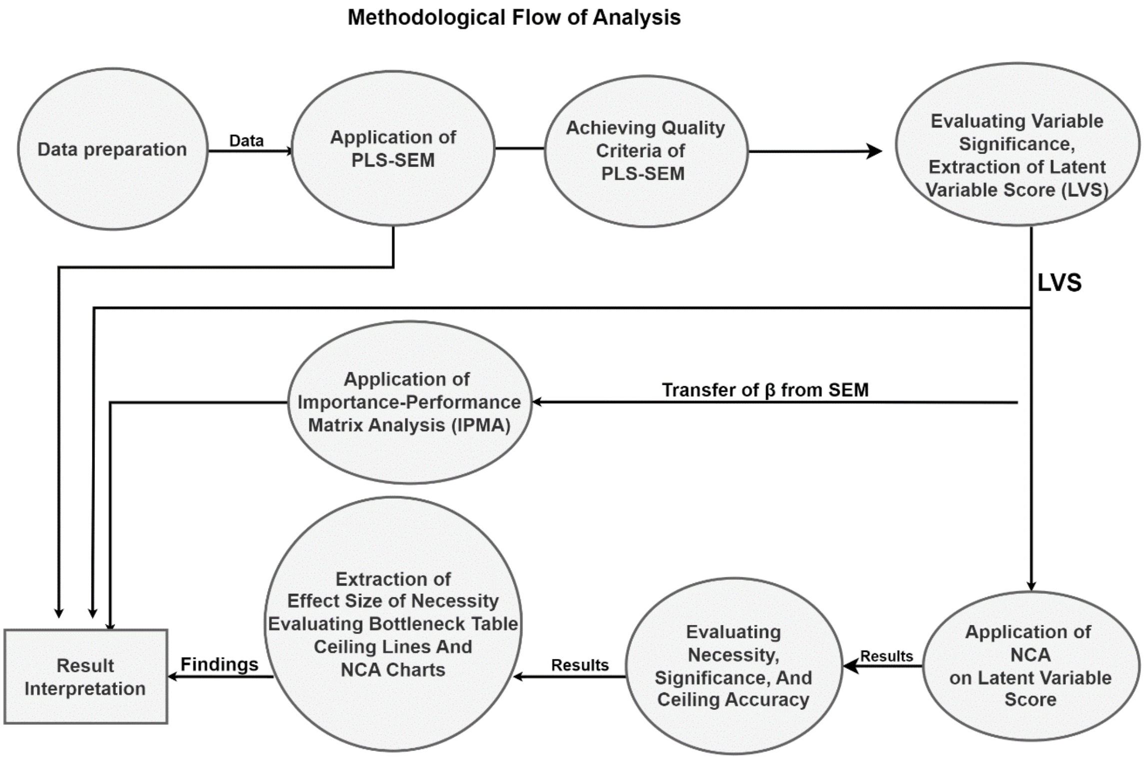


**Figure 3. 4 Flow chart of data analysis adapted from Richter et al. (2020)**

Figure 3.4 summarizes the information processing. Starting from the foundational step entails "Data Preparation," ensuring the collected data is cleansed and structured for subsequent stages. This step is paramount as the data quality dictates the research output's accuracy and relevance. The streamlined data then flows into SmartPLS software for PLS-SEM, a versatile technique enabling the estimation of complex cause-effect relationship models with latent variables. Following this, the "Achieving Quality Criteria of the PLS-SEM" becomes crucial, ascertaining that the model meets the requisite standards and ensuring the reliability and validity of the constructs (see Supplementary material). Subsequently, the "Evaluation of Level of Significance of Variables" comes into play, pinpointing the relevance of each variable and facilitating the "Extraction of Latent Variable Score (LVS)." This is a crucial process that identifies the underlying unobserved variables. The LVS serves as a precursor to the

"Application of Importance-Performance Matrix Analysis (IPMA)," which visually represents the prioritized variables based on their importance and performance. The direction of the "Transfer of β from SEM" arrow indicates the integration of standardized regression coefficients from the SEM to the IPMA, which is vital for determining variable significance. Simultaneously, the "Extraction of Necessity Effect Size, Bottleneck Table, Ceiling Lines & NCA Charts" elucidate the necessity of predictors. This extraction forms the foundation for the "Evaluation of Necessity and Significance of Variables." This further extends into the "Application of NCA on Latent Variable Scores," applying Necessary Condition Analysis to discern indispensable conditions for a given outcome. Conclusively, the "Interpretation of Results" phase synthesizes all preceding steps, drawing meaningful insights and conclusions. Every arrow symbolizes the seamless transition and dependency between stages, ensuring the research remains cohesive and systematic.

#### 3.3.4.1. Partial Least Squares Structural Equation Modeling (PLS-SEM)

For evaluating the sufficiency of predictors for an outcome variable, we employed PLS-SEM to assess the significance of the path coefficients (β) influencing farmers' motivations for displacement. This analytical approach incorporated a bootstrapping procedure on 10,000 samples and a two-tailed test at a 0.05 significance threshold. As illustrated in Figure 3.3, we mapped the Protection Motivation Theory (PMT) elements. Protection motivation is an outcome variable in the model, while all others are our predictors or independent variables. The line breadth shows the strength of the relationship based on the β coefficient. The p-values are shown in brackets.

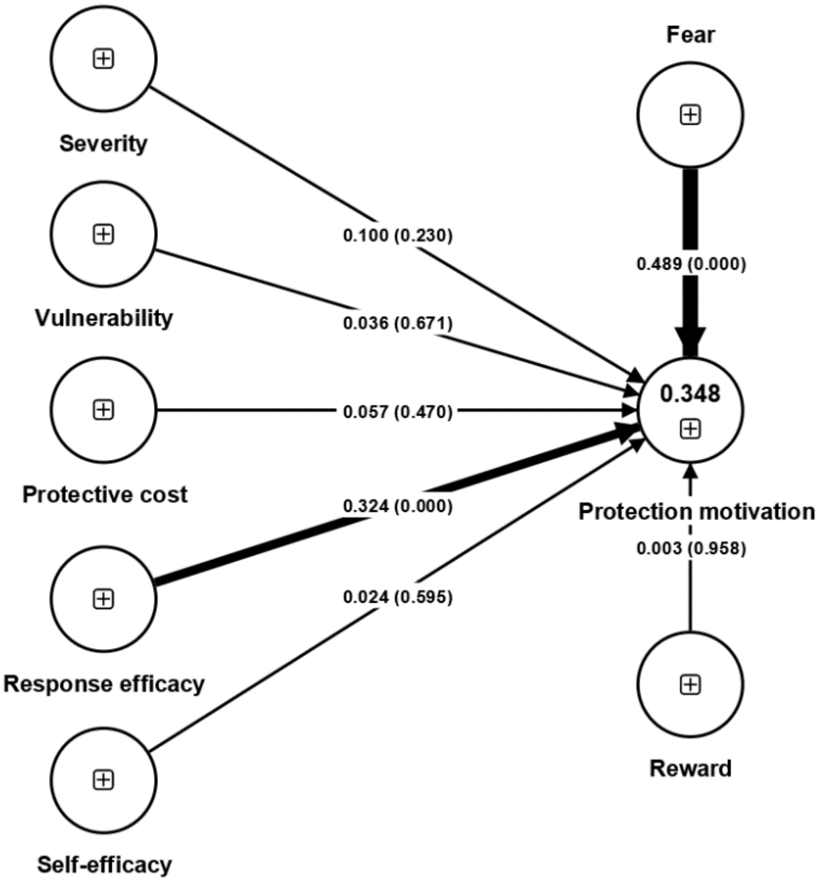


**Figure 3. 5 Evaluation of Protection Motivation Theory Through PLS-SEM with β and p-values**

#### 3.3.4.2. Necessary Condition Analysis (NCA)

To check the necessity of predictors with the decision of displacement as protection motivation, we supplemented PLS-SEM analysis with Necessary Condition Analysis (NCA). Figure 3.6 shows the arrangement of predictors and outcome variables on which we performed NCA. The line values are the predictors' effect sizes, while the significance level is shown in brackets. We followed the analytical procedure of setting up NCA suggested by Dul et al. (2021) and Richter et al. (2020). After importing the Latent variable score generated from the PLS algorithm, we run the NCA algorithm by putting bottleneck steps on 10, with permutation up to 10,000, to check the significance of every predictor against the outcome. To assess the relationship between the predictor and protection motivation, we used the recommended ceiling envelopment-free disposal hull (CE-FDH) line (see Figure 3.10), which is a non-decreasing step function generated on the scatterplot between the predictor and the outcome variables (Dul, 2016; Dul et al., 2020; Dul et al., 2021).

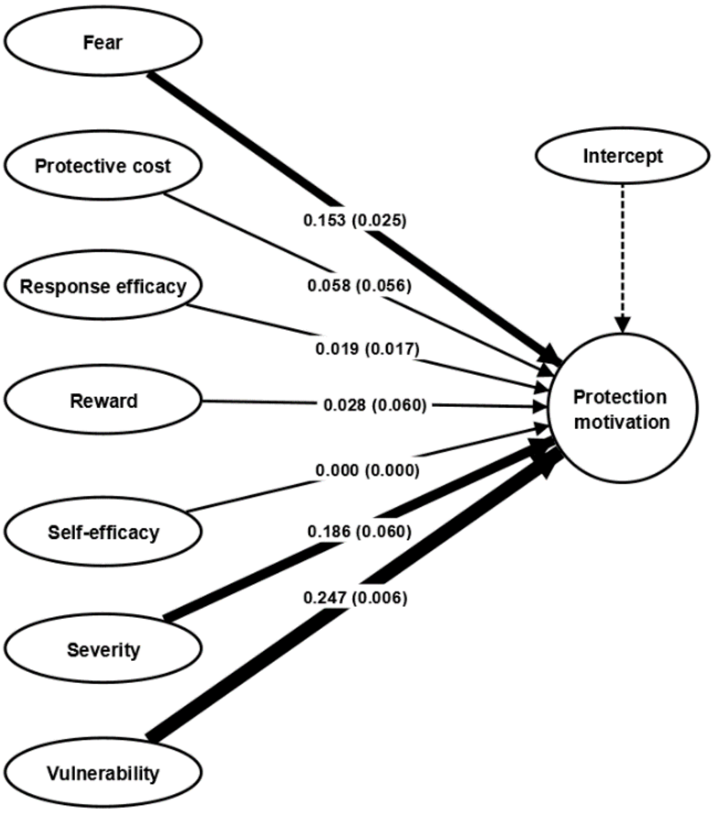


**Figure 3. 6 Necessary Condition Analysis of Protection Motivation Theory with effect size and P-values**

This allowed us to separate the space containing observations from the area not containing any observations, thus identifying how much each predictor's attribute constrains protection motivation. In the results section, we discussed these effect sizes and the CE-FDH line in detail.

### 3.3.4.3. Performance Matrix Analysis (IPMA)

To assess the performance and importance of constructs within our PLS-SEM, we employed the Importance-Performance Map Analysis (IPMA) to evaluate the results of our PLS-SEM (Schloderer et al., 2014) based on frameworks by Hock et al. (2010) and Völckner et al. (2010). This analytic technique yielded the Importance-Performance Matrix, visualized in Figure 3.11, and corresponding values tabulated in Table 3.4. The Result section will provide a comprehensive discussion and interpretation of these results.

### 3.4. Results

#### 3.4.1. Socio-demographic profile of respondents

We interviewed 195 farmers affected by a flood in 2022 and forced to leave their homes. The survey took place in July and August 2023. The respondents had recently experienced displacement from their homes due to a flood last year.

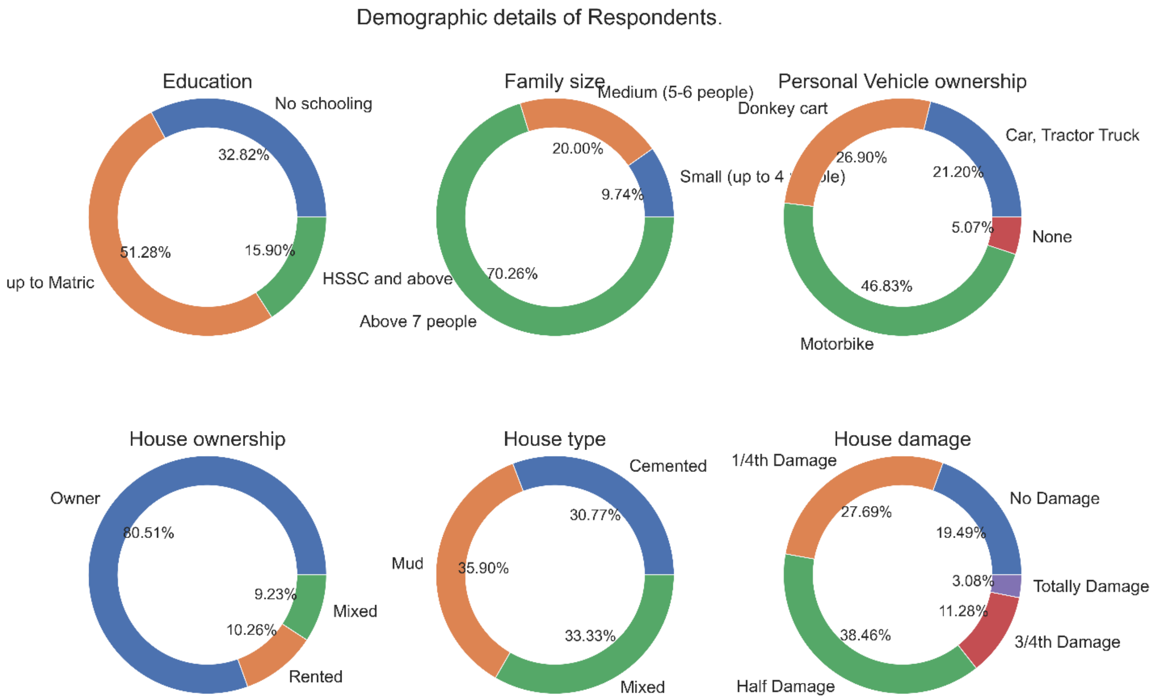


**Figure 3. 7 Demographic details of flood victim farmers**

Figure 3.7 summarizes the respondents' socio-demographic profile. The educational distribution reveals that 32.82% of respondents lacked formal schooling, 51.28% had completed up to Matriculation, and a smaller fraction of 15.90% had pursued education up to the HSSC level or beyond. From a family type perspective, 9.74% represented smaller families with a count of up to 4 members, 20.00% had families comprising 5-6 members, while 70.26% hailed from expansive families housing more than seven members. The housing landscape was dominated by homeowners, making up 80.51%, contrasted with 10.26% who resided in rented spaces and 9.23% in mixed housing conditions. Evaluating the type of houses, 30.77% lived in cemented structures, 35.90% in mud houses, and 33.33% in homes of mixed construction.

Regarding vehicular ownership, it was observed that 34.36% owned a car, tractor, or truck, while 43.59% had donkey carts. Surprisingly, motorbikes were the predominant mode of transportation, with 75.90% ownership, leaving 8.21% without any personal vehicle. In assessing housing damages, the results were distressing: 19.49% reported no damage, 27.69%

faced up to 25% damage, 38.46% contended with 50% damage, 11.28% experienced a grievous 75% damage, and 3.08% had their homes completely devastated. These findings furnish a granular understanding of the socio-economic landscape of the afflicted districts' farming populace, facilitating an empirical basis for calibrated interventions and strategic policy design.

### 3.4.2. Computation of variable score

Figure 3.8 presents the average computation scores for the variables measured in our model. This figure provides a visual summary of their collective behavior within the dataset. The variable Severity exhibits the highest average score, closely approaching 5, indicating that the overwhelming majority of the respondents perceived that the 2022 flood was very extreme. In contrast, "Self-efficacy" is characterized by the lowest median value, implying respondents perceive their capability of executing relocation decisions as very low. The "Response efficacy" and "Protective cost" variables display moderately high average scores, suggesting participants generally believe in the effectiveness of the recommended response but with the high protective cost. Additionally, the presence of outliers, particularly for "Severity" and "Vulnerability," necessitates a deeper inspection, as these might indicate varying interpretations or extreme viewpoints among the respondents.

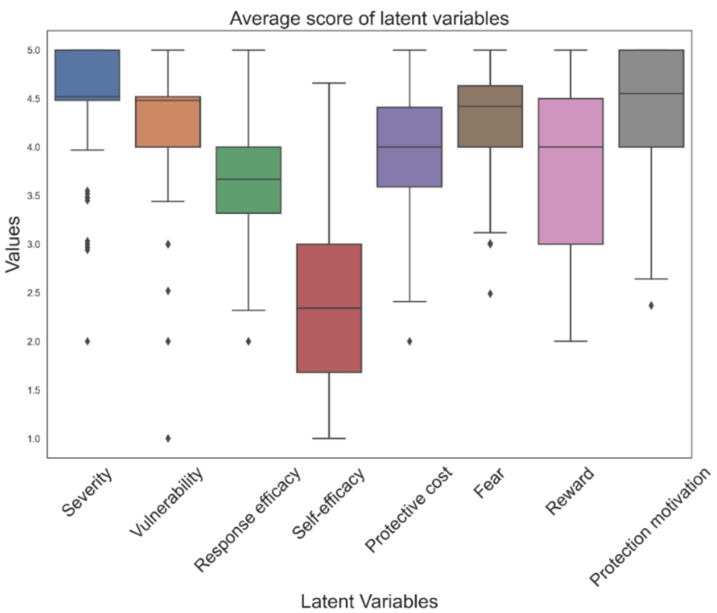


**Figure 3. 8 Computed scores of variables in the model**

### 3.4.3. Results of PLS-SEM and NCA

We applied PLS-SEM to evaluate the sufficiency and strength relationship between the variables in our model. Remarkably, the path from Fear to Protection Motivation and Response efficacy to Protection motivation demonstrated high significance, exhibiting β values of 0.489

and 0.324. Another significant finding was the strong relationship between Fear and Protection Motivation, with a coefficient of 0.489 ($p<0.001$). The overall model fit, represented by an R-squared value, indicates that the Protection Motivation explains about 35% of farmers' displacement decisions. To evaluate the necessity of predictors for protection motivation, we applied NCA, which identified the must-have variables for the outcome to happen.

**Table 3. 1 PLS-SEM and NCA results**

| **PLS-SEM** | | | | **NCA** | | |
|---|---|---|---|---|---|---|
| **Independent** | **Outcome** | **β** | **p-value** | **Role of NCA** | **Effect size** | **p-value** |
| Fear | PM | 0.489 | 0.000 | 19% | 0.153 | 0.025 |
| Protective cost | PM | 0.057 | 0.470 | 18% | 0.058 | 0.056 |
| Response efficacy | PM | 0.324 | 0.000 | 14% | 0.019 | 0.017 |
| Reward | PM | 0.003 | 0.958 | 15% | 0.028 | 0.060 |
| Self-efficacy | PM | 0.024 | 0.595 | 00% | 0.000 | 0.000 |
| Severity | PM | 0.100 | 0.230 | 18% | 0.194 | 0.060 |
| Vulnerability | PM | 0.036 | 0.670 | 15% | 0.247 | 0.006 |

Table 3.1 presents combined results from both NCA and PLS-SEM. The significant positive correlation between "Fear" and "Protection motivation" is evident through a path coefficient of 0.489 and a p-value. Furthermore, the NCA indicates an effect size of 0.153, accounting for 19% of the role in the model. "Response efficacy" also emerges as a strong influencer, with a significant PLS-SEM relationship and a 14% effect size in NCA, indicating its necessity.

However, the predictors "Reward," "Self-efficacy," and "Severity" exhibit ambiguous influences. "Reward" and "Severity" both reflect an insignificant PLS-SEM relationship but have borderline significance in NCA, indicating potential necessary condition roles. Notably, "Self-efficacy" lacks influence in both analyses, indicating its minimal role in this specific context. On the other hand, "Vulnerability" doesn't show a significant direct relationship in PLS-SEM but is highlighted as a necessary condition with a 15% effect size in NCA, emphasizing its subtle yet crucial role in protection motivation.

In sum, this intricate analysis paints a nuanced picture of the decision-making dynamics related to flood affectees, revealing that while some predictors directly influence protection motivation, others serve as indispensable necessary conditions. This comprehensive understanding paves the way for future research to delve deeper into potential interactions and contextual variables that might shape these relationships, contributing to a more robust and contextualized understanding of protection motivation.

### 3.4.4. Effect size and significance testing via CE-FDH

Utilizing Ceiling Envelopment with Free Disposal Hull (CE-FDH), we assessed the impact and efficiency of our predictors for the outcome variable. First, we evaluated the effect size (d) of our predictors and tested their level of significance based on the recommendation of Dul (2016) and Dul et al. (2021) using a sample size of 10,000. According to these studies, a condition must satisfy three criteria to be necessary. Firstly, It must be theoretically justified. Secondly, its effect size (d) must be greater than zero, and thirdly, it must be statistically significant ($p < 0.05$). Table 3.2 shows the effect size and p-value details, establishing that only Fear, Response efficacy, and Vulnerability meet these three criteria. But, Vulnerability found insignificance in our PLS SEM analysis. Therefore, we identify only Fear and Response efficacy as the necessary conditions for having enough protection and motivation to decide on displacement.

**Table 3. 2 Effect size and Ceiling Envelopment with Free Disposal Hull (CE-FDH)**

| Predictors | CE-FDH | P value |
|---|---|---|
| Fear | 0.153 | 0.025 |
| Protective cost | 0.058 | 0.056 |
| Response efficacy | 0.019 | 0.017 |
| Reward | 0.028 | 0.060 |
| Self-efficacy | 0.000 | 0.000 |
| Severity | 0.186 | 0.060 |
| Vulnerability | 0.247 | 0.006 |

Fear and Response efficacy established their statistical significance in PLS-SEM (see Table 3.1), according to the interpretation guideline given by Richter et al. (2020). The significance of a variable in both PLS-SEM and NCA also establishes that an increase in Fear and Response efficacy will increase protection motivation. We verified this result by calculating the correlation of these two variables with protection motivation. See the Correlation Heat Map (Figure 3.10), which shows the positive correlation between Fear and Protection motivation (coefficient 0.450) and between Response efficacy and Protection motivation (coefficient 0.450).

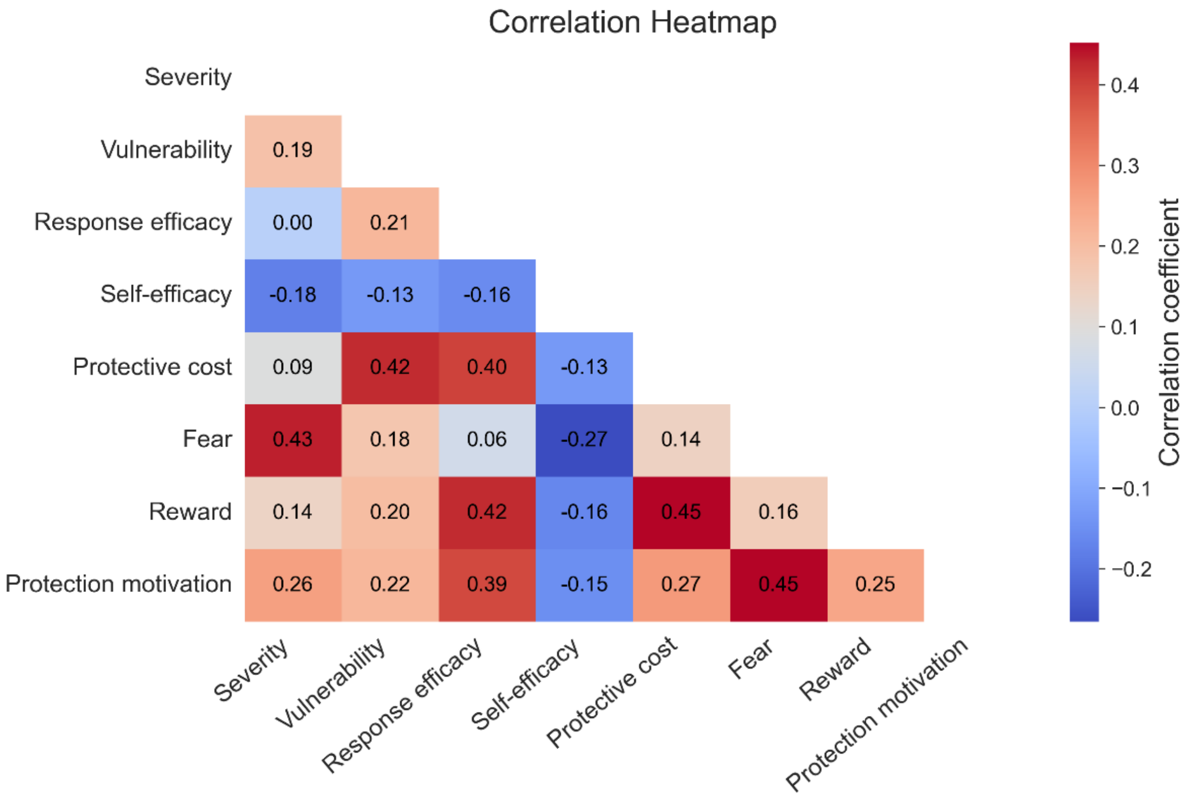


**Figure 3. 9 Triangular Correlation Heatmap of all variables under study**

### 3.4.5. Bottleneck analysis

The bottleneck analysis provides further details about protection motivation thresholds and their corresponding conditions. The leftmost column shows different levels of our outcome variable (protection motivation), which extend from 2.365 to 5.000 (see Table 3.2), exhibiting a diverse level of motivation intensity in our data. Notably, a protection motivation level up to 2.629 does not need any necessary condition. This suggests that none of these predictors are necessary for lower levels of protection motivation. However, at 2.892, Vulnerability emerges as a requisite, with a specific value of 2.000. Progressively, Fear becomes essential at a threshold of 3.419 and Severity at 3.683. An intriguing observation is the convergence of multiple predictors, including Fear, Protective cost, Response efficacy, Reward, Severity, and Vulnerability, at the threshold of 4.737.

**Table 3. 3 Bottleneck table (NN: Not Necessary)**

| | Protection motivation | Fear | Protective cost | Response efficacy | Reward | Self-efficacy | Severity | Vulnerability |
|---|---|---|---|---|---|---|---|---|
| 00% | 2.365 | NN | NN | NN | NN | NN | NN | NN |
| 10% | 2.629 | NN | NN | NN | NN | NN | NN | NN |
| 20% | 2.892 | NN | NN | NN | NN | NN | NN | 2.000 |
| 30% | 3.156 | NN | NN | NN | NN | NN | NN | 2.000 |
| 40% | 3.419 | 3.014 | NN | NN | NN | NN | NN | 2.000 |
| 50% | 3.683 | 3.118 | NN | NN | NN | NN | 3.000 | 2.000 |
| 60% | 3.946 | 3.118 | NN | NN | NN | NN | 3.000 | 2.000 |
| 70% | 4.210 | 3.118 | NN | NN | NN | NN | 3.000 | 2.000 |
| 80% | 4.473 | 3.118 | NN | NN | NN | NN | 3.000 | 2.000 |
| 90% | 4.737 | 3.118 | 3.000 | 2.323 | 2.495 | NN | 3.031 | 2.521 |
| 100% | 5.000 | 3.118 | 3.000 | 2.323 | 2.495 | NN | 3.031 | 2.521 |

These predictors maintain their necessity for all subsequent protection motivation levels surpassing 4.737. This indicates that a combination of several factors becomes indispensable for very high levels of protection motivation. Initially, factors like Vulnerability are pivotal. As the intensity of motivation increases, other factors, including Fear and Severity, become crucial. Intriguingly, some aspects like Self-efficacy don't emerge as necessary even at higher thresholds. This could indicate its potential redundancy or role as an enhancer rather than a core essential condition. It is important to note that Self-efficacy was not found necessary at any level of protection motivation decision.

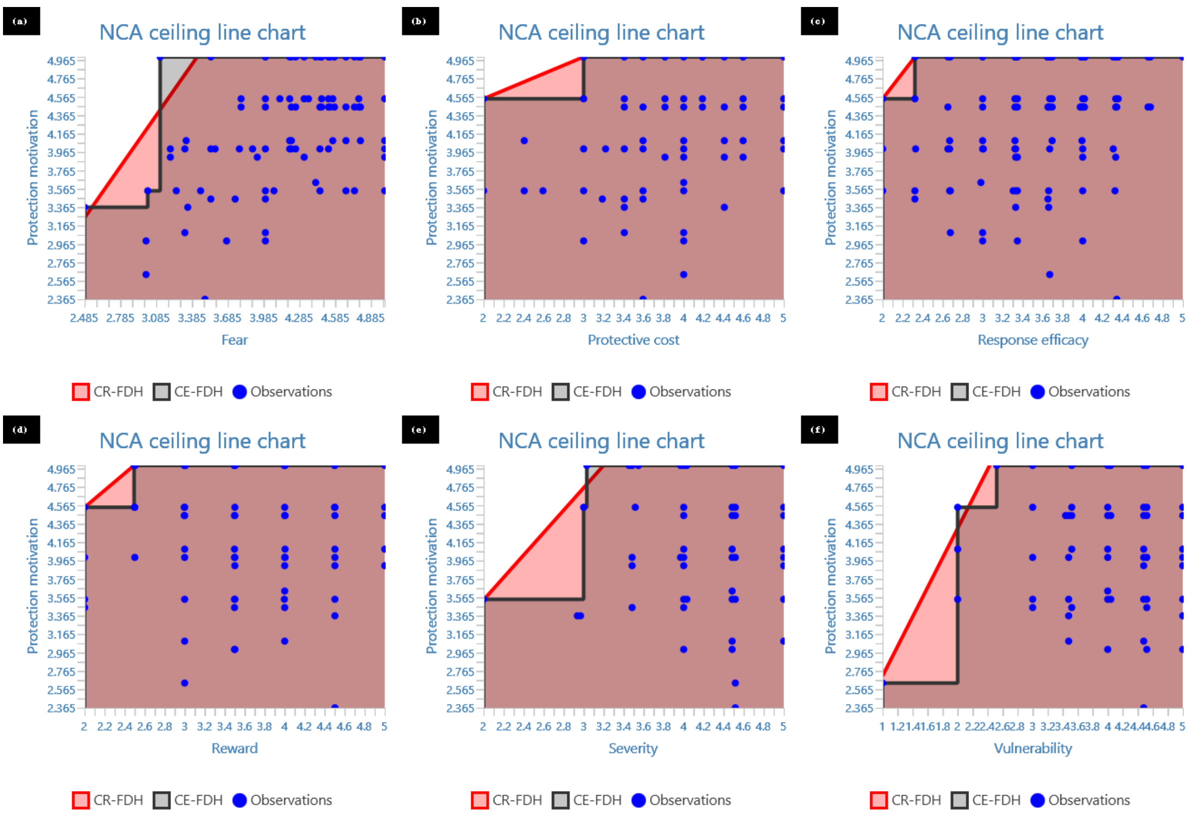


**Figure 3. 10 Bottleneck charts of all necessary variables**

Figure 3.10 is the ceiling line chart, visually representing the bottleneck table. Still, it further shows us the distribution of our data points under the Ceiling Envelopment with Free Disposal Hull (CE-FDH) line. For discussing the necessity logic base given in Table 3.2, For each desired level of outcome in protection motivation given in the first column, the other seven columns show the minimum values required for our predictors (Fear, Protective cost, Response efficacy, Reward, Self-efficacy, Severity, and Vulnerability). According to Table 3.2, to reach the 3.419 level of Protection motivation, the 3.014 level of Fear must be achieved; otherwise, no outcome is guaranteed. It is important to note that to increase the protection motivation from 3.419 to 3.683, we must increase the value to Fear up to 3.118, which is a bottleneck. The bottleneck is well untestable from the CE-FDH breaks in Figure 3.10 (a). The other bottleneck values are shown by underlining in Table 3.2. We cannot increase protection motivation from 80% to 90% for Vulnerability until we increase the vulnerability level from 3.00 to 3.031.

### 3.4.6. Importance-Performance Map Analysis

Importance-Performance Matrix Analysis (IPMA) helps evaluate the results of our PLS-SEM and NCA. This approach allows us to gauge the performance of each construct related to farmers' displacement choices in the context of the 2022 Sindh floods, quantified on a scale from 1 to 5 for importance and 1 to 100 for performance. IPMA juxtaposes the total effects as importance with the average latent variable scores as performance to pinpoint key determinants necessitating interventions for more results of a construct in future research.

Table 3.4 offers insights into the importance of our predictors, performance parameters, and outcome variables. 'Fear' emerges as the most crucial determinant, showing the highest priority at 0.489, yet it occupies a slightly lower position in performance, ranking third with a score of 77.55. Following closely, 'Response efficacy' stands as the second most significant factor, marked by a score of 0.324 in importance. However, it exhibits a stark contrast in its performance, achieving a mere 53.809 and highlighting a critical area needing immediate amelioration. 'Severity,' despite its lower importance at 0.100, excels in performance, clinching the top spot with a score of 89.133, suggesting that while it is performing exceptionally well, it might not necessitate urgent attention due to its relegated importance in the larger scheme of factors.

**Table 3. 4 Importance and Performance of construct against the outcome (Protection motivation)**

| Construct | Importance | Ranking | Performance | Ranking |
|---|---|---|---|---|
| Fear | 0.489 | 1 | 77.55 | 3 |
| Response efficacy | 0.324 | 2 | 53.809 | 6 |
| Severity | 0.100 | 3 | 89.133 | 1 |
| Protective cost | 0.057 | 4 | 67.444 | 5 |
| Vulnerability | 0.036 | 5 | 80.66 | 2 |
| Self-efficacy | 0.024 | 6 | 35.432 | 7 |
| Reward | 0.003 | 7 | 72.381 | 4 |

Conversely, 'Response efficacy' and 'Self-efficacy' are identified as pivotal areas demanding focused interventions in future research, as their performance rankings at 6th and 7th do not align with their recognized importance. The constructs 'Protective cost,' 'Vulnerability,' 'Self-efficacy,' and 'Reward' exhibit variability in performance and are placed lower in terms of importance, with 'Self-efficacy' in particular pinpointed as a potential area for substantial improvement, given its low-performance score of 35.432. Figure 3.11 presents the Importance-Performance Map Analysis (IPMA) in a plot (see Figure 3.11) showing the same data presented in Table 3.4.

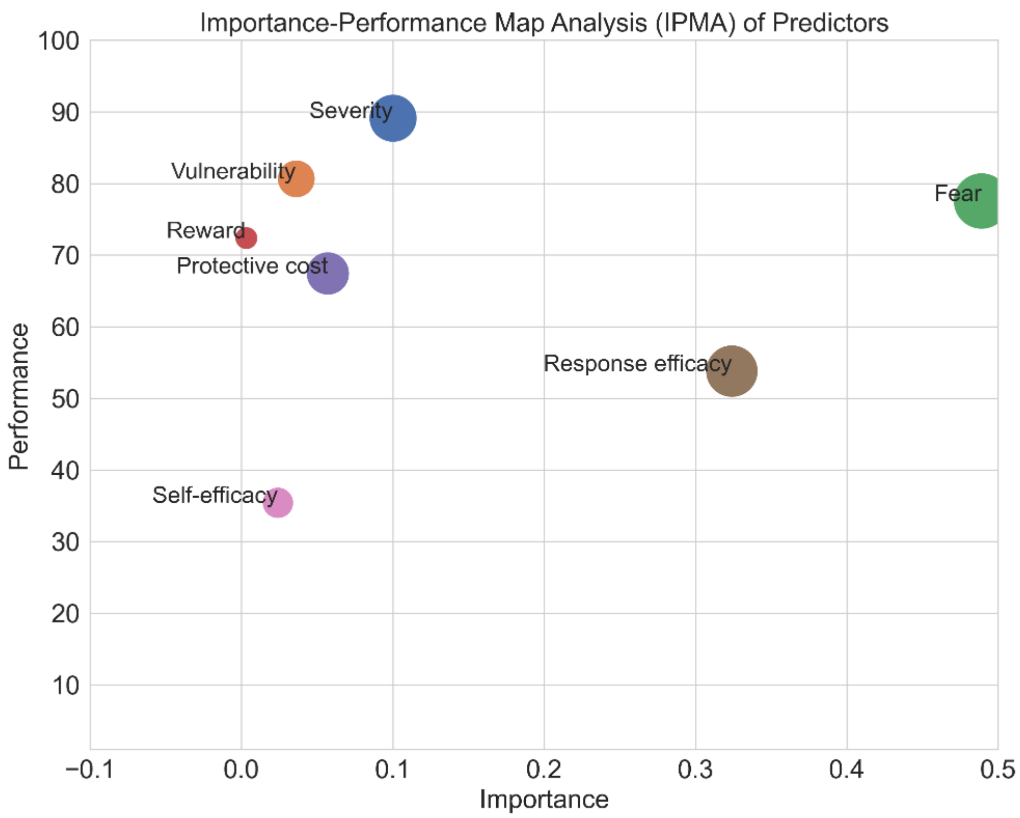


**Figure 3. 11 Importance-performance map of constructs used in the model**

## 3.5. Discussion

### 3.5.1. Criticality of Fear and Protective Cost from PLS-SEM

The results of this study have two main implications. Firstly, from PLS-SEM, Protective Cost and Fear emerged as significant determinants for Protection Motivation among farmers, indicating that the economic feasibility of relocation and emotional factors are vital in shaping displacement decisions. These significant relationships underscore the importance of designing disaster management policies that address financial and psychological aspects. Our results align with the findings of Faruk and Maharjan (2022), who identified Fear as a decisive factor in flood adaptation. Secondly, the observed insignificance of Severity and Vulnerability in influencing Protection Motivation is noteworthy and contradicts some previous applications of PMT (Ansari et al., 2022; Tasantab et al., 2022). This discrepancy could be attributed to the unique socio-economic context of Sindh province, which warrants further in-depth analysis to unpack the underlying reasons.

Meanwhile, our model explains about one-third of the variance in Protection Motivation. Acknowledging the presence of other potential contributing factors not accounted for in the current model is imperative. This realization opens up prospects for future research, aiming to achieve a more comprehensive understanding of the elements influencing Protection Motivation.

### 3.5.2. Necessity of Fear and Response efficacy in Farmers' displacement from NCA

We found Fear and Response efficacy are the necessary conditions for having enough protection motivation for deciding on displacement in floods. Foremost, "Fear" emerges as a critical determinant in influencing farmers' Protection motivation. Faruk and Maharjan (2022) and Weyrich et al. (2020) reported similar findings on the role of Fear. Our results suggest that as the inherent Fear or apprehension about the potential flooding increases, the likelihood of farmers considering protective measures or displacement also heightens. This aligns with the intuitive understanding that visceral emotional reactions, like Fear, can profoundly influence decision-making processes, especially in high-stakes situations like natural disasters.

Moreover, our findings suggest that a threshold level of Fear is required to activate protection motivation. This could imply that until farmers reach a certain level of apprehension or threat, they might not be prompted to take action. Our CE-FDH and bottleneck analysis identified Response efficacy as the necessary predictors, but this merely determines its one value sufficient for being motivated to its maximum. We recommend that response efficacy should be studied further by future researchers. This construct should be deconstructed with more items and an extended measurement scale.

### 3.5.3. Complexity of farmers' displacement dynamics

Based on the combined results of PLS-SEM and NCA, we found the complex dynamics influencing farmers' decisions to displace during the flood, complementing the findings of some previous studies on flood risk (Baishakhy et al., 2023; Budhathoki et al., 2020; Hair et al., 2022; Holstead et al., 2017; Pham et al., 2019; Richter et al., 2022). The significant impact of Fear underscores the importance of psychological drivers in such decisions, resonating with the broader literature on disaster-induced displacements. On the contrary, the limited role of Protective Cost in the PLS-SEM suggests that economic considerations might be secondary or interlinked with other factors. The noticeable difference between PLS-SEM and NCA outcomes for Vulnerability highlights the necessity of using complementary methodologies to derive a comprehensive understanding. Specifically, the pronounced effect size of Vulnerability in NCA suggests its potential as a conditional factor whose influence might manifest only under specific circumstances. Our analysis, therefore, not only contributes to the existing body of knowledge on Protection Motivation Theory but also underscores the significance of methodological diversity in drawing robust conclusions in the realm of post-disaster farmer displacements. It is important to note that PMT is just one of many frameworks that can be used to understand displacement behavior during floods. Other factors that may influence displacement behavior include the impact of floods on crop production, the vulnerability of rural households to climate change and hazards, and the impact of displacement on food security and livelihoods (Babcicky & Seebauer, 2019; Tasantab et al., 2022; Weyrich et al., 2020).

### 3.5.4. Hierarchical Influence of PMT elements

PLS-SEM and NCA results accentuate a hierarchy of influences among the PMT elements. Specifically, "Severity" and "Protective cost" consistently appear as primary drivers of protection motivation. This hierarchy suggests that certain factors within the PMT are more pivotal than others in shaping individuals' motivations to protect themselves. Notably, the borderline significance of "Self-efficacy" and "Reward" in the NCA analysis underscores the importance of methodological choices in research. Different analytical techniques might yield varying insights into the same dataset, highlighting the need for a comprehensive and multifaceted approach to understanding complex phenomena as the results lose divergent significance across methods.

### 3.5.5. Reassessing Financial Factors and Redundancy of Self-efficacy

On the other hand, variables such as "Protective cost" and "Reward" showed no significant influence on protection motivation. Surprisingly, this could mean that the financial implications or potential benefits of displacement (Weyrich et al., 2020) may not be primary considerations for farmers. One could argue that the intrinsic value of safety, land attachment, or historical ties to their farmland might overshadow monetary or tangible rewards. In the intricate web of factors influencing farmers' displacement decisions during flood risks, "Response efficacy" plays a crucial role in assessing farmers' belief in the effectiveness of displacement as a preventive measure against floods. This belief is paramount; when farmers are convinced that relocation will safeguard them from the looming threat of floods, their propensity to move increases, highlighting the critical need for effective communication about the benefits of displacement in times of flooding.

Our investigation uncovers a potential phased progression in protection motivation formulation. The early stages primarily hinge on Vulnerability, but as the intensity augments, other factors like Fear and Severity gain prominence. Surprisingly, specific predictors, such as self-efficacy, remain absent across higher thresholds, raising questions about their fundamental role in this context. The amalgamation of various elements at the 4.737 threshold hints at a sophisticated interrelationship among them.

### 3.5.6. Role of Vulnerability

The findings revealed that Vulnerability, Severity, and Fear are key variables shaping displacement choices of flood-affectees in Sindh. The redundancy of Self-Efficacy indicates that it may not be a crucial factor in these circumstances. Moreover, the considerable impact of Vulnerability highlights its essential role in the decision-making process. These outcomes underscore the need to holistically address vulnerabilities and threat perceptions to devise targeted interventions for affected populations. Given the observed patterns, policymakers and practitioners could prioritize addressing vulnerabilities and understanding the magnitude of threats for effective response strategies. Future research might also explore why constructs like Self-Efficacy remained insignificant, contradicting previous studies (Faruk & Maharjan, 2022; Westcott et al., 2017).

### 3.5.7. Balancing Emotional and Practical Considerations via IPMA

The Importance-Performance Matrix Analysis (IPMA) elucidates the importance and performance of determinants influencing farmers' decision-making during flood events. The Severity of an imminent flood appears as a dominant factor, highlighting farmers' heightened sensitivity towards the potential destructiveness of such events. Though the emotion of Fear remains significant, it's somewhat overshadowed by other factors, suggesting a balancing act between emotional and practical considerations, such as protective costs and potential rewards. These insights hint at an underlying cost-benefit analysis farmers undertake before deciding on displacement. Less influential yet relevant factors include Response efficacy and Vulnerability, pointing toward farmers' trust in mitigation measures and their flood risks. Surprisingly, Self-efficacy, representing personal capability in managing displacement actions, isn't a primary concern. To effect meaningful interventions in Sindh, addressing these predictors is crucial, especially the Severity of floods with the protective measures and potential rewards.

### 3.5.8. Limitations of the study

This study's revelation of factors influencing farmers' displacement decisions amidst the 2022 Sindh floods must be contextualized within its methodological and situational limitations. The extreme temperatures during data collection likely imposed a physiological burden on respondents, raising concerns about the potential impact on their responses, which could skew the Severity of and Vulnerability against flood threats. The sample, restricted to farmers directly affected by displacement, may not encapsulate the full spectrum of flood responses among Sindh's diverse socio-economic and geographical profiles, thereby limiting the generalizability of the findings. The analytical approach, anchored in linear assumptions through PLS-SEM and NCA, may not do justice to the intricate and often non-linear patterns of human behavior in the face of natural disasters. Moreover, while robust, the theoretical lens of Protection Motivation Theory may not entirely capture the unpredictability and complex array of factors shaping human responses in such crises. Consequently, the study's insights, while significant, offer a snapshot that is necessarily partial and context-bound, signaling the need for further research that would extend the demographic reach, incorporate richer methodological diversity, and embrace a broader theoretical perspective to more accurately reflect the multifaceted nature of displacement decisions under the duress of flooding.

### 3.6. Conclusion

The practical implications of the insights of our study are profound for disaster management strategies. By recognizing the necessity thresholds for crucial motivators such as Fear and Response efficacy, interventions on these variables can be more precisely targeted to cultivate a protective motivation at various levels of urgency. As elucidated in our data, the delineation of 'bottleneck' values provides actionable benchmarks for policymakers to prioritize resources and education that enhance farmers' propensity to take protective action. This evidence reinforces the importance of nuanced, multifactorial approaches in understanding and influencing farmers' protective behaviors in disaster-prone regions, ultimately contributing to more effective disaster risk management and mitigation strategies. We substantiate these practical implications based on the following takeaways from this study;

This research aimed to evaluate the necessity and sufficiency of the predictors that influence farmers' decisions to relocate during flood occurrences. Our study utilized a combination of PLS-SEM and NCA to examine the factors motivating farmers to protect themselves against the floods that occurred in Sindh, Pakistan, in 2022. Fear and Response efficacy are necessary for the decision to displace among the various factors considered. These two predictors satisfy the theoretical and statistical criteria of necessity and demonstrate a positive correlation with protection motivation, with coefficients of 0.45 and 0.39, respectively, for different levels of protection motivation engaging distinct predictors. For lower levels of protection motivation, no single factor is needed. However, specific predictors become critical as the desired threshold of protection motivation increases. Notably, Vulnerability is required to achieve moderate protection motivation (2.892), while Fear becomes essential at a higher threshold (3.419). Beyond this point, the convergence of multiple predictors is required, with Severity joining the list at 3.683 and various factors, including Protective cost and Reward, becoming necessary for the highest motivation levels (above 4.737). These results indicate that a broader array of conditions must be met for significant elevation in protection motivation, emphasizing the complexity of the decision-making process during disasters. Interestingly, Self-efficacy did not emerge as a necessary condition at any level, suggesting that it may function more as a supporting factor rather than a critical determinant in the context of flood-induced displacement.

## Chapter 4: Climate change perception, adaptation, and constraints in irrigated agriculture in Punjab and Sindh, Pakistan.

**Abstract**

Pakistan's irrigated agriculture suffers from climate change due to its high exposure to extreme events and the low adaptation of its farming systems. Understanding the human aspects of adaptation decisions in a vulnerable climatic environment is integral for policymakers who want to enhance farmers' adaptive capacity. This study investigates how farmers perceive climate change and what adaptation strategies they consider. Furthermore, we assess the enabling and constraining factors influencing farmers' adaptation decisions. We conducted in-person interviews with 800 farmers spread out across Pakistan's irrigated districts of the Punjab and Sindh provinces. We used a standardized questionnaire to gather primary cross-sectional data, which we analyzed with descriptive statistics. The results show that farmers in the Indus Plain have noticed changes in climate extremes along with longer summer and shorter winter seasons during the last ten years. Most farmers are aware of adaptation options and have already applied some measures. However, the dominant adaptation strategies differ between regions. The farmers in Punjab primarily adapted crop and farm management, while farmers in Sindh focused on implementing irrigation measures. In both provinces, farmers regarded rainwater harvesting as the least desirable adaptation strategy. The main constraints in the region are a lack of financial resources, water scarcity, and poor soil fertility. The availability of financial capital and climatic conditions primarily influence farming decisions. Our findings can help policymakers design better policy instruments that account for farmers' perceptions, motivations, and constraints and are thus more effective in promoting sustainable farming practices in Pakistan.

**Keywords**: Climate change perception; adaptation; constraints; irrigated agriculture; Indus plain; Pakistan

### 4.1. Introduction

Pakistan is highly vulnerable to climate change because of its arid meteorological conditions (Schilling et al., 2013a). In 2020, Pakistan was ranked the fifth most highly affected country in the global climate risk index from 1999 to 2018 (Eckstein et al., 2019). In Pakistan, 38.5% of the labor force is engaged in agriculture, contributing 19.2% to the country's GDP in 2020

(Maqbool et al., 2022). The country's agricultural sector faces severe challenges from rising temperatures, droughts, floods, and low crop yields (Ahmed & Schmitz, 2011). Studies reporting future climate projections show further climatic variation leading to increasing vulnerability in the region (Easterling et al., 2000).

The productivity of staple crops such as wheat and rice has been estimated to decrease by 6–8% and 16–19%, respectively, under the B2 and A2 storyline scenarios in Special Report on Emissions Scenarios (SERS) (Abid et al., 2019; IPCC, 2014; Nakicenovic, 2000). For instance, agricultural yields have declined, and crop diseases have increased in the southern part of Punjab due to climate extremes like floods, droughts, and heat waves (Ishfaq et al., 2019). Without adequate adaptation measures in cultivation practices, climate change is likely to reduce crop yield further and increase hardships for the farming community. Therefore, effective adaptation strategies are needed to cope with the consequences of climate change (Shaffril et al., 2018). Effective adaptation strategies face many challenges (Bryan et al., 2013) and depend on farmers' risk perception and adaptative behavior (Abid et al., 2019; Talanow et al., 2021). The farmers' adaptation decisions are not simple and face several constraints and environmental drivers (Robert et al., 2016).

The agricultural sector in Pakistan has been the focus of a large body of scholarly research on climate change perception and adaptation strategies. However, the empirical evidence for these publications is restricted or limited to fewer agro-ecological units, making it challenging to unearth an accurate picture of perceptions and adaptation strategies related to climate change and challenging to develop effective policy (Abid et al., 2015; Abid et al., 2019; Abid, Schilling, et al., 2016b; Abid, Schneider, & Scheffran, 2016; Ali & Rose, 2021; Gorst et al., 2018; Salman et al., 2018; Sargani et al., 2022; Syed et al., 2022). Covering both Punjab and Sindh for the field survey can produce a holistic understanding of the entire irrigated agricultural area of the Indus Plain.

To close this gap, we studied Punjab and Sindh provinces, which cover 89% of the total irrigated plains of the Indus River (Hasan et al., 2021). We conducted a field survey of a significantly larger area with a larger sample size (n = 800) in the irrigated agriculture of Pakistan's Punjab and Sindh provinces. We did a field survey of a significantly wider area with a larger sample size (n = 800) spread across the irrigated agriculture of Punjab and Sindh province of Pakistan. In this study, we analyze farm-level perception, adaptation, constraints, and factors of adaptation in the upper and lower irrigated plains of the Indus basin. Mainly, we answer the following three questions;

1. How do farmers perceive climate change and its impacts on agriculture?

2. Which adaptation options do they know, and what is their adoption status in the study area?
3. Which factors and constraints influence farmers' adaptation decisions?

## 4.2. Data and methods

### 4.2.1. Research design

We applied a quantitative research approach and developed a questionnaire to collect the data through face-to-face interviews with farmers from December 2021 to April 2022. We included small farmers with landholding up to 16 acres (Hussain & Thapa, 2012) in the irrigated plains of Punjab and Sindh, Pakistan. We employed a sampling frame of 800 farmers from 10 districts covering 39 Tehsils/Talukas (district's subunits) with 80 samples from each district. Figure 4.1 shows the geographical location of our survey. In addition, we did not include farmers with landholdings outside of canal command areas in our surveyed districts.

### 4.2.2. Description of the study area

The Indus Basin Irrigation System (IBIS) covers 16.85 million hectares (Mha). It consists of the Indus River and its tributaries; Kabul, Jhelum, Chenab, Ravi, Beas, and Sutlej (shown in Figure 4.1). For irrigation control, the IBIS comprises three significant reservoirs, 12 inter-river link canals, and 44 main canals (Hasan et al., 2021; Steenbergen et al., 2015). The region has the world's most extensive irrigation system, where almost 80% of the cultivated area is irrigated (Muhammad et al., 2016), producing 90% of the country's harvests (Zhu et al., 2013b).

We chose the irrigated areas of Punjab and Sindh provinces, covering major rivers except for Kabul, all link canals, and 39 main canals. Out of 16.85 Mha, 7.8 Mha of Punjab is irrigated with the help of 25 canals, two reservoirs, and seven barrages, while 5.3 million hectares of Sindh are irrigated with the help of three barrages and 14 canals. We selected this study area for two reasons; first, it contributes considerably to the country's agricultural output and is vulnerable to climatic change. The area shares borders with neighboring India from the east and the Khyber Pakhtunkhwa (KPK) and Baluchistan provinces from the west. It is approximately 40% of the total area of Pakistan, where 74% of the country's total population lives.

The soil of these plains comprises alluvium deposits accumulated by the river actions of the Indus River and its associated tributaries in the geological past. This soil property makes the area fertile for agricultural purposes. Pakistan is among the world's top ten producers of cotton, sugarcane, wheat, mango, dates, and Kinnow (citrus). Major crops (rice, cotton, wheat, and sugarcane) alone contribute 4.9% of Pakistan's economy. However, water resources in the region are highly stressed, whether judged by per capita water availability or by the ratio of withdrawals to runoff (Archer et al., 2010). The mean average temperature in Punjab ranges from −2° to 45 °C, and exceptionally reaches 50 °C in summer and drops down to −8 °C in winter. In Sindh, temperatures rise above 46 °C from May to August and drop to 2 °C in winter. The interior of lower Sindh experienced up to 53.5 °C in 2010, the fourth-highest reading ever recorded in Asia (Abbas et al., 2018; Daniel Huber & Jay Gulledge, 2011). Recent calculations in 2021 estimate a decreasing precipitation trend all around Pakistan with − 1.11 mm/year (Ali et al., 2021). Most of the regions in Punjab province receive moderate to high rainfall ranging from ~ 275 to 830 mm/year, while Sindh province receives ~150 to 180 mm/year. The amount of rain declines if we approach from north to south.

The elevation of the Indus plains varies from 300 meters in northern Punjab to 75 meters near the southern border of Punjab, down to the Arabian Sea. The slope fall rate in the plains is 0.3 meters per 1.6 km (Khan, 2016). The lower Indus Plain is part of Sindh province, the second largest province in population. Figure 4.1 shows the Digital Elevation Map of the area where we conducted our fieldwork. The area of both provinces is mainly agricultural, which is under stress due to the region's lack of rain and desertification trends.

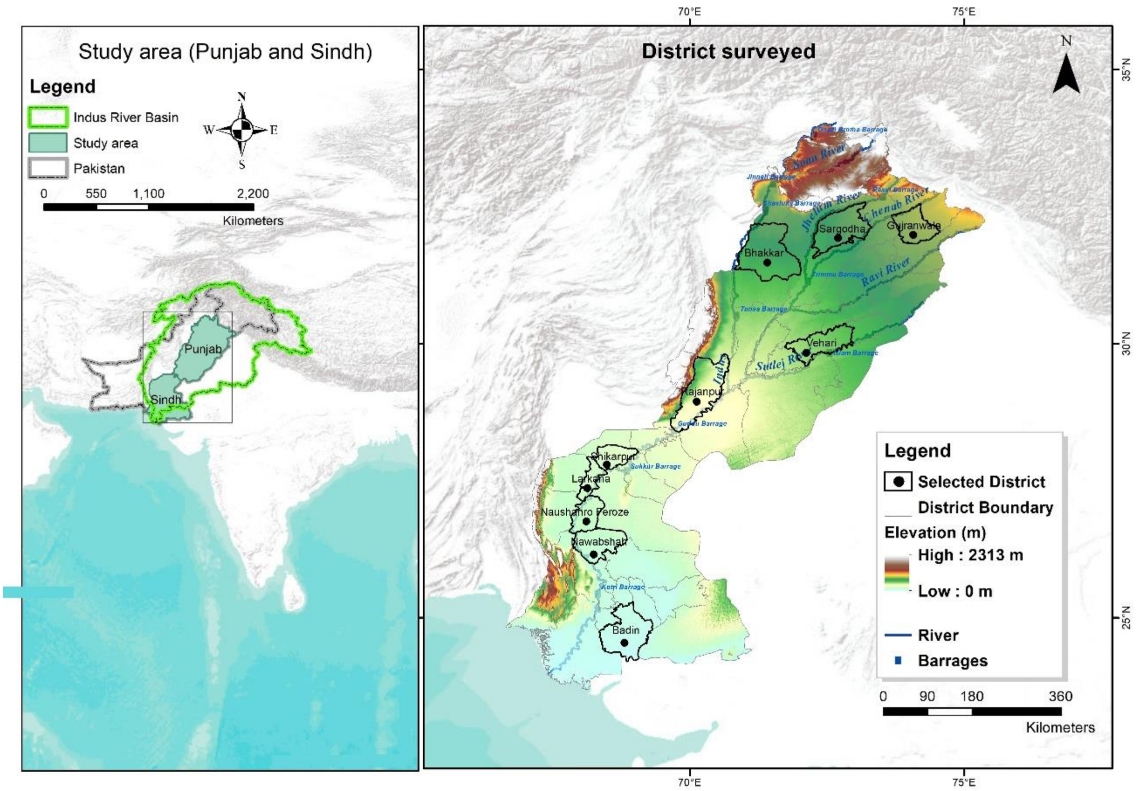


**Figure 4. 1 Digital Elevation Model (DEM) of the study area**

### 4.2.3. Population and sampling

Small farmers (with landholdings ≤ 16 acres) cultivating irrigated areas of Punjab and Sindh were the population under study. In Pakistan, 80% of farmers own 28% of cultivable land. There are 7.4 million small farmers in Pakistan who hold less than 12 acres of land (5 hectares) (Naseer et al., 2016). We chose small farmers because they are important to Pakistan's agriculture for several reasons. Firstly, most of them live in rural areas and make their living through agriculture. Secondly, small landholdings are so common throughout the country. Therefore, they are so important for a country's food security. Thirdly, small farmers are often the ones most affected by economic shocks and natural disasters because they don't have the money or credit that commercial farmers do. Therefore, small farmers are important for promoting sustainable farming practices because they depend more on natural resources and have more at stake in keeping them around for future generations. These small farmers are distributed in the entire IBIS of Punjab and Sindh province, which have 66 (36+30) districts. We used a multistage spatial cluster sampling strategy to select the respondents from these districts. Table 4.1 contains the distribution of our interviewees in our selected locations.

In the first stage, we chose an equal number of districts from both provinces. We selected five districts from Punjab and five from Sindh based on the physiographic and irrigation control of the provinces. We used the Punjab and Sindh physiographic and irrigation maps to select districts. Punjab plains are divided into four interfluves, while Sindh has relatively uniform physiography. In Punjab, Terbela and Mangal reservoirs provide water for irrigation. In Sindh, Guddu, Sukkur, and Kotri Barrage irrigate its agricultural land.

In Punjab, we randomly selected at least one district from each interfluve. We selected Bhakkar from Sagar doab, Vehari from Bari doab, Sargodha from Chaj doab, Gujranwala from Rachna doab, and Rajanpur from the lowermost part of Punjab. Terbela Reservoir controls the irrigation of Bhakkar, Vehari, and Rajanpur, while Mangal controls the irrigation of the Sargodha district. Sindh province has not had much physiographic heterogeneity in its irrigated areas. Therefore, in Sindh, we selected districts based on irrigation-controlling structures. We selected Shikarpur from the Guddu Barrage, Badin from the Kotri Barrage, and Larkana, Naushahro Feroze, and Shaheed Benazirabad from the Sukkur Barrage.

In stage two, we covered all Tehsils and Talukas (Sub-unit of the district) in every district and visited a total of 39 Tehsils. In stage three, we randomly selected mauzas (the smallest revenue-collecting unit in Pakistan) based on the best spatial coverage of the Tehsil. In the last stage, we selected farmland and the respondents for the interview based on our convenient road connectivity to reach any farmer. Overall, 800 and precisely 80 farmers from each district were interviewed. We interviewed a minimum of 10 and a maximum of 35 farmers from each Tehsil, but our target for each district was 80 interviews. The number of Tehsils in each district is different, which varies the number of interviews in each Tehsil. Table 4.1 shows the valid samples in every district and tehsil which we included in the study.

**Table 4. 1 Valid Sample details from every Tehsil and Taluka**

| Province | Districts | Tehsils/Taluka | Valid Sample |
|---|---|---|---|
| Punjab | Sargodha | Sargodha | 12 |
| | | Bhalwal | 23 |
| | | Sahiwal | 32 |
| | | Shahpur | 13 |
| | Bhakkar | Bhakkar | 25 |
| | | Mankera | 22 |
| | | Darya Khan | 20 |
| | | Kallur Kot | 13 |
| | Gujranwala | Gujranwala | 07 |
| | | Wazirabad | 24 |
| | | Noshera | 17 |
| | | Kamoke | 32 |
| | Rajanpur | Rajanpur | 29 |
| | | Jampur | 26 |
| | | Rojhan | 25 |
| | Vehari | Vehari | 24 |
| | | Mailsi | 35 |
| | | Burewala | 21 |
| Sindh | Badin | Tando Bago | 24 |
| | | Matli | 17 |
| | | Badin | 25 |
| | | Golarchi | 14 |
| | Larkana | Larkana | 08 |
| | | Rato Dero | 22 |
| | | Shahdad Kot | 13 |
| | | Dokri | 23 |
| | | Kambar Ali | 14 |
| | Shaheed Benazirabad | Nawabshah | 33 |
| | | Daulat Pur | 23 |
| | | Sakrand | 24 |
| | | Garhi Yasin | 23 |
| | Shikarpur | Shikarpur | 23 |
| | | Khanpur | 15 |
| | | Lakhi | 19 |
| | Naushahro Feroze | Naushahro Feroze | 14 |
| | | Bhiria | 28 |
| | | Kandiaro | 26 |
| | | Moro | 12 |
| **Total** | | | **800** |

### 4.2.4. Development of questionnaire and data collection

Similar to previous studies (Abid, Schilling, et al., 2016b; Bhalerao et al., 2022; Bhalerao et al., 2021), we developed a standardized questionnaire comprising 51 questions to study our research question. We divided perception into 16 questions, adaptation into 18 questions, constraints into eight questions, and decision-making variables into nine statements.

We subdivided the perception part into the following categories: Perception about climatic indicators (CI), Perception about soil (SO), Perception about climatic hazards (CH), Perception about farming (FA), and Perception about water (WA). We categorized adaptation into three categories; Crop management (CM), Farm management (FM), and Irrigation management (IM). We adapted these categories from the adaptation paradigm model of farmers (Zobeidi et al., 2022). We grouped the constraints section into Human constraints (HCO) and Natural constraints (NCO), while factors of decision-making are classified as Climatic Factors (CF) and Non-climatic Factors (NF).

We then asked the respondents to rate each of these items on a five-point Likert scale ranging from strongly disagree to strongly agree. The scale contains a neutral option in the middle of disagreement and agreement. The Likert scale is a psychometric response scale in which respondents indicate their level of agreement with a statement ranging from strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5) (Robinson, 2014). In addition to survey data, we used smartphone GPS applications to gather coordinates of the farmland to provide a more accurate spatial representation of our inquiries.

At the start of the questionnaire, we added a section of basic socio-demographic information about our respondents. Figure 4.2 shows our respondents' education, farming experience, and secondary occupation.

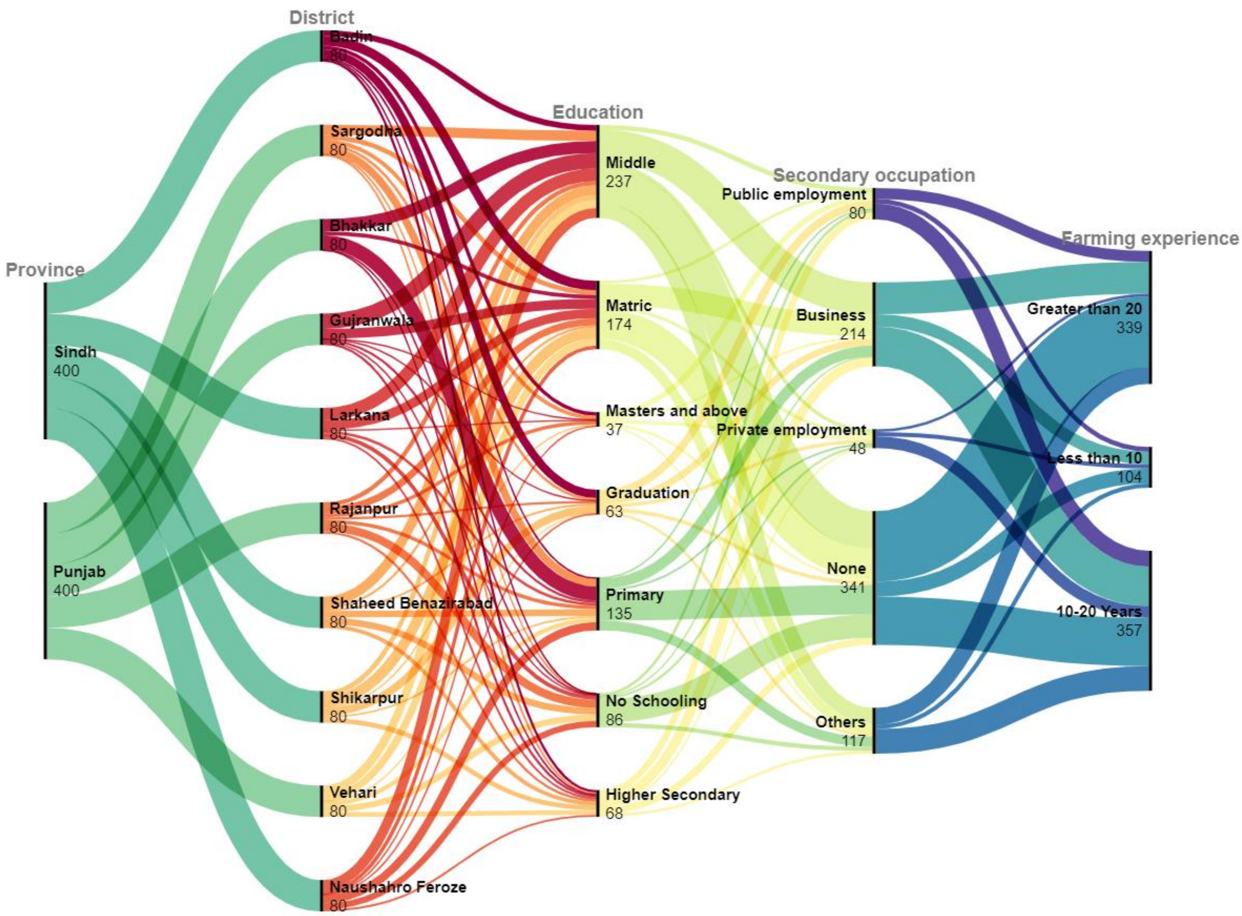


**Figure 4. 2 Socio-demographic traits of respondents**

Before field visits, we provided off-field and in-field training to the enumerators. We briefed them regarding the objective of our study and data collection methods. We conducted five online interviews with farmers in the Gujranwala district to pre-test the questionnaire. We paraphrased the questions statements and added measurement units of area and distance with the open-ended questions based on the pre-test results.

We were able to collect 913 questionnaires in total. However, out of 913 questionnaires, we rejected 113 because of their multiple quality issues, such as double entries (27), incomplete (19), respondents' misconduct (44), and legibility issues (23). In the end, we were left with 800 questionnaires for our analysis.

### 4.2.5. Data analysis

We used the Statistical Package for the Social Sciences (IBM SPSS Statistics; Version 28.0.1.1) for data tabulation and coding. We employed the Likert package in RStudio for the Likert plots and analysis and ArcGIS 10.8 to map the Digital Elevation Model (DEM) and the spatial distribution of adaptation in our study area. DEM Shuttle Radar Topography Mission (SRTM) was applied with a spatial resolution of 3 arcsecs (~90 m) as input, derived from C-band images obtained during 11-22 February 2000 flown over the study area. The DEM dataset was downloaded from USGS Earth Explorer using the link: https://earthexplorer.usgs.gov/. We used an open-source online platform, i.e., https://app.rawgraphs.io/, for alluvial visualization (Figure 4.2) of the socio-demographic information of our respondents.

To explore the respondents' perceptions of climate change, we prepared the Likert scale data into SPSS. We imported this data into RStudio for the Likert plot, which ranked respondents' perceptions from low to high (Figure 4.3). A similar method was used to plot the adaptation (Figure 4) on a five-point scale. To investigate the adaptation level, we recorded the data from a five-point scale of adaptation to a four-point scale ranging from no adaptation to low, medium, and high (see Figures 4.5 and 4.6). We summarized the score of all crop, farm, and irrigation management items and plotted results (Figure 4.7) to understand the trends in different adaptation categories. To explore the spatial variation of adaptation in the study area, we calculated the mean for the adaptation levels of every Tehsil and mapped it (Figure 4.8). We separated the number of adaptors and non-adaptors in crop, farm, and irrigation management (see Table 4.2) in Punjab and Sindh province. To analyze constraints and factors of decision-making, we used the same ranked Likert plots by using the Likert package in RStudio (Figures 4.9 and 4.10).

## 4.3. Results

### 4.3.1. Farmer's perception of climate change and its impact

More than 94% of farmers perceive the lengthened summer (CI-1) and shortened winter (CI-2) (Figure 4.3). About 65% of the farmers noticed an increase in the summer temperature, while 26% believed the winter temperature increased. 76% of respondents agreed that the frequency of rainy days (CI-5) has increased, as 76% of our respondents agreed with our statement.

Regarding the perception of climate change impacts on soil (SO), 71% of farmers noticed a decline in soil fertility (SO-2), while 58% perceived salinity problems in the soil (SO-1) over the last ten years. Regarding the Perception of Climatic Hazards (CH-), farmers believed heat waves (CH-2) to be the most common climatic hazard, with 92% agreeing. In comparison, 55% of farmers saw frequent flooding and drought (CH-1) as their region's most common climate extremes. Regarding the impacts of climate change on farming, 87% perceived low crop yields (FA-1) due to climate change over the last ten years. We also found perceived changes in the cropping calendar. 49% of farmers noticed delays in sowing during Rabi and Kharif (FA-2, FA-4) season. The same percentage of farmers (49%) perceived that the harvesting in the Kharif season has also been delayed in the last ten years.

Interestingly, our results reveal that the vast majority of the farmers (more than 90%) perceived changes in the climatic indicators. However, only half of the respondents (49%) could translate these changes to their cropping calendar. Finally, regarding climate change's effects on water quality, we found that 73% believed groundwater quality has deteriorated. In comparison, 72% of the respondents' irrigation water quality has declined over the last ten years.

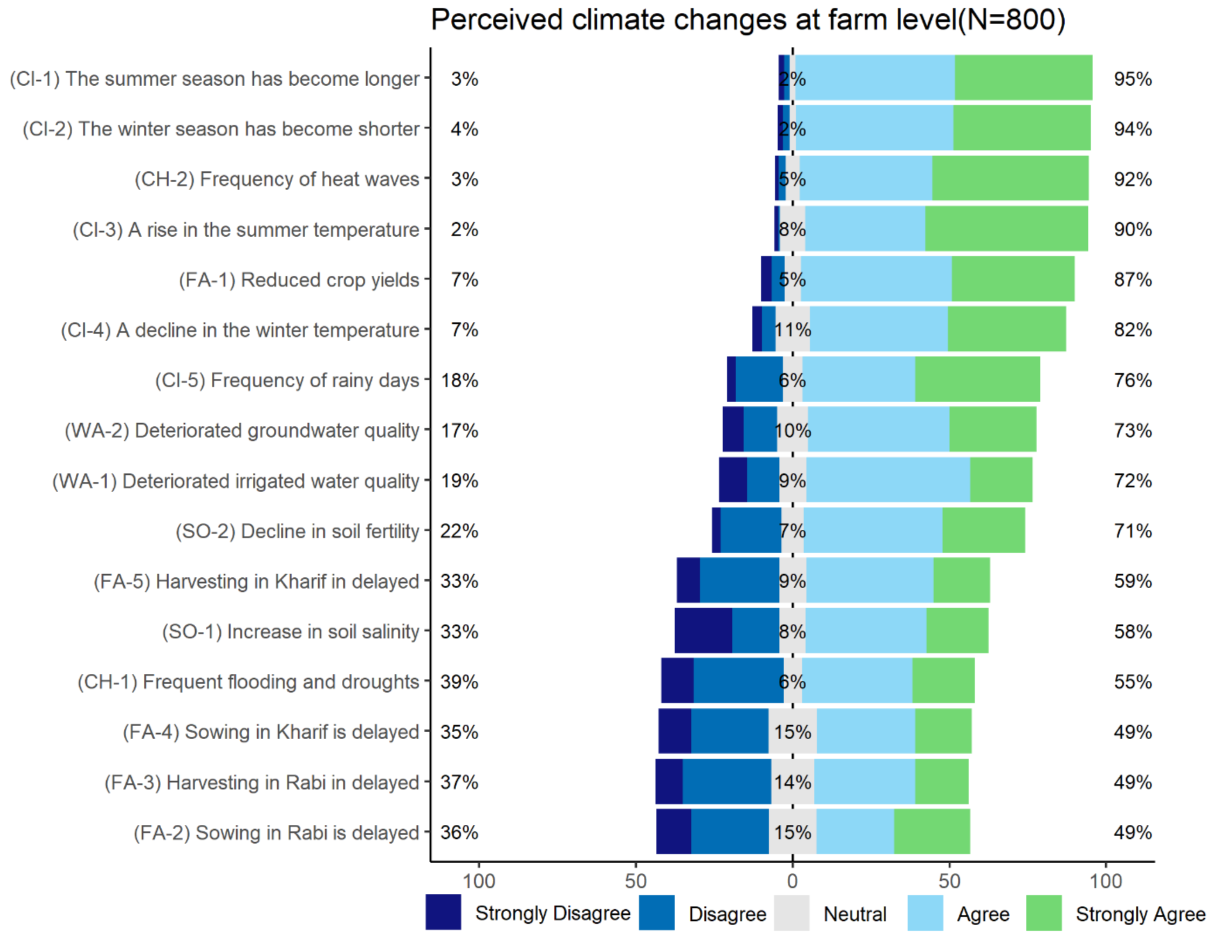


**Figure 4. 3 Perception of climate change impacts**

### 4.3.2. Adaptation measures and their implementation

Our results show that most farmers (60%) have adapted to changes in their cultivation techniques (see Figure 4.4). They started using hybrid seeds and shifting to a crop variety that a farmer could harvest early. Due to the recent hike in inflation in Pakistan, farmers have shifted to cost-effective crops (56%). The farmers prioritized cheaper seeds rather than their higher productivity. More than half of the farmers (53%) changed their fertilizers. However, the underlying reason for fertilizer change was inflation or the marketing of fertilizer and pesticide companies.

As the study area was the irrigated region of Pakistan, rainwater harvesting is not even known to most farmers. Few farmers are just aware of the practice but are not applying it. Cultivating salt-tolerant crops has been introduced by some agriculture research institutes, especially in the Punjab region. However, most people (56%) are unaware of them, and some are aware but unable to implement them on their farms. Regarding Irrigation-related management (IM), canal dredging (IM4) is the most widely implemented (55%) adaptation practice. Tube well installation has been adapted by 46%, while almost half of them cannot install it due to its high economic cost. In some areas, local modification of irrigation rules (IM5) is in practice (19%), but most farmers are unaware of it. Only 25% are applying plantation on the farm (FM4).

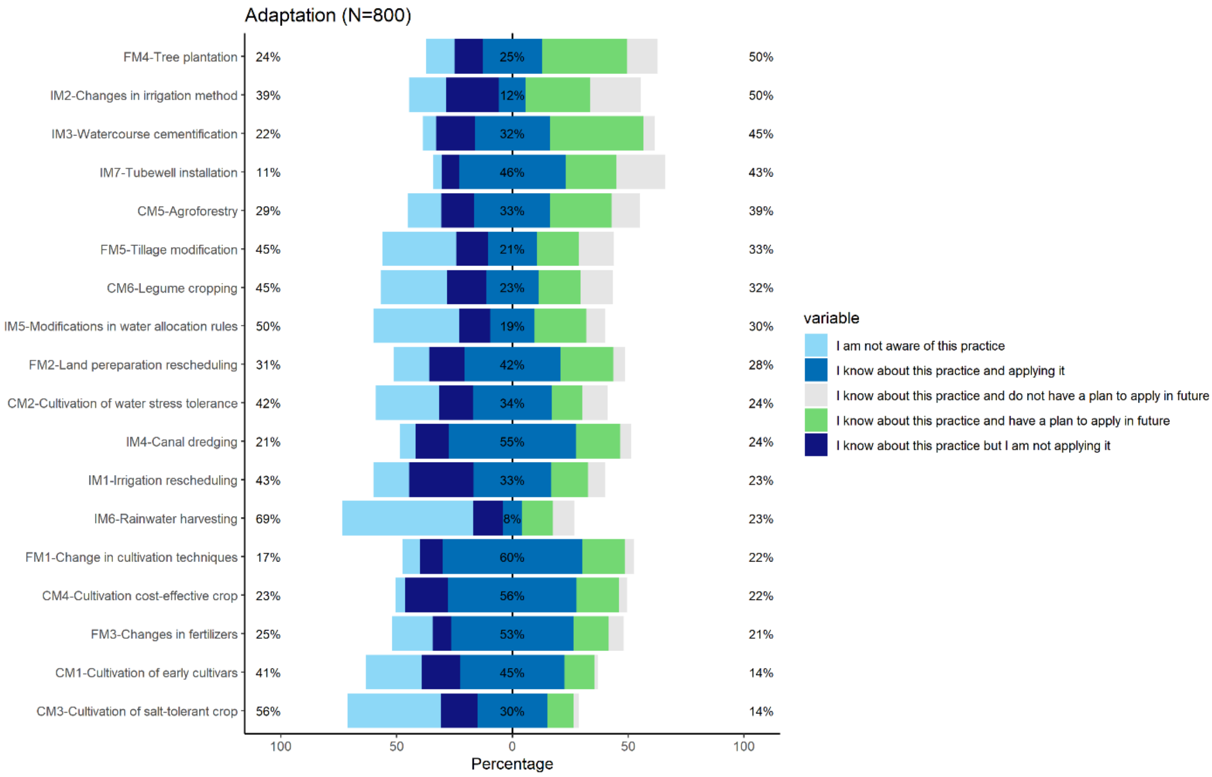


**Figure 4. 4 Implementation of adaptation strategies**

### 4.3.3. Adaptation level in Punjab and Sindh

Figures 4.5 and 4.6 compare the adaptation levels in both provinces (Punjab N=400 and Sindh N=400) in our study area. To represent the degree of adaptation, we categorized adaptation into no adaptation, low, medium, and high adaptation levels in crop, farm, and irrigation management adaptation practices.

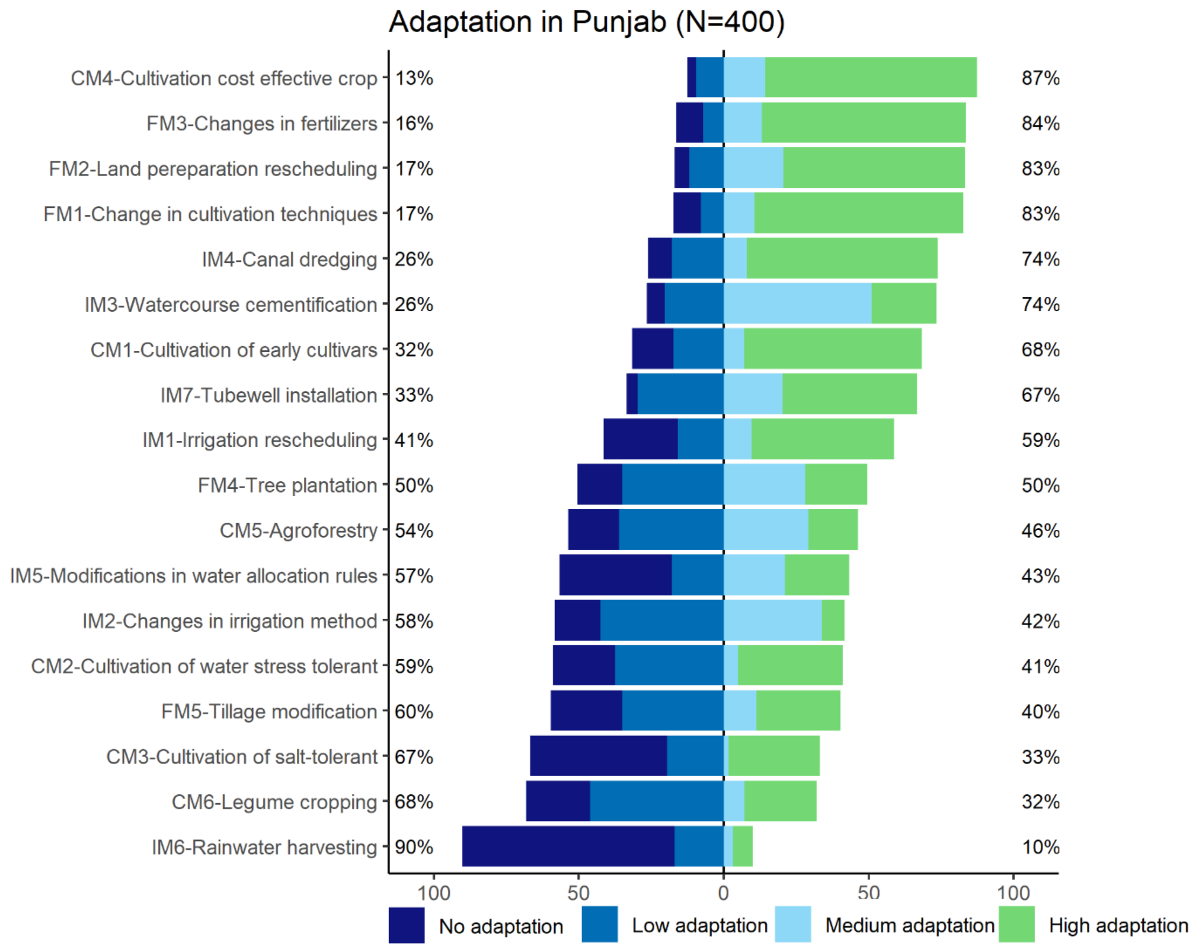


**Figure 4. 5 Adaptation strategies and levels in Punjab**

In Punjab, the overwhelming majority (87%) practice cost-effective cropping (CM4), 84% tried different fertilizers (FM3), and 83% adapted changes in the scheduling of their farmland preparation (FM2). Regarding the least practiced adaptations, only 10% adapted to rainwater harvesting (IM6), 32% adapted through legume cropping (CM6), and 33% sifting to salt-tolerant cropping (CM3).

Farmers in Punjab adapted early cultivars (68%). The agriculture of Punjab is more market-oriented than that of Sindh because 87% of the farmers in Punjab adapted to cultivate cost-effective crops, while this percentage is 60% in Sindh (see Figure 4.6).

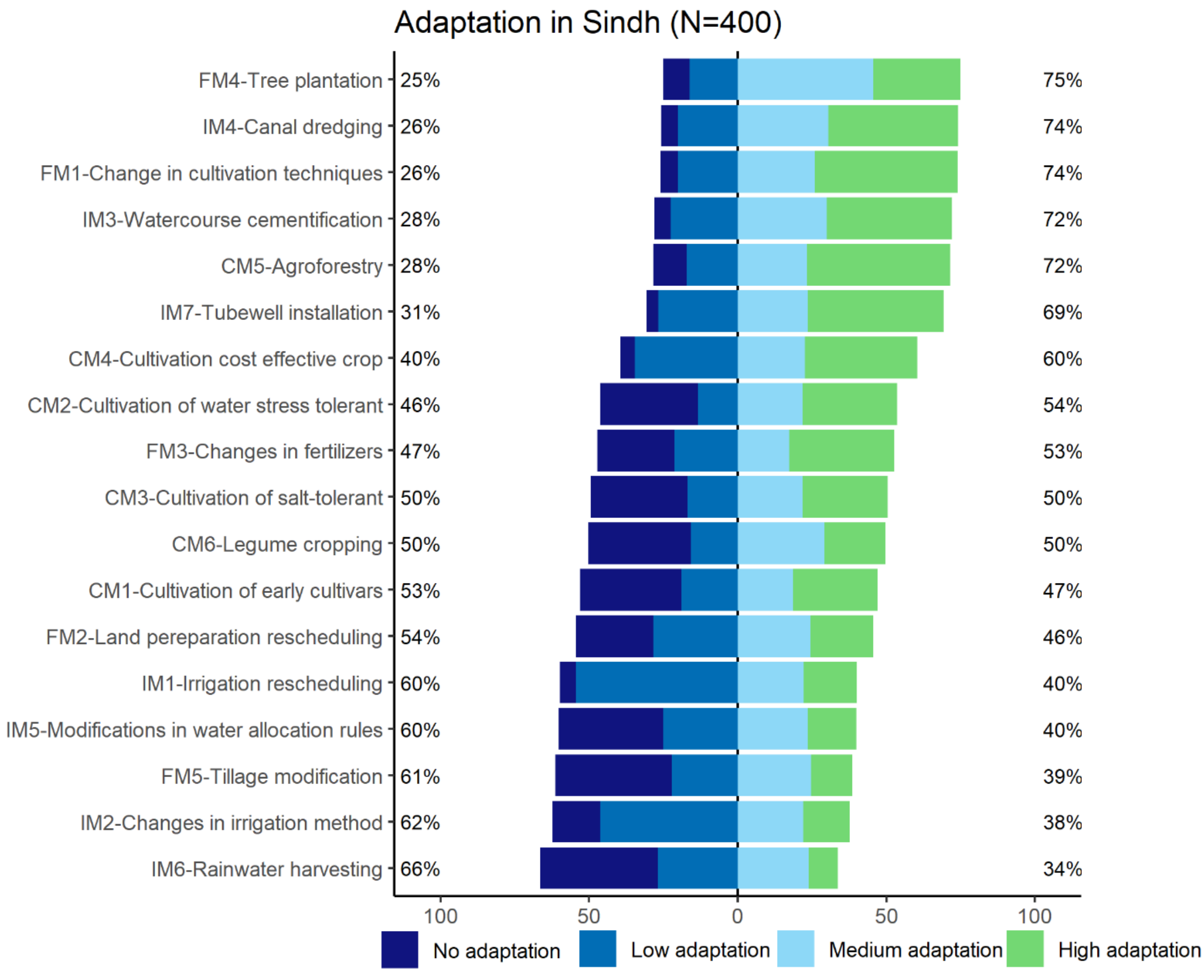


**Figure 4. 6 Adaptation strategies and levels in Sindh**

In Sindh, 75% adapted with on-farm tree plantation (FM4) due to intense heat waves during recent times, 74% applied canal dredging (IM4), and 74% adapted through changes in cultivation techniques (FM1). On the other hand, only 34% apply rainwater harvesting (IM6), and 38% change their irrigation methods (IM2). In addition, almost 40% are employing tillage and water allocation rules. Table 4.2 shows our field survey data on individual adaptation practices by farmers in the Punjab and Sindh provinces. Here, we show both provinces' adaptors and non-adaptors in crop, farm, and irrigation management. In Sindh, tree plantation (75%) and agroforestry (72%) are better adapted than in Punjab (50% and 46%, respectively). It is because of the heat waves and hotter summer in the region where the temperature touches 52 to 53$^{o}$C.

**Table 4. 2 On-farm adaptation in Punjab and Sindh, Pakistan**

| **Adaptation** | | **Punjab (n=400)** | | **Sindh (n=400)** | |
|---|---|---|---|---|---|
| Crop Management | Code | Adaptors | Non-Adaptors | Adaptors | Non-Adaptors |
| | CM1 | 343 | 57 | 264 | 136 |
| | CM2 | 314 | 86 | 268 | 132 |
| | CM3 | 210 | 190 | 269 | 131 |
| | CM4 | 389 | 11 | 381 | 19 |
| | CM5 | 330 | 70 | 355 | 45 |
| | CM6 | 312 | 88 | 262 | 138 |
| | Avg. | 316 | 84 | 300 | 100 |
| Farm Management | | | | | |
| | FM1 | 363 | 37 | 377 | 23 |
| | FM2 | 381 | 19 | 296 | 104 |
| | FM3 | 364 | 36 | 296 | 104 |
| | FM4 | 338 | 62 | 365 | 35 |
| | FM5 | 301 | 99 | 243 | 157 |
| | Avg. | 349 | 51 | 315 | 85 |
| Irrigation Management | | | | | |
| | IM1 | 298 | 102 | 379 | 21 |
| | IM2 | 337 | 63 | 336 | 64 |
| | IM3 | 376 | 24 | 379 | 21 |
| | IM4 | 367 | 33 | 378 | 22 |
| | IM5 | 244 | 156 | 259 | 141 |
| | IM6 | 105 | 295 | 242 | 158 |
| | IM7 | 386 | 14 | 385 | 15 |
| | Avg. | 302 | 98 | 337 | 63 |

Figures 4.7 (a) and (b) compare adaption in the provinces of Punjab and Sindh. Farmers in Punjab switched to farm management strategies rather than irrigation. Adaptive crop management practices are also more common in Punjab than in Sindh. In irrigation management, however, farmers in Sindh (337) adapted better than those in Punjab (302). Table 4.2 and Figure 4.7 (a) show our findings from individual adaptation measures.

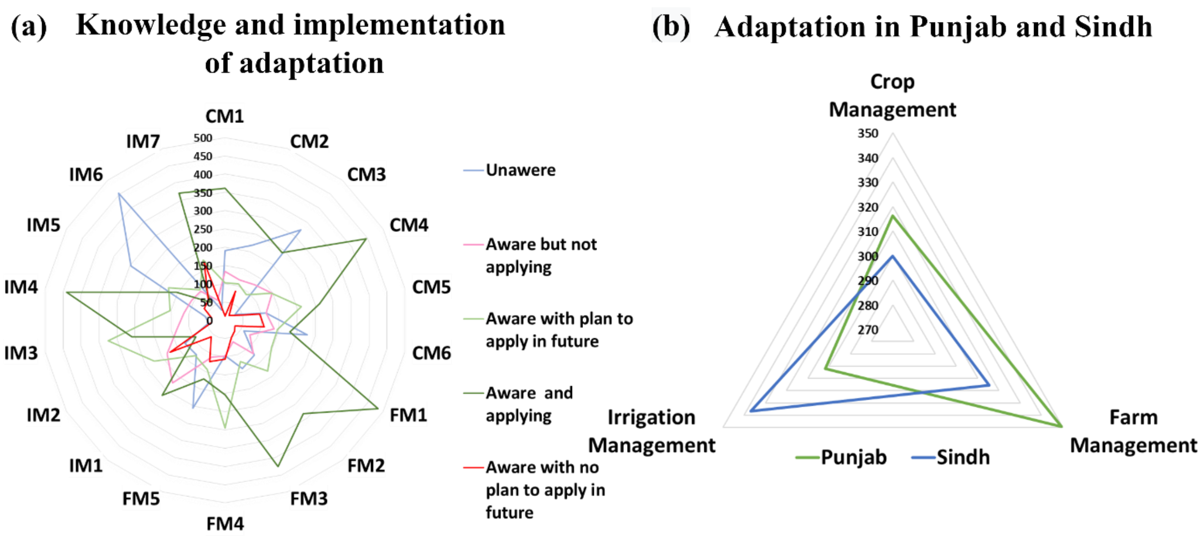


**Figure 4. 7 (a and b) Provincial comparison of adaptation levels in different categories**

The map below (Figure 4.8) shows our study units' spatial distribution of adaptation actions. In our study area, we plot the computed adaptation score of crop management, farm management, and irrigation management for 39 spatial units (Tehsils and Talukas).

In crop management, the northernmost (Gujranwala) and the southernmost (Badin) districts have the highest adaptation, while the southern Punjab region (Vehari and Rajanpur) has very low or no adaptation. In Farm management, the two northern districts in Punjab province (Gujranwala and Sargodha) showed the highest adaptation score. District Vehari in Punjab is again found to have low adapting strategies at the farm. Interestingly, irrigation management is the highest in Gujranwala and medium in Rajanpur. District Bhakkar (half desert) was the lowest in adapting irrigation-related adaptation strategies. There is no clear trend in the lower Indus plains (Sindh), which shows a mix-up of all possible adaptation scores (low to high).

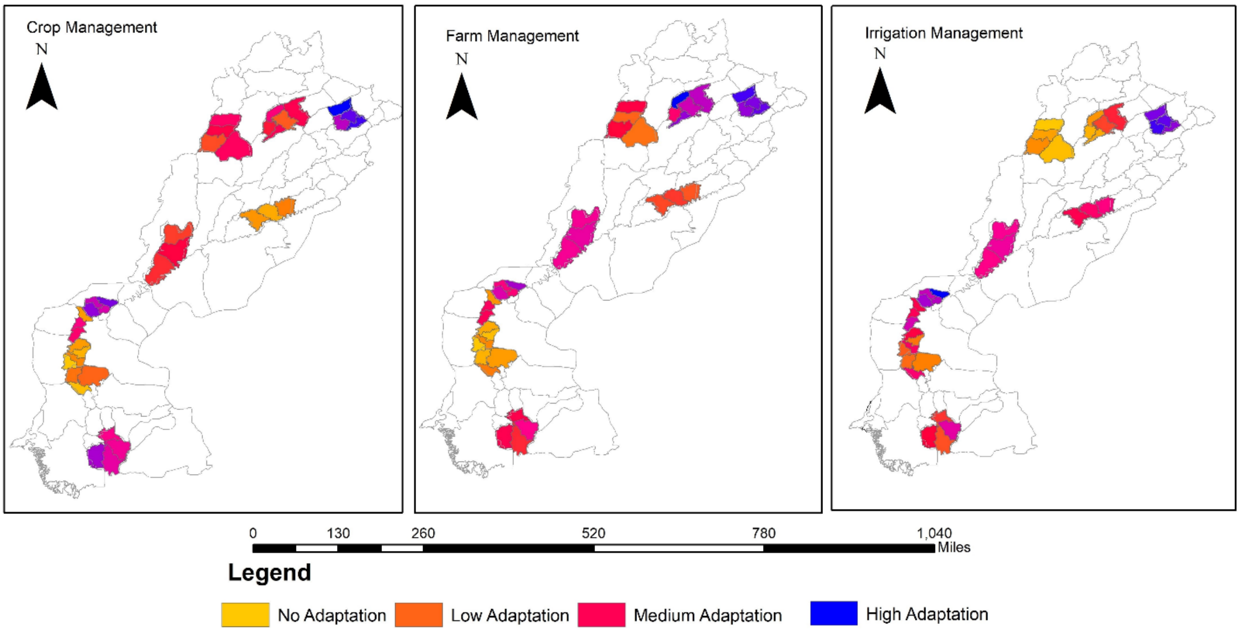


**Figure 4. 8 Spatial distribution of adaptation strategies in Punjab and Sindh**

### 4.3.4. Constraints and factors in adaptation

Despite having enough realization regarding climate change in our study area, many farmers did not make significant adjustments to their farming. We identified and ranked some constraints preventing farmers from adopting different climate change mitigation strategies. We found that a lack of financial resources (cited by 69% of respondents) was the most significant barrier to adaptation.

We found that Water Scarcity (57%) and poor soil fertility (44%) are second and third if we rank the constraints to adaptation. Figure 4.9 expresses the constraints faced by the farmers in our study area. A previous study found inadequate irrigation supplies and knowledge about appropriate adaptation options were significant roadblocks to the adaptation process (Ali & Rose, 2021). (Shah et al., 2022) recently reported financial constraints (28%), lack of knowledge and information (25%), and inadequate farm resources (23%) in the northwestern province of Pakistan.

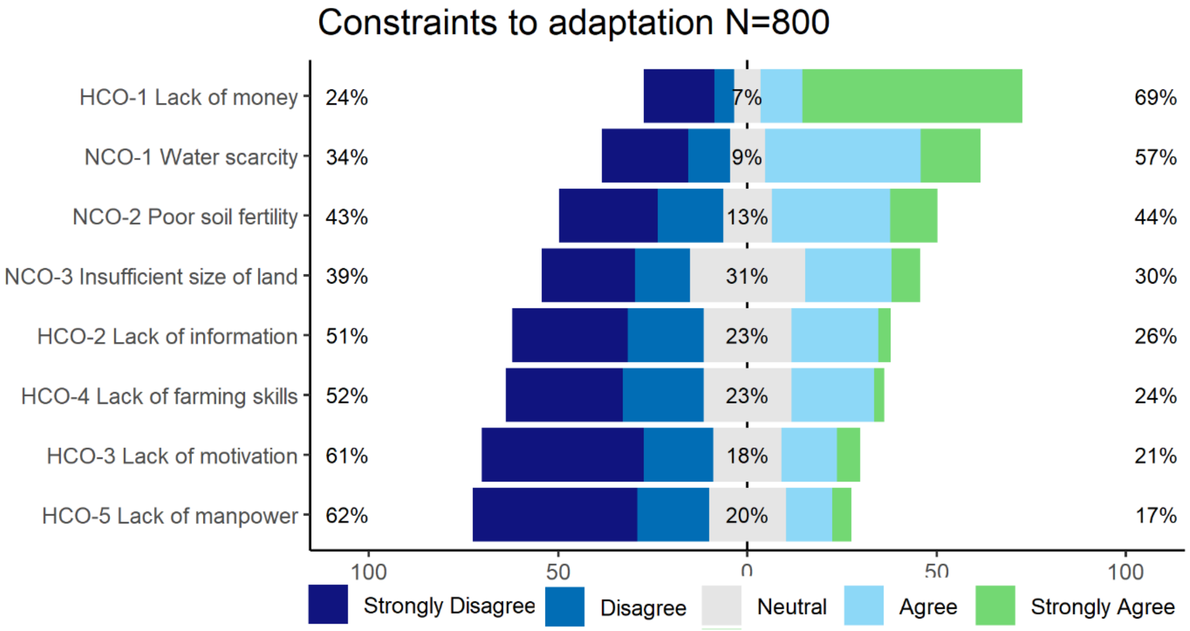


**Figure 4. 9 Constraints to adaptation (HCOs are Human constraints; NCOs are Natural constraints)**

We see factors as variables that influence farmers' decisions. Figure 4.10 shows the ranking of agricultural decision-controlling factors in our study area. We found that money and crop market price (78% and 77%, respectively) are the critical factors controlling farmers' farming decisions in our study area. Interestingly, climatic factors (temperature 70%, rain 68%, water availability 63%, and pest attacks 55%) are secondary if we compare them with money-related factors. According to Bryan Bryan et al. (2013), wealth, access to extension services, credit, and knowledge of the local climate are all factors that affect farmers' decisions to adapt in South Africa and Ethiopia.

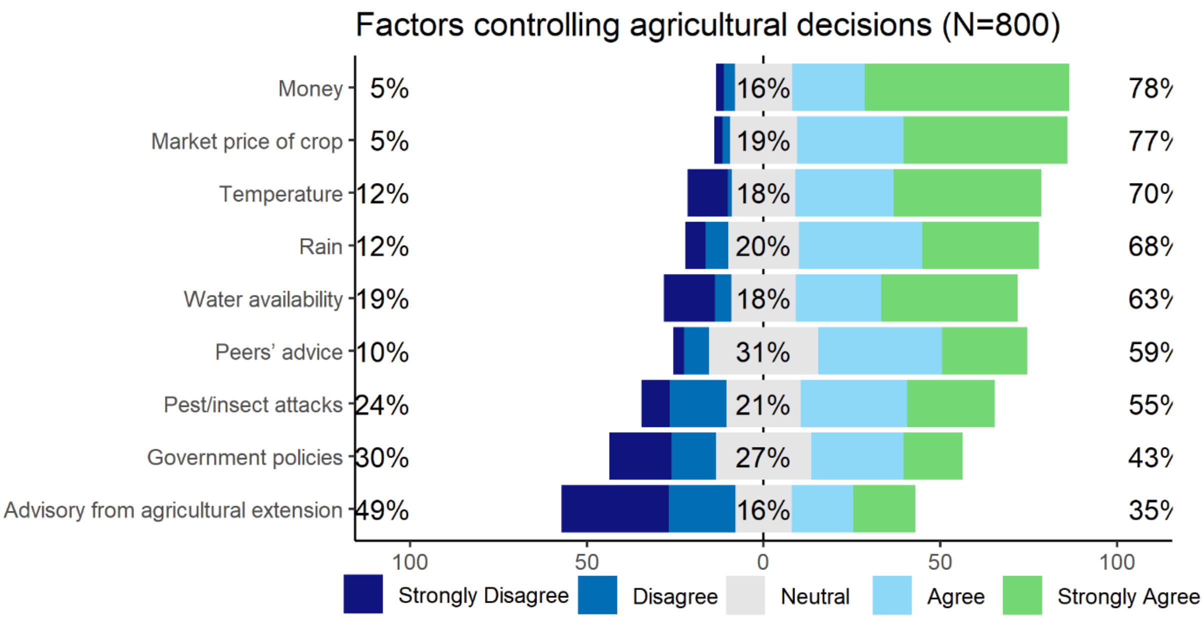


**Figure 4. 10 Factors of farmer's adaptation decision making**

## 4.4. Discussion

Climate change is a daunting challenge for a fragile farming system in Pakistan (Syed et al., 2022). Rising temperatures and shifts in precipitation patterns in the Indus Plains are reported (Mobeen et al., 2017). According to our survey results, farmers in Punjab and Sindh provinces perceive changing seasonal patterns, which is in line with Bhatti et al. (2019). According to Abbas (2013), rising heat waves and more rainy days are severe challenges for agricultural practices in Pakistan. Several studies (Abid et al., 2019; Arshad et al., 2017) have yielded similar outcomes in the last five years. In situ meteorological observations from 1981-2010 also reported extended summers by 4.19 nights and 0.92 days per decade (Abbas, 2013).

Most farmers are well aware of climate change and believe it is one reason for their low crop yield. In addition, most respondents believe climate change is responsible for deteriorated irrigated water and groundwater quality in the last ten years. S. I. A. Shah et al. (2019) also reported the perceived decline in irrigated water quality and groundwater table.

Climate changes and subsequent regional perception shifts influenced agricultural practice in all respects. Especially the effects of climate change on agricultural output in Punjab province have been the subject of extensive research (Abid, Schneider, & Scheffran, 2016; Bashir & Mobeen, 2018), which reported a decline in productivity due to climate change. Scientific literature highlights that climate change is fueling existing problems and creating new ones, such as changes in rainfall and temperature, which are pushing farmers to change their cultivation practices for better results.

Scheffran et al. (2012) investigated this nexus of defining the role of climate change, which was later reported on by Froese and Schilling (2019); Ide et al. (2016).

Adaptation to climate change is a complex process requiring a sound understanding of how farmers perceive and interpret climatic changes locally (Abbas et al., 2022). According to our survey, the awareness of adaptation strategies varies from place to place. Farmers in Sindh are less likely to be aware of improved crop varieties and cultivation methods, which is not the case in Punjab. Therefore, the farmers in Punjab have strongly adapted to salt-tolerant and water-stress-tolerant crop varieties. Farmers in Punjab are also adapted to cultivating early cultivars, especially in upper Punjab. Another contrast is that the agriculture of Sindh is less market-oriented than that of Punjab because 87% of the farmers in Punjab adapted to cultivate cost-effective crops, while this percentage is 60 in Sindh. Tree plantation (75%) and agroforestry (72%) are more adapted in Sindh, while in Punjab, the percentage is 50 and 46, respectively. The underlying cause of this disparity could be heat waves and a hotter summer in the region where temperatures reach 52 to 53 $^{o}$C.

Lack of knowledge regarding adaptation measures is a significant cause of low adaptation rates in rural areas. We found that many farmers in the Indus Plain were unaware of many useful adaptation measures. For example, farmers do not know enough about using salt-tolerant crop varieties, legume cropping, tillage modification, local modification of irrigation rules, and rainwater harvesting. The agriculture extension department should address the lack of awareness by launching an awareness campaign in rural areas.

Many farmers knew the possible adaptation practice but could not apply it despite their positive adaptation intention. For example, cultivation of high revenue-producing crops, irrigation rescheduling, watercourse certification, and new tub well installation are those measures that are well known to most farmers. They want to adopt these measures but cannot do it due to insufficient resources. Therefore, we recommend that governmental financial institutions and banks dispense interest-free loans and subsidies.

An appropriate adaptation strategy needs a clear understanding of farmers' perception of climatic patterns and the drivers and constraints to adaptation (M. Esham & C. Garforth, 2013). However, despite having enough realization regarding climate change in our study area, many farmers did not make significant adjustments to their farming.

Surprisingly, there were a large number of farmers who were well aware of some helpful adaptation practices but were not ready to implement them. We can attribute this adaptation delay to perceived constraints and decision-making factors. Nevertheless, we need to explore this further from the behavioral study viewpoint. In our results, we found that some farmers were not ready to adapt even though they were pretty sure about the benefit of some adaptation measures. For example, farmers avoided ($n = 168$) installing new tube wells to address water shortage due to their high cost. However, they did not apply even the low-cost measures, i.e., Changing irrigation methods ($n = 174$) and local modification of irrigation rules ($n = 65$). The reason behind this behavior is worth exploring for future research regarding climate change adaptation in Pakistan's agriculture sector. Some studies dealt with this behavior as cognitive dissonance of the people (Oswald & Bright, 2022).

The main constraints to adaptation in the study area are lack of money, water scarcity, poor soil fertility, and small landholdings. The fact is in line with the findings of a study (Ali et al., 2020) in different agro-ecological units of Punjab province, which also identified that lack of money, high cost of farm inputs, and lack of knowledge about appropriate adaptations are the most critical constraints in adaptation practices. In another study (Bhalerao et al., 2022) in mountainous regions in India, most farmers (68.1%) indicated that the high cost of agricultural inputs is the most significant constraint, which slows down the adaptation process. Financial resource is a universal factor as it is equally influential all around the globe. Even in the developed world, Australia's major adaptation constraint was high production costs and debt (Brown et al., 2016). These constraints work as a deterrent factor in the adaptation process. On the other hand, larger farmer landholding size, capital, farming experience, farmer education level, soil fertility, water availability, and access to the latest information can positively affect the adaptation process. The lower value of these factors limits the farmer's capability to adapt or act.

We found an evident spatial variation in adaptation levels across the study area. This contrast may be due to farmers' heterogeneous capabilities and constraints across the region. In our findings, the magnitude of constraints is also different in different areas. Lack of financial resources is our study area's most widespread constraint on adaptation. To address this constraint, the government of Pakistan introduced many subsidies and financial loan schemes through banks. However, most farmers were reluctant to use bank credit financing due to high interest rates and cumbersome documentary procedures. Simplifying this loan procurement procedure through banks can help farmers to deal with their problems (Saqib et al., 2016). However, it is reported in the literature that such loans are not used to address agricultural challenges. Instead, they are used for non-farm expenditures like farmers' leisure activities and purchasing household items of daily use (Shabir et al., 2020).

Our findings show poor soil fertility is another critical constraint in the Indus Plain. Low soil fertility is also a limiting factor that deters farmers from adopting new crop varieties. The studies have reported multiple soil nutrient deficiencies in the intensive cropping regions, especially cotton-wheat cropping areas of Sindh (Bux et al., 2022). The soil fertility loss was significantly improved when sustainable soil management and fertilizer treatment were applied in the affected regions of Punjab (Qazi & Khan, 2021). Smaller landholdings are another constraint in adapting new adaptation measures. Saqib et al. (2016) reported that smaller landholdings in Sindh were a significant factor in farmers' low credit access.

Various factors influence farmers' decisions, and there are multiple ways of grouping these factors (Chilonda & Van Huylenbroeck, 2001). We grouped these factors into climatic and non-climatic factors. The farmers rated climatic factors significantly, but financial resources from the non-climatic factor group were found to be the most influential factor influencing their decisions. We also found that the role of government agricultural advisory and government policies significantly influences farmers' decisions. Peer advice is rated more important than advisory services in the region. This is typical of underdeveloped social structures where informal social capital is trusted more than formal, which Escandon-Barbosa et al. (2019) studied.

### 4.5. Conclusion

The farmers in the Indus Plains have a significant perception of frequent heat waves, an extended summer, and a contracted winter. However, half of them can translate this seasonal change into changes in their cropping calendar. They strongly perceive the decline in crop yields in the last ten years because of climate change. Farmers in our study area report a loss of soil fertility and a decline in irrigated water quality. Most farmers are already aware of the majority of adaptation options and have already adopted the measures. In Punjab, the farmers adapted more to crop and farm management; in Sindh, the farmers adapted to irrigation-related arrangements. It indicates that the water problem is more pronounced in the lower riparian region than in the upper riparian region. Future research can explore this variation of adaptation strategies in the Indus Plains. Rainwater harvesting is unknown to most of the farmers in the region. We recommend promoting rainwater harvesting to cope with water challenges, using solar energy for tube wells to deal with energy crises, and integrating credit financing to cope with financial challenges.

Subsidizing cash crops can positively impact farmers' financial capacity, as current cotton subsidies in the south Punjab region have shown. Organic fertilizers (manure use) should be promoted as they incur a meager cost. We found knowledge gaps about some important adaptation options. For example, there is a lack of knowledge about new irrigation methods, legume cropping, and crop varieties. An information campaign with the help of the agriculture extension department can be helpful to close these gaps. We also revealed that some farmers are not ready to adapt despite knowing the benefits of adaptation, and some have delayed their adaptation actions for the future. Exploring the reluctance to make adaptation decisions should be the subject of future research. Constraints and factors, we believe, play moderating roles in the adaptation process. Lack of financial assets, limited water availability, poor soil fertility, inadequate land size, and a lack of information related to adaptation measures were significant constraints at the farm level. We also discovered that money and the market were important factors in Pakistani farmers' decisions. The farmers perceive the role of natural factors (temperature, rainfall, and water availability) as less important than the availability of financial resources. To address the lack of financial resources, timely payment for the crop from the mill owners, credit financing from banks, and subsidies on electricity can show good results.

**Compliance with ethical standards**

**Conflicts of interest:** The authors declare that they have no conflict of interest.

**Acknowledgment**

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# Chapter 5: Sustainable Livelihood Capital and Climate Change Adaptation in Pakistan's Agriculture: Structural Equation Modeling Analysis in the VIABLE framework

## Highlights

- The VIABLE-SEM model explains approximately two-thirds of the farmers' adaptation strategies in the irrigated agricultural regions of Sindh and Punjab, Pakistan.
- Livelihood capital alone accounts for 57% of the adaptation process; other variables, such as farming purpose, investment options, factors, and constraints, appear less important.
- The moderation analysis shows that non-climatic factors negatively influence the relationship between capital and adaptation, while climatic factors positively influence it.
- The presence of influencing factors increases the adaptive capacity of farmers.

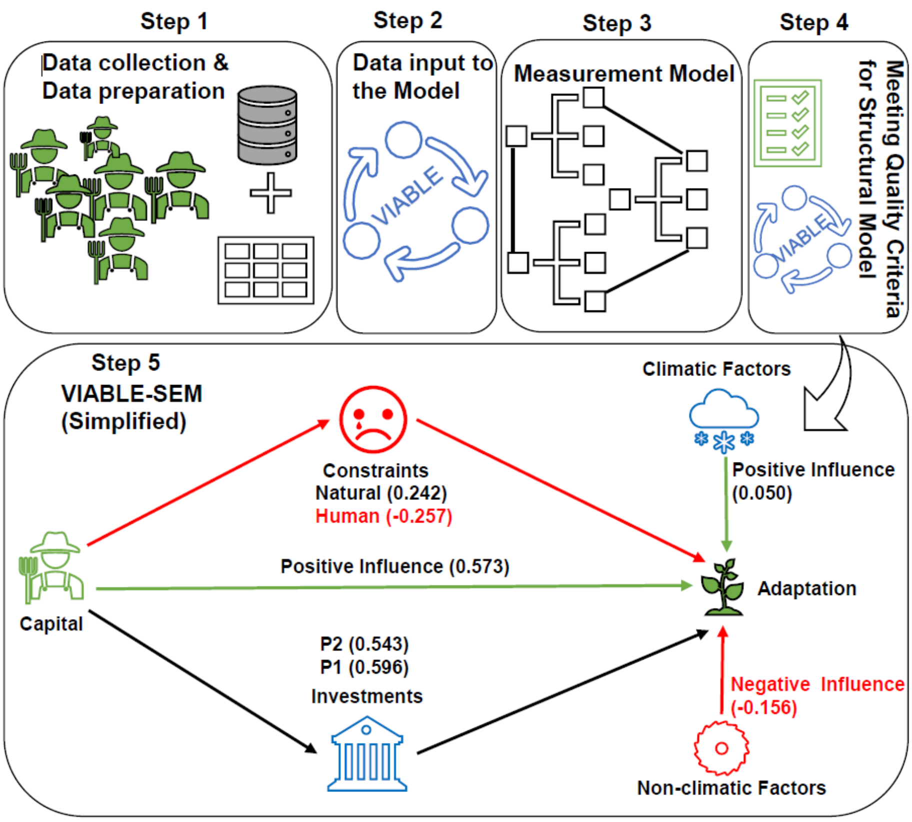


**Figure 5. 1 Graphical Abstract**

**Abstract**

This study aims to assess the role of sustainable livelihood capital, the mediation of investments and farming purposes, and the moderation of climatic and non-climatic factors in the adaptation process, particularly in the aspects of Crop, Farm, Irrigation, and Economic Management. Moreover, guided by the VIABLE (Values and Investments for Agent-Based Interaction and Learning in Environmental Systems) theory, we analyze stakeholders' actions, priorities, and goals in the climate change adaptation process. A structured questionnaire was designed based on a five-point Likert scale covering the concepts of livelihood capital, climate change adaptation, investment priorities, farming constraints, and farmers' decision-making factors. Field data were collected from 800 farmers during December 2021 to February 2022 in the irrigated agricultural regions in the Indus Plain of the Punjab and Sindh provinces, Pakistan. We employed the PLS-SEM approach to the VIABLE framework (VIABLE-SEM) to analyze the collected data. The results confirm livelihood capital as the most significant determinant (beta=0.57, effect size=0.503) for farmers' adaptation strategies in the Indus plain. Other variables, such as the principal purpose of farming, available investment options, natural and human constraints, appear less important. We identified 13 significant viability pathways that show investment priorities, farming purposes, and constraints faced by the farmers in climate change adaptation. The study also found that non-climatic factors negatively influence (beta=-0.156) the relationship between capital and adaptation, while climatic factors positively influence (beta=0.050) this relationship. Interestingly, the presence of these influencing factors increases the adaptive capacity of farmers. These findings have important implications for policymakers and researchers in designing and implementing effective climate change adaptation strategies in Pakistan's agricultural sector.

**Keywords:** Capital, Adaptation, VIABLE framework, Agriculture, Pakistan.

## 5.1. Introduction

### 5.1.1. Climate change adaptation in Pakistan's agriculture

According to the Global Climate Risk Index, Pakistan was ranked as the fifth most climate-affected country from 1999 to 2018 (Eckstein et al., 2019). Climate risk is estimated to increase further if the temperature rises to 2–3° by 2050 (Kreft et al., 2013). The country's agricultural sector is more vulnerable to climate risk due to its reliance on water and temperature (Wheeler & von Braun, 2013). Studies reported that Pakistan already suffers from noticeable impacts of climate change, including floods, droughts, heat waves, and erratic rainfall (Abid et al., 2015; Schilling et al., 2013b). The domestic food supply is already under stress due to reduced crop yields caused by climate change (Ahmed & Schmitz, 2011). Farmers respond to climate change in multiple ways (Osbahr et al., 2010). Adaptation of agricultural practices can reduce losses in rural livelihoods and agricultural productivity thus alleviating adverse effects of climate change (Abid, Schneider, & Scheffran, 2016; Jezeer et al., 2019) on individual farms and agricultural communities (Uttam Khanal et al., 2018; Pandey et al., 2017). While the adaptation of farming practices to climate change is a widespread response in the agriculture sector, not all individuals do it effectively, resulting in unfavorable outcomes (Adger et al., 2005; Evans et al., 2016). The existing body of research requires further exploration into understanding the role of Sustainable Livelihood Capital for climate change adaptation in this critical sector. This is particularly true within the unique context of the irrigated regions of the Indus plain. The aim of this study is to address this deficit.

Many recent studies on climate change adaptation have focused on the agricultural sector (Bryan et al., 2013; Deressa et al., 2011; Deressa et al., 2009; Kato et al., 2011). Some presented climate change assessments on agricultural practice and its productivity (Ali & Abdulai, 2010; Schlenker & Lobell, 2010; Seo & Mendelsohn, 2008) and some on mitigation studies (Bradshaw et al., 2004). This article investigates the role of sustainable livelihood capital, the mediation of investments and farming purposes, and the moderation of climatic and non-climatic factors in the adaptation process by developing the VIABLE framework i.e., Values and Investments for Agent-Based Interaction and Learning in Environmental Systems together. It has three main contributions. First, from a brand-new perspective, the findings from this study based on VIABLE framework reveal that livelihood capital as the most significant determinant for farmers' adaptation strategies in the Indus plain. Other variables, such as the principal purpose of farming, available investment options, natural and human constraints, appear less important. This study identified 13 significant viability pathways that show investment priorities, farming purposes, and constraints faced by the farmers in climate change adaptation. The study also found that non-climatic factors negatively influence the relationship between capital and adaptation, while climatic factors positively influence this relationship. Interestingly, the presence of these influencing factors increases the adaptive capacity of farmers. These findings offer empirical evidence for VIABLE framework which is a supplement for this research domain, and have significant implications for policymakers and researchers in designing and implementing effective climate change adaptation strategies in the agricultural sector of Pakistan. Second, studies with farm surveys are limited to comparatively small areas and sample sizes. To overcome the limitations of small samples, we surveyed a relatively large area of irrigated regions in Pakistan and collected empirical data (N = 800) on farmer's adaptation decisions, their capital, priorities for investing in crop, land, and water, and goals of farming such as profit maximization, subsistence, social status, and competition with neighboring farmers; constraints farmers face; and factors influencing their decision. Third, many studies assess the adaptation process as a linear causal relationship dependent upon one or two variables that ignore the influence of other intervening variables, such as investment priorities, farming goals, and constraints. To address the limits of a linear depiction of adaptation processes, we develop a comprehensive structural equation model based on the VIABLE (Values and Investments from Agent-Based interaction and Learning in Environmental systems) model framework with the role of livelihood capital as a predictor, investment priorities of farmers, farming goals, constraints as a mediator, and factors affecting farming decisions as moderator. Despite a large body of scientific literature on climate change adaptation, only a few studies incorporate other intervening variables like investment priorities, the purpose of farming, and constraints of farming in making adaptive decisions (Esteve et al., 2018). Comprehensive empirical farm-level estimations for understanding the role of these variables are scarce (Bastakoti et al., 2014; Bradshaw et al., 2004). Little is known from previous literature when attempting to model the adaptation process in the presence of multiple variables under the climatic and non-climatic factors of farmers' decision-making. This research aims to address these gaps.

We used a sustainable livelihood framework (DFID, 1999) to explore how livelihood capital can lower climate change risks and vulnerabilities (Baffoe & Matsuda, 2018; Ellis, 2000). This framework identifies five key types of capital (human, social, natural, physical, and financial) that people need to maintain their sustainable livelihoods. We use capital as a cumulative measure that represents human, social, natural, and financial capital as one variable. Capital is the capability of farmers to enable them to make decisions. In adaptation, the capital provides the resources, opportunities, and necessary skills to adapt to the changing climatic conditions, which are strongly linked to adaptive capacity (Bryan et al., 2015). Different types of livelihood capital influence agricultural decision-making and the choice of livelihood strategy (Dehghani Pour et al., 2018; Jezeer et al., 2019; Wu et al., 2017).

In our analysis, we apply the VIABLE framework, which combines actors' capabilities, action priorities, values, and goals along with the feedback they receive in response to their actions and environmental changes (BenDor et al., 2009; BenDor & Scheffran, 2019; Scheffran, 1989).

This study attempts (1) to evaluate the role of Sustainable Livelihood Capital for agricultural adaptation to climate change in the Indus plain; (2) to highlight the pathways of farmers' adaptation options investment priorities, their purpose of farming, and constraints they face in adaptation process; (3) to evaluate the influence of climatic and non-climatic factors on adaptation actions.

## 5.2. Theoretical background

### 5.2.1. Hypothesis Development

The concept of sustainable livelihood framework (DFID, 1999) was used to explore how livelihood capital can lower climate change risks and vulnerabilities (Baffoe & Matsuda, 2018; Ellis, 2000). This framework identifies five key types of capital (human, social, natural, physical, and financial) that people need to maintain sustainable livelihoods. Capital is the capability of farmers to enable them to take a decision. In adaptation, the capital provides the resources, opportunities, and necessary skills to adapt to the changing climatic conditions, which are strongly linked to adaptive capacity (Bryan et al., 2015). Different types of livelihood capital influence agricultural decision-making and the choice of livelihood strategy (Dehghani Pour et al., 2018; Jezeer et al., 2019; Wu et al., 2017). In this study, human, social, natural, and financial capital were combined to form a single variable representing the farmers' capabilities. According to Pretty and Ward (Pretty & Ward, 2001), livelihood capital, investment opportunities, farming goals, financial resources, and other constraints are critical factors for farming decisions. McDowell and Hess (McDowell & Hess, 2012) reported that the endowment with livelihood capital limits adaptation options and increases vulnerability to climatic variability. As we stated, investment priorities, goals, constraints, and factors are equally important. Therefore, a better understanding of these variables can provide a comprehensive policy action to respond to climatic changes (Pandey et al., 2017).

Therefore, we stated our null hypothesis H0 that "No significant relationship is found by taking farmers' capital as an independent variable, investment priorities, farming purpose and as a mediator and factors of farmers decisions as moderator and adaptation as an outcome. For exploring the role of livelihood capital, we state H1 that "Significant relationships exist by taking farmers' capital as an independent variable, investment priorities, farming purpose and constraints as a mediator and factors as moderator and adaptation as an outcome. We refer here study by Malek et al. (2018) which found that farmers' capital investments in more efficient irrigation technologies can significantly improve the agricultural economy, especially in the context of climate change adaptation. Li et al. (2023); Saptutyningsih and Dewi Nurcahyani (2022) highlighted that social capital has the significant role in climate change adaptation actions. These studies provide robust foundation for our hypotheses H0 and H1 testing the role of different factors in climate change adaptation.

To understand the role of intermediate variables, we state our mediation hypothesis H2 as "the Investment options and farming purpose and constraints mediate the relationship between capital and adaptation. The complexity of adaptation process is underscored by several studies. As Lobell et al. (2008) elucidated that investments intended to enhance climate change adaptation tend to be context-specific, favoring certain crops and regions over others. This suggests that the effectiveness of investment options is not uniform but varies depending on the specific context. Furthermore, Okada et al. (2015) provided evidence that investments in water could lead to positive results in crop yield. However, the potential benefits were not without their challenges. Specifically, Ozor et al. (2011) highlighted land as a significant constraint preventing farmers to adapt. Abid, Schneider and Scheffran (2016) identified finances and resources as key adaptation constraints. Collectively, these studies underscore the multifaceted nature of the adaptation process and provide a solid foundation for further investigation of our hypothesis H2. To explore how external factors are influencing the farmers' decisions, we stated our moderation hypothesis H3 as "Climatic factors and Non-climatic Factors moderate the relationship between capital and adaptation." This hypothesis is grounded in the work of Karki et al. (2020) who conducted a study in Nepal and found that both climatic and non-climatic factors posed a significant direct threat to the livelihoods of rural farmers who are heavily reliant on natural resources. However, it is important to note that non-climatic factors also play an important role in shaping adaptation practices. To gain a more nuanced understanding of the moderating effect, we have subdivided H3 into H3a and H3b. Therefore, we state H3a as "Climatic factors moderate the relationship between capital and adaptation" and H3b as "Non-climatic factors moderate the relationship between capital and adaptation.".

### 5.2.2. The VIABLE framework

The VIABLE modeling approach is rooted in viability theory which looks into the development of constrained dynamic systems (Aubin & Saint-Pierre, 2007; Saint-Pierre, 2011). This framework can help to understand decision-making and agent interactions related to adaptation and conflict. This is a modeling technique that examines the evolution of human actions and interactions in constrained dynamic systems. The framework (shown in Figure 5.2) is comprised of five major components: Capability (K), Investments (C), Action paths (A), environmental states (X), and Values (V). In response to the environment, actors invest their capabilities in actions to reduce risks and increase net benefits. The investments may include capital, resources, and financial investments that can be allocated across multiple action pathways based on their priority. Action paths are the strategies by which actors increase their values and accomplish their goals. Actor investments influence the state of the environmental system, and the risk-benefit analysis measures the likelihood of conflict and the need for adaptation (BenDor & Scheffran, 2019).

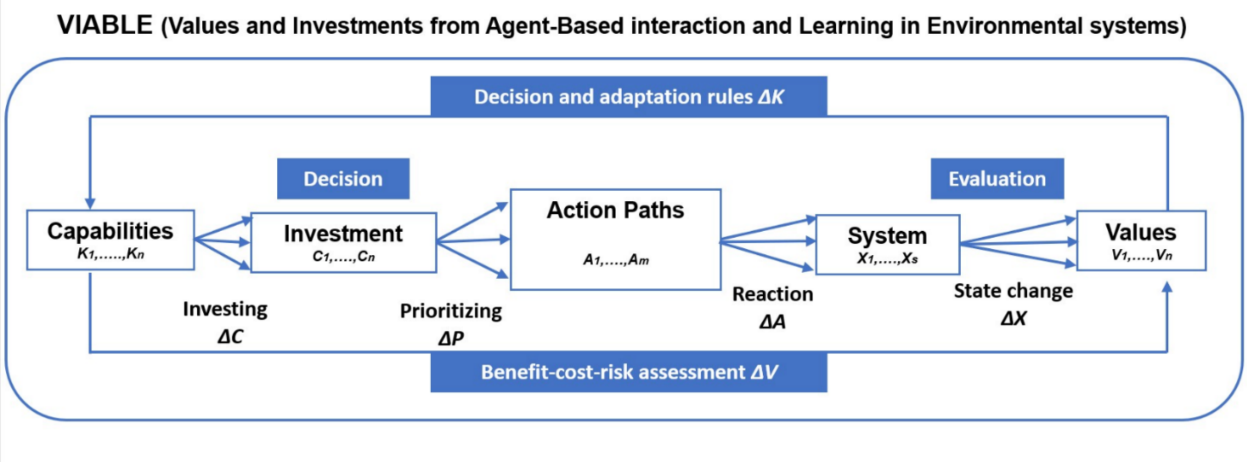


**Figure 5. 2 Schematic diagram of the VIABLE framework**

The VIABLE framework has been extensively used in agent-based modeling and system dynamics studies for understanding stability and conflict in socio-ecological systems. Scheffran (1989) developed this approach to understand strategic stability in the context of the arms race (Jathe et al., 1997; Scheffran, 1996; Scheffran, 1989) and then generalized it to analyze the stability and complexity of conflict, which is a dynamic interaction among agents driven into non-viable states and social learning to contain conflict potential to tolerable levels or transform it to cooperation. Later the model was expanded to understand environmental conflicts (Eisenack et al., 2006; Link et al., 2012; Scheffran, 2000, 2004; Scheffran & BenDor, 2009; Scheffran & Leimbach, 2006; Scheffran & Jathe, 1996; Shaaban et al., 2019). Previous studies have utilized the VIABLE framework as a basis for assessing agent-based models in various fields, such as emission trading (Scheffran & Leimbach, 2006; Scheffran, 2002), fisheries (BenDor et al., 2009), sustainable energy (Shaaban et al., 2019), flooding (Hokamp et al., 2020), as well as mobility (Peng et al., 2023; Rodriguez-Lopez et al., 2021).

The VIABLE framework has demonstrated its extensive interdisciplinary utility in multiple fields. These include the contestation dynamics of conflict studies, resource economics, energy transition, climate change, and social-ecological agroecosystems (Shaaban, 2023). Such an extensive reach of this framework with distant fields provides a testament to its adaptability and robustness in handling different systems, making it a prime candidate for this study. For the first time, we incorporate a statistical approach within this framework, introducing another novelty in the current study. We find that this innovative method significantly enhances our understanding of the complex linkages of capital adaptation relationships.We operationalize this in this study as farmers holding livelihood capital that serves as their capabilities. Farmers can invest in crops, land, or water to improve their capabilities, reduce risks, and increase benefits. The priorities for investing can vary based on the farmer's goals, which can include profit maximization, subsistence, social status, or competition with neighboring farmers. The actors face constraints that can limit their capability to invest. These constraints are classified as either human or natural. Additionally, we introduced factors such as climatic and non-climatic conditions that can influence farmers' decision-making and adaptation processes.

We chose the VIABLE framework for our study due to its exceptional capacity to dissect how Pakistani farmers employ their sustainable livelihood capital to accommodate climate change adaptations in their agricultural practices. Despite encountering a variety of constraints, both natural and human-made, resulting from an interplay of climatic and non-climatic factors, farmers are often tasked with making decisions about the allocation of their capital towards land or water resources. The VIABLE framework's unique ability to assimilate these variables into a cohesive structure is what makes it fit for addressing our research questions.

## 5.3. Methodology

### 5.3.1. Study area

We conducted a field survey in the irrigated agricultural plains in the Indus basin (Figure 5.3). The Indus Basin's irrigated agricultural plains are vital to Pakistan's economy and food security. The Indus River and its tributaries provide irrigation water to the basin's fertile lands through a vast network of canals and dams. This irrigation network supports cultivating numerous crops, including wheat, rice, sugarcane, cotton, and various fruits and vegetables. The area is famous for its highly productive agriculture due to the use of a relatively modern farming technique (Steenbergen et al., 2015). This area has a high number of small farmers who rely on farming for their livelihood, and they have experienced significant improvements in crop yields and productivity, which has increased food security. We conducted face-to-face interviews with small farmers in the irrigated agricultural regions of Punjab and Sindh provinces using a structured interview schedule. This area was chosen for our study due to its significant contribution to the country's agricultural output and its vulnerability to the impacts of climate change.

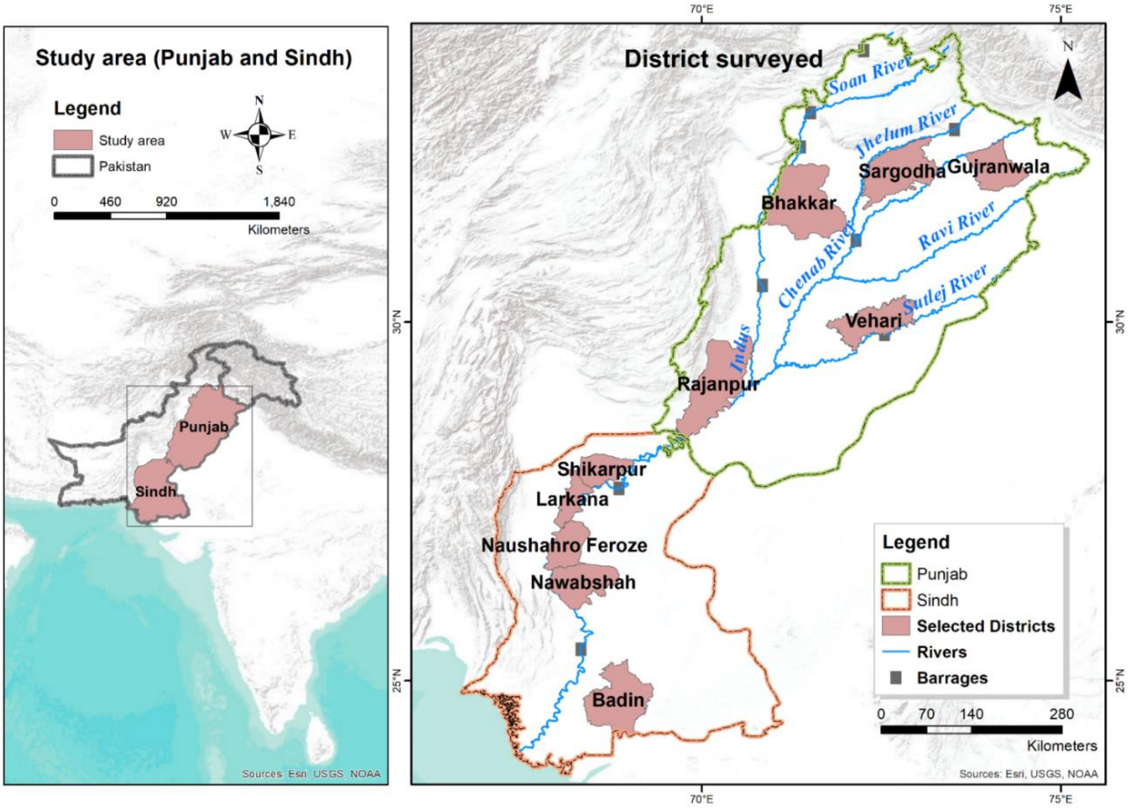


**Figure 5. 3 Map of the study area and data collection**

The study area spans 16.85 million hectares (Mha) and includes three major reservoirs, 12 inter-river link canals, and 44 main canals for irrigation control (Steenbergen et al., 2015). It possesses the world’s largest irrigation system, with nearly 80% of cultivated land irrigated (Muhammad et al., 2016), producing 90% of the country's harvests (Zhu et al., 2013). The region represents about 40% of Pakistan’s total area and is home to 74% of the country’s population. The soil of these plains comprises alluvium deposits accumulated by the actions of the Indus River and its associated tributaries in the geological past. This soil property makes the area fertile for agricultural purposes. Pakistan is among the world’s top ten producers of cotton, sugarcane, wheat, mango, dates, and Kinnow (citrus). The four dominating crops (rice, cotton, wheat, and sugarcane) contribute 4.9% to Pakistan’s gross domestic product. However, water resources in the region are highly stressed, whether judged by per capita water availability or by the ratio of withdrawals to runoff (Archer et al., 2010).

The mean average temperature in Punjab ranges from −2° to 45 °C, and exceptionally reaches 50 °C in summer and drops down to −8 °C in winter. In Sindh, temperatures rise above 46 °C from May to August and drop to 2 °C in winter. The interior of lower Sindh experienced up to

53.5 °C in 2010, the fourth-highest reading ever recorded in Asia (Abbas et al., 2018; Daniel Huber & Jay Gulledge, 2011). Most regions in Punjab province receive moderate to high rainfall ranging from ~ 275 to 830 mm/year, while Sindh province receives ~150 to 180 mm/year. The region experiences a decrease in rainfall if we approach from north to south. Recent calculations in 2021 estimate a decreasing precipitation trend all around Pakistan with − 1.11 mm/year (Ali et al., 2021).

The elevation of the Indus plain varies from 300 meters in northern Punjab to 75 meters near the southern border of Punjab, down to the Arabian Sea. In the plains, the slope fall rate is 0.3 meters per 1.6 km (Khan, 2016). The lower Indus Plain is part of Sindh province, the second largest province in population. Both provinces' areas are mainly agricultural, which is under stress due to the region's lack of rain and desertification trends.

### 5.3.2. Population and Sampling

The distribution of farmland among Pakistani farmers is highly skewed. In Pakistan, 28% of the land is cultivated by 80% of the farmers. Pakistan has 7.4 million small farmers who own less than 12 acres (5 hectares) of land (Naseer et al., 2016). In this study, we deal with small farmers (with landholdings of ≤ 16 acres) cultivating in irrigated Punjab and Sindh areas. These small farmers are spread across the entire 66 districts of Punjab and Sindh provinces. We used a multicriteria-based spatial cluster sampling strategy in various stages to select respondents from these districts.

In the first stage, we chose five districts from Punjab and five from Sindh with the help of their physiographic and irrigation maps. Punjab province has five rivers containing interfluve with distinct physiographic and soil characteristics. These interfluves are irrigated by Terbela and Mangal reservoirs, while Guddu, Sukkur, and Kotri irrigate the farmlands of Sindh province. We randomly chose one district from each interfluve in Punjab. We selected Bhakkar from Sindh Sagar doab, Sargodha from Chaj doab, Gujranwala from Rachna doab, and Rajanpur to represent the area out of the interfluve areas. Another criterion of selection was irrigation control of the Punjab plains. Bhakkar, Vehari, and Rajanpur take their irrigated water from the Terbela reservoir, while Sargodha is from the Mangla reservoir. Gujranwala is not controlled by any of the reservoirs directly. The Terbela reservoir irrigates Bhakkar, Vehari, and Rajanpur districts, while the Mangla reservoir irrigates Sargodha. Gujranwala is not controlled by any of the reservoirs directly.

For selecting districts from the Sindh province, we only considered their irrigation control because the irrigated land of Sindh is not physiographically diverse. As a result, we chose the districts of Shikarpur (next to the Guddu barrage), Badin (close to the Kotri barrage), Larkana, Naushahro Feroze, and Shaheed Benazirabad (near Sukkur barrage).

In stage two, we covered all Tehsils and Talukas (sub-unit of the district) in every district and visited 39 tehsils. In stage three, we randomly selected mauzas (the smallest revenue-collecting unit in Pakistan) based on the best spatial coverage of the Tehsil. In the last stage, we selected the respondents for the interview based on our convenient road connectivity to reach out to their households and farmland. Overall, 800 and precisely 80 farmers were interviewed from each district. We conducted a minimum of 10 and a maximum of 35 interviews with farmers from each Tehsil, with an overall target of 80 interviews per district. The number of Tehsils in each district is different, which varies the number of interviews in each Tehsil. We also noted the geographic coordinates of the farmlands of the respondents.

### 5.3.3. Development of scale and data collection

We deconstructed the components of the VIABLE framework into a set of questions and statements asking about the agreement and disagreement of farmers. Previous studies (Abid, Schilling, et al., 2016b; Bhalerao et al., 2022; Bhalerao et al., 2021) also used a similar approach to questionnaire development. We deconstructed farmers' capabilities, agricultural investment, farming purpose, factors, constraints, and adaptation. We itemized these constructs into a close-ended questionnaire (see S1 in Supplementary Materials) based on a five-point Likert scale with some open-ended basic demographic information about the respondents. Figure 5.3 shows our respondents' education, farming experience, and secondary occupation. Other than the basic information of the respondents, we had 72 questions addressing the key components of the VIABLE model.

To represent the components of the VIABLE model, we subdivided the capabilities of farmers into Financial Capital (FC), Human Capital (HC), Natural Capital (NC), and Social Capital (SC). Our categories of farmers' capabilities are based on a sustainable livelihood framework that encompasses the factors that enable individuals to live (Chambers & Conway, 1992; Natarajan et al., 2022; Reed et al., 2013; Serrat, 2017). We categorized adaptation into four categories: Crop management (CM), Farm management (FM), Irrigation management (IM), and Economic Management (EM). We adapted these categories from the adaptation paradigm model of farmers (Zobeidi et al., 2022) and grouped the constraints section into Human constraints (HCO) and Natural constraints (NCO), while factors of decision-making are classified as Climatic Factors (CF) and Non-climatic Factors (NF). In the field survey, we asked the respondents to rate each of these items on a five-point Likert scale ranging from strongly disagree to strongly agree. The scale contains a neutral option in the middle of disagreement and agreement. The Likert scale is a psychometric response scale in which respondents indicate their level of agreement with a statement ranging from strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5) (Robinson, 2014).

We started our data collection in December 2021 and completed it in March 2022 with the help of enumerators. Before field visits, we provided off-field and in-field training to the enumerators. We briefed them regarding the objective of our study and data collection methods. We conducted five online interviews with farmers in the Gujranwala district to pre-test the questionnaire. After these interviews, we rephrased the statements of some of the questions and added measurement units of area and distance in our demographic information section. We were able to obtain responses from a total of 913 farmers. However, we rejected 113 responses due to several quality concerns, such as double entries (27), incomplete submissions (19), respondents' misconduct (44), and readability issues (23). Finally, we were able to narrow the pool of surveys down to 800 usable responses.

### 5.3.4. Data analysis

To evaluate the research model, we employed PLS-SEM with the SmartPLS 4 software (Sarstedt & Cheah, 2019). PLS-SEM is a statistical technique that combines factor and regression analysis to evaluate a model's relationship among variables (Khan et al., 2019). It assesses the factor loadings, reliability, and validity of constructs, including the relationships among variables in a research model. This technique has established its predictive success in multiple studies (Akter et al., 2017). In PLS-SEM, the emphasis is placed on discovering the combinations of variables that are most strongly associated with a particular latent construct instead of focusing on individual variables. This method is particularly useful when working with complex models (Akter et al., 2017). Assessing a research model using PLS-SEM involves evaluating the measurement and structural models in two separate steps.

### 5.3.5. Measurement model

The measurement model (Figure 5.4) specifies the relationships between the latent and observed variables through factor loadings. Table 5.1 shows the details of latent and observed variables, while Table 5.2 contains the factor loadings of observed variables that we used in the model. These factor loadings represent the strength and direction of the relationships between the latent and observed variables (Hair et al., 2022). The values of factor loadings help in defining latent constructs that are well correlated (see Figure 5.5). For VIABLE-SEM, we measured 80 variables in the field with the questionnaire. 72 questions were addressing VIBLE framework. These 72 observed variables were approaching 19 first-order latent constructs. A group of items leads to a first-order latent construct which we computed based on the factor loading value of each item. PLS-SEM computes these values as Latent Variable Scores (LVS). Table 5.2 shows the factor loading details of our first-order latent variables. The first-order latent construct leads to second-order formative constructs which we used in our structural model in section 3 of this paper.

**Table 5. 1 Details of constructs and their codes**

| Construct/Latent variables | Role of variable | Code | Items/Observed variables | Removed |
|---|---|---|---|---|
| **Capital** | Independent Variable | - | | |
| Financial Capital | | FC | 77,78,79,80 | - |
| Human Capital | | HC | 81,82,83,84 | - |
| Natural Capital | | NC | 89,90,91,92 | 91 |
| Social Capital | | SC | 93,94,95,96,97,98,99 | 93 |
| **Adaptation** | Dependent Variable | **-** | | **-** |
| Crop Management | | CM | 100,101,102,103,104, 105 | 104 |
| Farm Management | | FM | 106,107,108,109,110 | 106,109 |
| Irrigation Management | | IM | 111,112,113,114,115, 116,117 | 111,113,114, 117 |
| Economic Management | | EM | 118,119,120,121,122, 123, 124 | 119,122,124 |
| **Constraints** | Mediators | **-** | | **-** |
| Human Constraints | | HCO | 130,131,132,133,137 | 132,137 |
| Natural Constraints | | NCO | 134,135,136 | 134 |
| **Factors** | Mediator + Moderator | - | | |
| Climatic Factors | | CFA | 151,152,153,155 | - |
| Non-Climatic Factors | | NFA | 154,156,157,158,159 | 159,157 |
| **Investment Priorities** | Mediators | - | | |
| Crop Investment | | INC | 140,141 | - |
| Land Investment | | INL | 142,143,144 | 143 |
| Water Investment | | INW | 145,146 | 145 |

The quality criteria for the measurement model are assessed through convergent and discriminant validity (see Supplementary Material S3). Convergent validity is assessed with factor loadings (>=0.70), Average Variance Extraction (AVE >=0.50) (Henseler et al., 2015), and Composite reliability (>=0.70) (Ringle et al., 2020). Hence, all constructs in our model possess convergent validity (Figure 5.6). AVE is calculated as the proportion of variance in an observed variable explained by the latent variable it is supposed to measure. If the AVE values are high (i.e., close to 1.0), the observed variables measure the same construct with high reliability. If the AVE values are low (i.e., close to 0.0), it indicates that the observed variables may be measuring different constructs or that the measure of the construct is unreliable (Wetzels et al., 2009). Our model establishes a good range of the AVE values, as shown in Figure 5.6**.**

**Table 5. 2 Factor loadings**

| Construct | Item code | Loadings | Construct | Item code | Loadings |
|---|---|---|---|---|---|
| Financial Capital | FC77 | 0.55 | Crop Management | CM100 | 0.66 |
| | FC78 | 0.64 | | CM101 | 0.88 |
| | FC79 | 0.91 | | CM102 | 0.84 |
| | FC80 | 0.85 | | CM103 | 0.68 |
| Human Capital | HC81 | 0.64 | | CM105 | 0.81 |
| | HC82 | 0.79 | Farm Management | FM107 | 0.82 |
| | HC83 | 0.73 | | FM108 | 0.88 |
| | HC84 | 0.87 | | FM110 | 0.70 |
| Natural Capital | NC89 | 0.68 | Irrigation Management | IM112 | 0.72 |
| | NC90 | 0.86 | | IM115 | 0.72 |
| | NC92 | 0.79 | | IM116 | 0.86 |
| Social Capital | SC94 | 0.69 | Economic Management | EM118 | 0.62 |
| | SC95 | 0.83 | | EM120 | 0.78 |
| | SC96 | 0.55 | | EM121 | 0.69 |
| | SC97 | 0.75 | | EM123 | 0.74 |
| | SC98 | 0.77 | Climatic Factors | FA151 | 0.91 |
| | SC99 | 0.77 | | FA152 | 0.82 |
| Human Constraints | CO130 | 0.60 | | FA153 | 0.59 |
| | CO131 | 0.91 | | FA155 | 0.65 |
| | CO133 | 0.88 | Non-Climatic Factors | FA154 | 0.83 |
| Natural Constraints | CO135 | 0.85 | | FA156 | 0.87 |
| | CO136 | 0.82 | | FA158 | 0.65 |
| Crop Investment | IN140 | 0.95 | Competition | V1/PUR45 | 1.00 |
| | IN141 | 0.95 | Revenue Maximization | V2/PUR46 | 1.00 |
| Land Investment | IN142 | 0.90 | Social Status | V3/PUR47 | 1.00 |
| | IN143 | 0.94 | Subsistence | V4/PUR48 | 1.00 |
| Water Investment | IN146 | 1.00 | | | |

Discriminant validity represents the distinctiveness of a variable or the degree to which each latent construct is distinct from the other construct in the model. This is a measure of the uncorrelatedness of variables in the model. This is typically done by examining the correlations between constructs and the cross-loadings of the manifest variables onto their respective constructs. In PLS-SEM, the measurement model is assessed through the Fronell-Larcker Criterion (F&L), Cross Loadings, and Heterotrait-monotrait Ratio of Correlations (HTMT).

The most conservative threshold value of the HTMT ratio is less than or equal to 0.90. In this study, all the values of HTMT are less than the threshold value of 0.90 (Henseler et al., 2015) (see Supplementary Material S3). Our model established the required quality criteria of discriminant validity. To achieve this validity criterion, we removed the indicators with lower factor loadings (Gefen & Straub, 2005). Out of 72 items, we removed 19 questions due to lower factor loadings (see Table 5.1 and 5.2). After achieving the quality criteria of the measurement model, we were left with 53 items for analysis for the higher-order construct in our structural model.

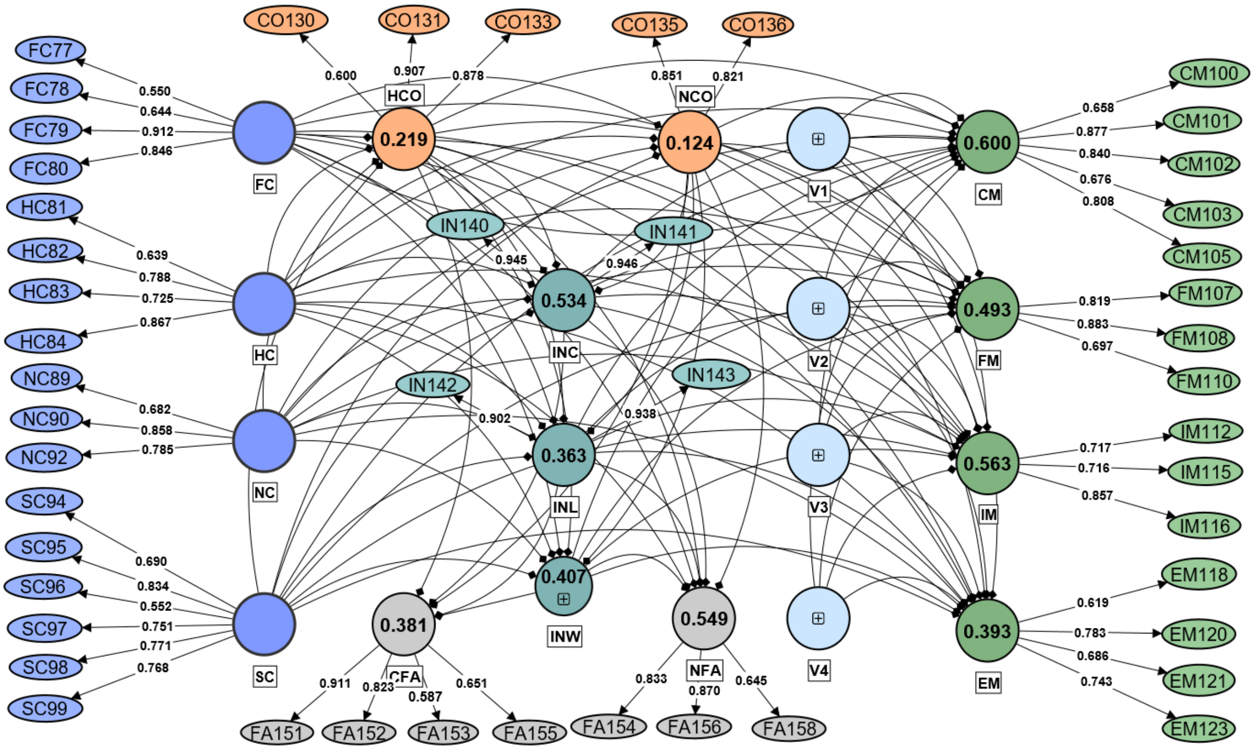


**Figure 5. 4 Measurement Model based on the VIABLE framework, Circles representing latent constructs with their R2 values inside, and lines representing path coefficient and factor loadings**

Cluster map Figure 5.5 is a graphical representation of a data matrix that uses hierarchical clustering to arrange the rows and columns of the matrix into clusters based on the similarity of their values. The Figure 5.5 reveals the quality criteria of our constructs because the cluster map indicates the distinctiveness and mutual connection of the variables. In the map, we can identify different groups of constructs that are correlated to each other.

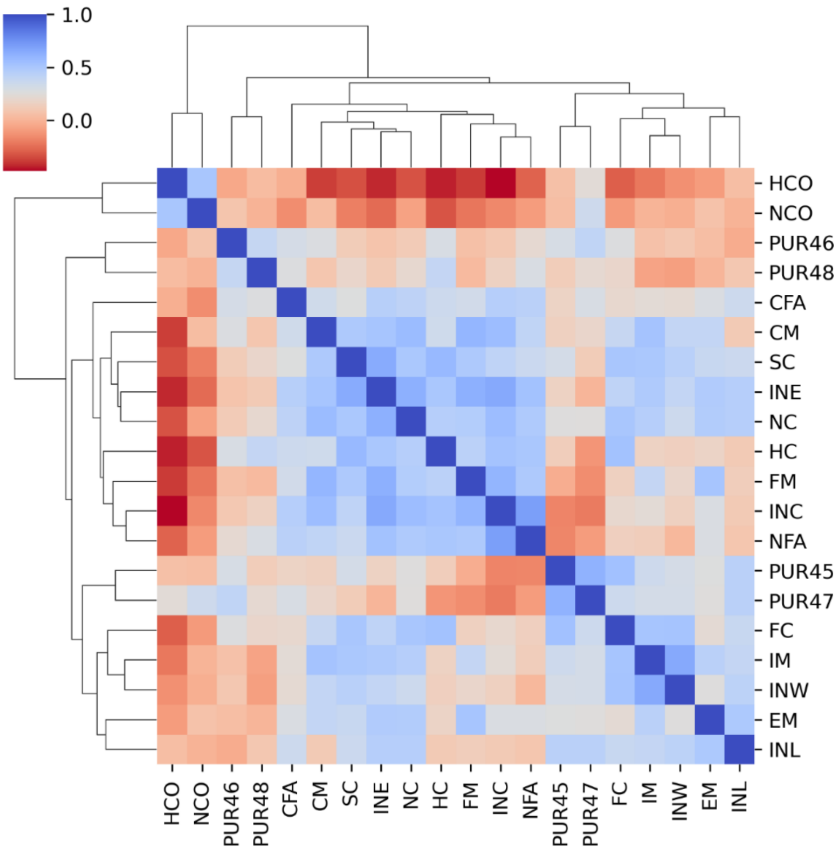


**Figure 5. 5 Cluster map of mutual correlations of latent variables used in the model**

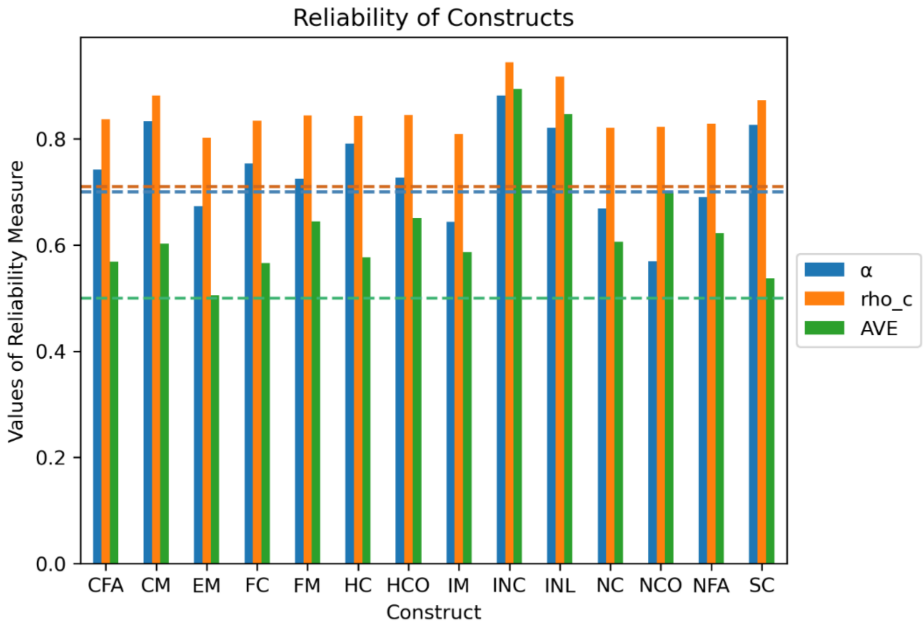


**Figure 5. 6 . Reliability measures Cronbach's alpha, Composite reliability (rho_c), and Average variance extracted (AVE) of constructs with their respective cut of value lines**

### 5.4. Results

#### 5.4.1. Profile of Respondents

Our respondents were farmers cultivating in the irrigated agricultural plains of Punjab and Sindh province. Figure 5.7 shows the details of the basic information of our respondents. The respondents were aged 20 to 77 years. Many of the respondents (90%) were educated, but only 12.5% had higher education (Graduation and above), while the rest of the farmers (76.75%) were up to a higher secondary level of education. Most of the farmers were experienced; only 13.3% had less than ten years of experience in farming, while 44.6% had 10 to 20 years of experience. All other farmers (42%) had been farming for more than 20 years or had inherited farming from their ancestors. We also asked about the secondary occupation of farmers other than farming. We found that more than half of our respondents (57%) are attempting to cover their living expenses through other means, such as running their businesses (26.7%), working in the public sector (10%), working in the private sector (8%), and performing other odd other jobs (14%).

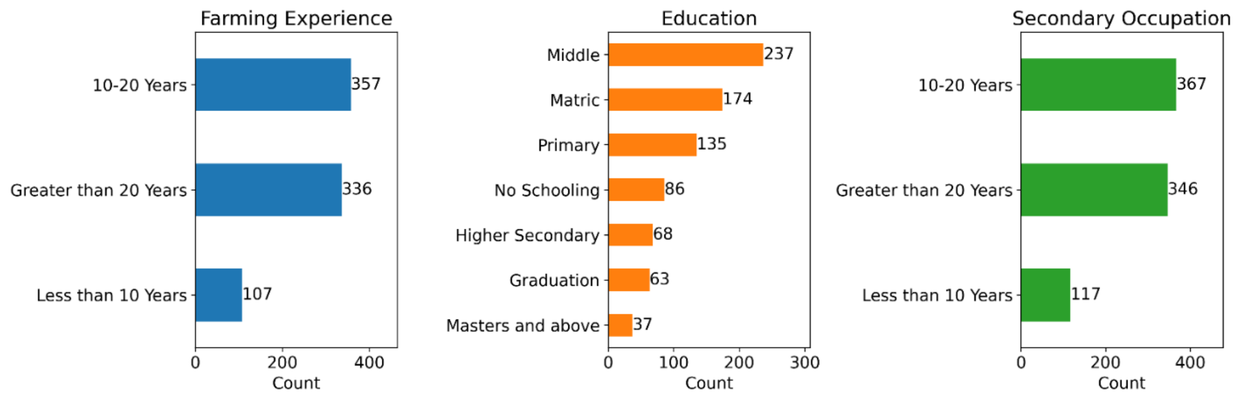


**Figure 5. 7 Socio-demographic traits of respondents**

#### 5.4.2. Structural model

The structural model specifies the relationships between the latent and observed variables through a set of paths and their coefficients. Figure 5.8 is the schematic display of our model which we termed VIABLE-SEM. The values shown on the connecting lines of variables are their path coefficients and their corresponding p values. These path coefficients represent the strength and direction of the relationships between the latent and observed variables (Hair et al., 2022; Hair Jr et al., 2017). The lines represent the interconnection of constructs in our model, while the width of each network represents the strengths of a connection. The breadth of lines or connections represents the magnitude of the path coefficient among the variables.

The lines are more comprehensive, which had a more path coefficient, and the lesser the path coefficient, the lesser the breadth of the line.

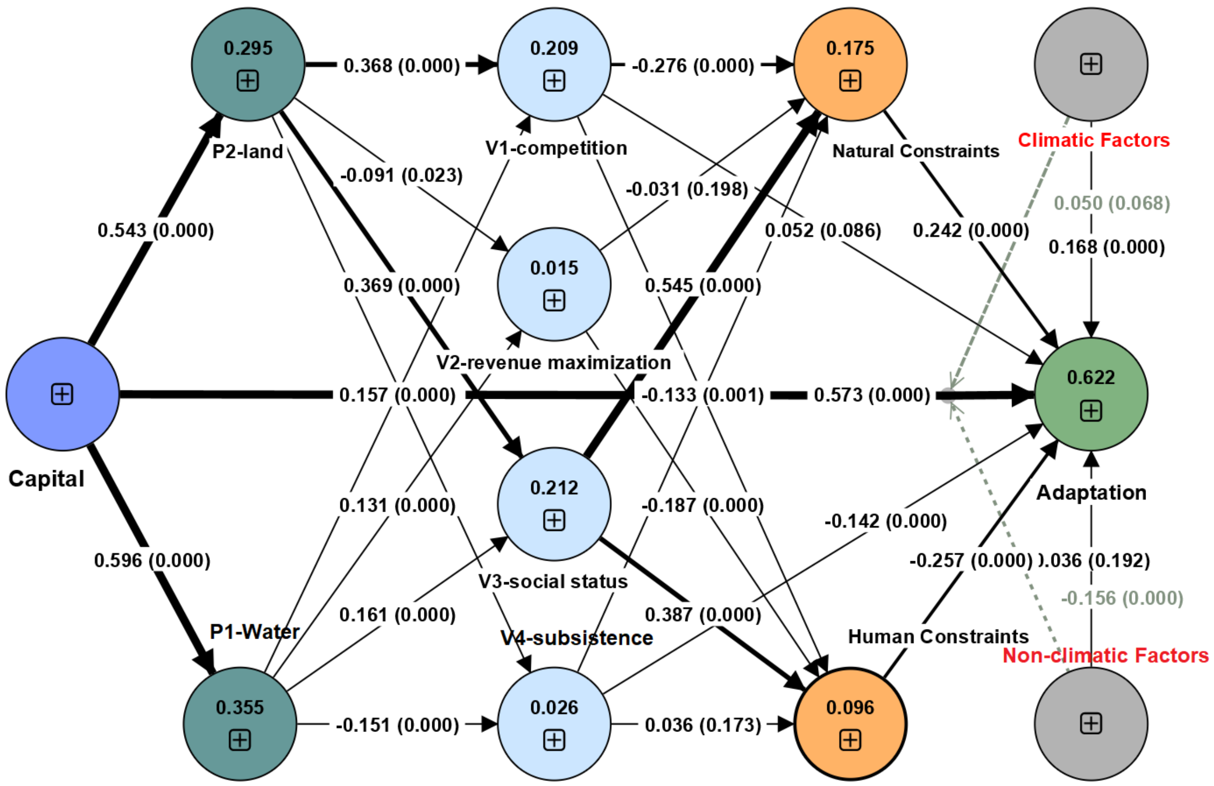


**Figure 5. 8 VIABLE Structural Equation Model, with circles representing second-order latent constructs with their R2 values inside and lines showing β coefficient and p values.**

Our hypothesis (H1) evaluates whether a significant model emerges by employing the VIABLE framework for assessing the role of farmers' livelihood capabilities in farming adaptation practices. We tested our hypotheses by employing mediation and moderation analyses in the model. We found multiple significant pathways by evaluating the model's total and specific indirect effects. Based on path coefficients of pathways in the model, we found "Capital" has a significant impact (total effect) on "Adaptation" ($\beta = 0.573$, $t = 17.05$, $p = 0.00$). Figure 9 (a) and Table 5.3 show the 13 highly significant pathways in the model. We found that there is a stronger relationship between capital and adaptation, capital and P1 (investment in water, $\beta = 0.60$, $f2=0.550$, $t = 23.50$, $p = 0.00$), and Capital and P2 (Investment in Land, $\beta = 0.54$, $t = 21.94$, $f2=0.418$, $p = 0.00$). Hence, our H1 was supported.

### 5.4.3. Quality Criteria for structural model

In PLS-SEM, R-squared ($r^2$), F-squared ($f^2$), and beta Coefficient (β) represents the quality of the model. Table 5.3 shows the values of $r^2$, $f^{2,}$ and β. R-squared is a statistical measure representing the proportion of variance in the dependent variable explained by the independent variables in a regression model (see Supplementary Material S4). It is calculated as the ratio of variance explained by the model to the total variance in the data. $r^2$ ranges from 0 to 1, with higher values indicating a better fit of the model to the data. At the same time, F-Square is the change in R-Square when an exogenous variable is removed from the model.

Moreover, f-square is also called effect size, which is interpreted as small when it is >=0.02, medium for >=0.15, and >=0.35 for large (Cohen, 1988). F-square can be interpreted as a measure of the strength of the relationship between the dependent and independent variables. The results of our model show good values of $f^{2,}$ which shows the strengths of relationships as shown in Figure 9 (a) and Table 5.3.

Our model reveals that capital has the most significant effect on (P1) Investments in Water ($f^2$=0.550), followed by adaptation ($f^2$=0.503). The Social status (V3) effect on Natural constraints (NCO) ($f^2$=0.202), Capital on (P2) Land related management ($f^2$=0.418), (V3) Social status effect on (HCO) Human constraints ($f^2$=0.093), (P2) land related management on (V3) Social status ($f^2$=0.142), (P2) land related management on (V1) Competition ($f^2$=0.141), (NCO) Natural constraints on Adaptation (f2=0.103), and Climatic factors (CFA) on Adaptation ($f^2$=0.048).

**Table 5. 3 Path coefficients**

| Relationships | β Coefficient | Effect size ( $f^2$ ) | std | stats | p-value |
|---|---|---|---|---|---|
| Capital → P1 | 0.60 | 0.550 | 0.03 | 23.50 | 0.00 |
| Capital → Adaptation | 0.57 | 0.503 | 0.03 | 17.05 | 0.00 |
| V3 → NCO | 0.55 | 0.202 | 0.04 | 12.37 | 0.00 |
| Capital → P2 | 0.54 | 0.418 | 0.03 | 21.94 | 0.00 |
| V3 → HCO | 0.39 | 0.093 | 0.03 | 11.43 | 0.00 |
| P2 → V3 | 0.37 | 0.142 | 0.04 | 10.21 | 0.00 |
| P2 → V1 | 0.37 | 0.141 | 0.04 | 10.38 | 0.00 |
| NCO → Adaptation | 0.24 | 0.103 | 0.04 | 6.96 | 0.00 |
| CFA → Adaptation | 0.17 | 0.048 | 0.03 | 5.58 | 0.00 |
| P1 → V3 | 0.16 | 0.027 | 0.03 | 5.11 | 0.00 |
| P1 → V1 | 0.16 | 0.025 | 0.04 | 4.29 | 0.00 |
| P2 → V4 | 0.15 | 0.020 | 0.05 | 3.30 | 0.00 |
| P1 → V2 | 0.13 | 0.014 | 0.04 | 3.33 | 0.00 |

### 5.4.4. Mediation analysis

Mediation analysis was performed to assess the mediating role of investment options (for land P1 and water P2), the purpose of farming (V1 competition, V2 social status, V3 profit maximization, and V4 subsistence), constraints (NCO natural constraints, HCO human constraints) and factors (CFA climatic factors and NFA non-climatic factors) affecting farming practice.

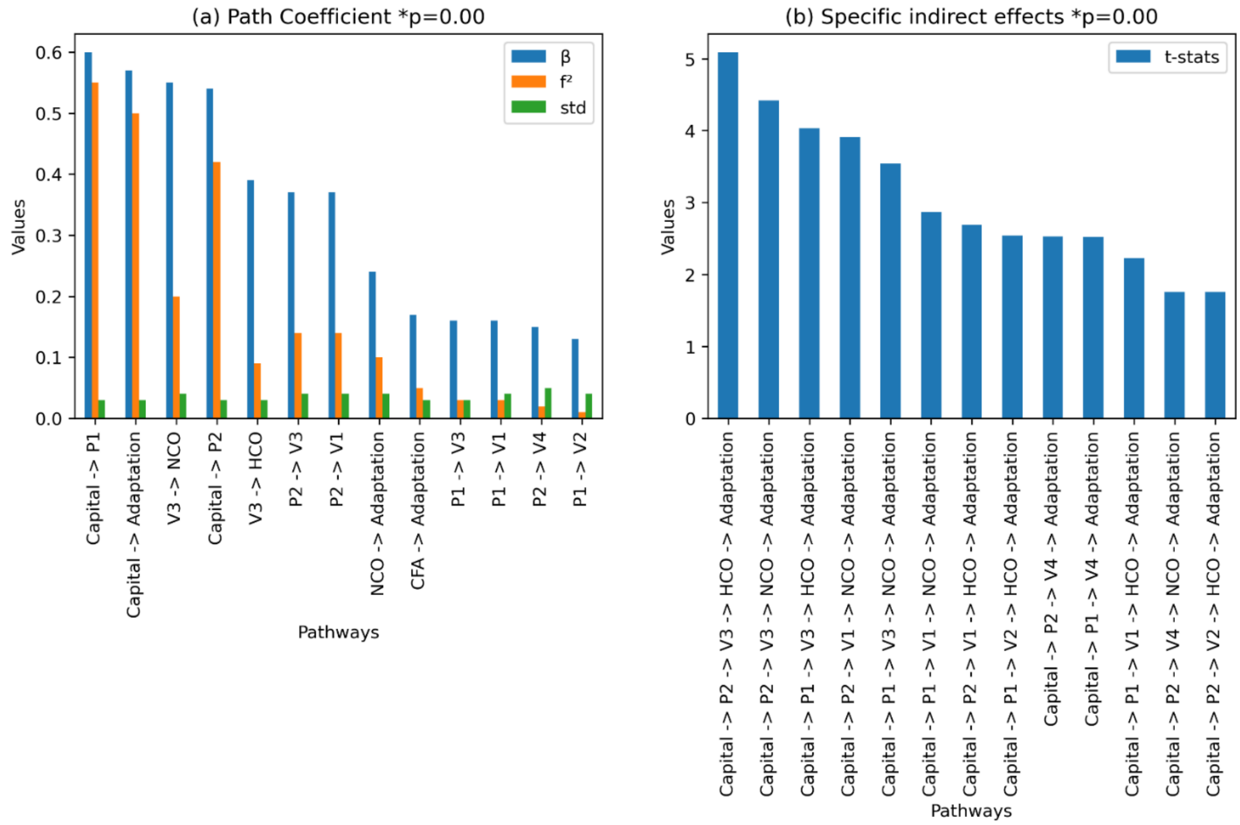


**Figure 5. 9 Highly significant pathways (models) based on total and specific indirect effects of the VIABLE-SEM.**

For further analysis of H1, we evaluated the specific indirect effects in the model (Figure 5.9 (b)). The results of specific indirect effects also supported our H1. We found 11 pathways with high significance and good t statistics value. Figure 5.9 (b) shows the pathways ranging from capital to investment options (i.e., P1 and P2) to the purpose of farming (i.e., V1, V2, V3, and V4). The values of t statistics for pathways with p=0.00 range from 5.09 to 2.69 (see Table 5.3). We found that investment options and the purpose of farming mediate the relationship between Capital and Adaptation. The results show that the total effect (H1) was positive and significant (β = 0.573, t = 17.05, p = 0.00).

**Table 5. 4 Mediation analysis through specific indirect effects**

| Path | beta | std | t-statistics | p-values |
|---|---|---|---|---|
| Capital → P2 → V3 → NCO → Adaptation | 0.03 | 0.01 | 4.42 | 0.00 |
| Capital → P1 →V3 → NCO → Adaptation | 0.01 | 0.00 | 3.54 | 0.00 |
| Capital →P2 → V1 → HCO → Adaptation | 0.01 | 0.00 | 2.69 | 0.00 |
| Capital →P1 → V4 → Adaptation | 0.01 | 0.01 | 2.52 | 0.01 |
| Capital → P1 → V2 → HCO → Adaptation | 0.00 | 0.00 | 2.54 | 0.01 |
| Capital → P1 → V1→ HCO → Adaptation | 0.00 | 0.00 | 2.23 | 0.01 |
| Capital → P2 → V4 → NCO → Adaptation | 0.00 | 0.00 | 1.76 | 0.04 |
| Capital → P2 → V2 → HCO → Adaptation | 0.00 | 0.00 | 1.76 | 0.04 |
| Capital → P1 → V3 → HCO → Adaptation | -0.01 | 0.00 | 4.03 | 0.00 |
| Capital → P2 → V1 → NCO → Adaptation | -0.01 | 0.00 | 3.91 | 0.00 |
| Capital → P1→ V1 → NCO → Adaptation | -0.01 | 0.00 | 2.87 | 0.00 |
| Capital → P2 → V4 → Adaptation | -0.01 | 0.01 | 2.53 | 0.01 |
| Capital → P2 → V3 → HCO → Adaptation | -0.02 | 0.00 | 5.09 | 0.00 |

The results revealed a significant total effect (β = 0.591, t = 17.94, p = 0.00). When the mediators were introduced into the model, this effect was slightly decreased, and the direct relationship between Capital and Adaptation was still found to be significant (β = 0.573, t = 17.05, p = 0.00). Hence, this shows mediators' complementary partial mediation role in the relationship between Capital and Adaptation (See Figure 5.9 and Table 5.4). Some mediators also showed competitive partial mediation with negative coefficients (see Figure 6), but we are extending our analysis toward competitive partial mediation. Therefore, our H2 is supported.

### 5.4.5. Path Coefficient specific indirect effects

We stated H1: "Significant pathways emerge by taking farmers' livelihood capabilities as an independent variable, investment priorities, farming purpose and constraints as mediator and adaptation as an outcome." Hence our H1 is accepted that multiple significant pathways (ranges from p-value 0.00 to 0.01) emerge (see Table 5.4) by employing farmers' capital as independent and adaptation as a dependent variable with multiple mediators.

### 5.4.6. Moderating effect

The moderating effect refers to the influence of one variable (the moderator) on the relationship between two other variables (Hair Jr et al., 2017). A moderating effect occurs when the strength or direction of the relationship between the predictor and criterion variables varies depending on the level of the moderator variable (Dawson, 2014; Dawson & Richter, 2006).

The study assesses the moderating role of climatic factors and non-climatic factors on the positive relationship between capital and adaptation. Without including the moderating effect (NFA x Capital & CFA x capital), the $R^2$ value for adaptation was 0.556. This shows that capital accounts for a 55% change in adaptation. Including the first interaction term NFA x Capital, the $R^2$ increased to 0.599. Furthermore, by introducing the second interaction term CFA x Capital, the $R^2$ increased to 0.622, which shows an increase of 6.6% in variance can be explained in the dependent variable (Adaptation) after introducing the moderators in the model. Further, the significance of moderating effect was analyzed, and the results ($\beta$ =-0.156, t=5.456, p=0.00) revealed (Table 5.5) a negative and highly significant moderating impact of NFA on the relationship between Capital and Adaptation. At the same time, there is a positive ($\beta$ =0.050, t= 1.494, p=0.068) and weakly significant moderating effect of CFA on the relationship between capital and Adaptation. This result shows that the relationship between capital and adaptation strengthens with increased NFA. With the rise in CFA, the relationship between capital and adaptation weakens. Hence our H3 is accepted as both factors are moderating significantly, but both types of factors are moderating oppositely.

Further, slope analysis is presented to understand the moderating effects (Figure 5.10). As shown in Figure 5.10 (b), the line is much steeper for low NFA; this indicates that at low NFA, the impact of capital on adaptation is much more robust compared to high NFA. In other words, if we increase capital, adaptation will increase. However, As shown in Figure 5.10 (a), at higher CFA and lower CFA, the adaptation does not show much difference. In conclusion, with lower CFA, lower adaptation, and higher CFA, the adaptation is also slightly higher.

**Table 5. 5 Moderation analysis**

| Relationship | β | SE | t-statistics | p-value |
|---|---|---|---|---|
| Moderating effect (NFA x Capital) →Adaptation | -0.156 | 0.029 | 5.456 | 0.000 |
| Moderating effect (CFA x Capital) →Adaptation | 0.050 | 0.033 | 1.494 | 0.068 |
| Capital → Adaptation | 0.573 | 0.034 | 17.050 | 0.000 |
| CFA → Adaptation | 0.168 | 0.030 | 5.575 | 0.000 |
| NFA → Adaptation | 0.036 | 0.042 | 0.872 | 0.192 |

According to the Cohen (Cohen, 1988) f-square criteria, the effect is small when it is >=0.02, medium for >=0.15, and >=0.35 for large. Therefore, the f-square for CFA x Capital → Adaptation is insignificant, while for NFA x Capital → Adaptation, the effect size is 0.043, which is very small but significant (at p=0.003).

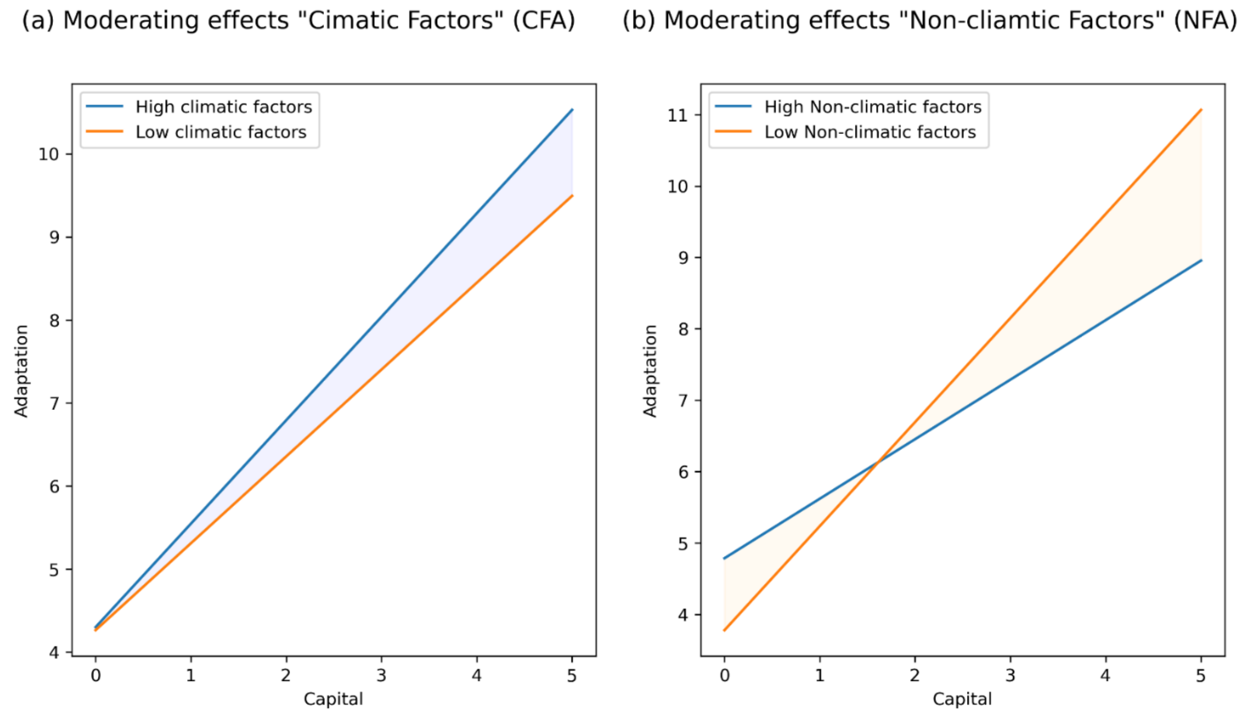


**Figure 5. 10 Simple slope analysis explaining moderating effects of Climatic and Non-climatic factors on the Capital-Adaptation relationship**

A negative interaction effect suggests that the relationship between NFA and the dependent variable is weaker when capital is high than when capital is low.

## 5.5. Discussion

This study investigates the relationship between livelihood capital and climate change adaptation in the Indus Plains' irrigated agricultural regions. It also examines how this relationship is affected by investment priorities, farming constraints, and various climatic and non-climatic factors. The findings of our model suggest that capital has the most significant and influential role in the farmers' adaptation strategies. All other variables, including investment options, farming purposes, and constraints, are less important than capital. This explains two-thirds of the observed variance in adaptation. The capital alone explains up to 57% of the adaptation variance. Sargani et al. (2022) and (2021) reported similar findings in their study conducted in Sindh province. Our results are consistent with those reported in previous studies conducted in developing countries and align with those from other studies in neighboring countries of Pakistan, such as Nepal (Adhikari et al., 2004), China (Kuang et al., 2020; Kuang et al., 2019), and Iran (Dehghani Pour et al., 2018).

Our model determined thirteen statistically significant adaptation pathways. These pathways explain the influence of livelihood capital with the mediating role of investment priorities, constraints, and purpose of farming in the adaptation process, which supports our mediation hypothesis. The role of capital is important in intermediate actions other than adaptation alone. Our model suggests that farmers' investments in water and land resources are equally significant. Furthermore, maintaining social status was the primary motivation for many farmers, rather than subsistence, profit maximization, or competition. The impact of natural constraints is stronger than human constraints, but both are highly significant. Our findings are consistent with Abid, et al. (Abid, Schilling, et al., 2016a) who reported that natural constraints like water scarcity were significant in farming in the Punjab region. According to this study, irrigated water is insufficient to fulfill crop requirements and maximize productivity. By contrast, some studies identified resource limitation as a barrier to adaptation (Mahmood et al., 2019; Saddique et al., 2022a; Shahid et al., 2021).

The moderation analysis of our model revealed that climatic and non-climatic factors significantly influence the capital and adaptation relationship. This reveals that in the presence of climatic and non-climatic factors, a higher amount of capital can no longer help in achieving a higher adaptation rate. We expected this and stated it as our moderation hypothesis in the beginning. Chandio et al. (2022)Chandio et al. (2022)Chandio et al. (2022)Chandio et al. (2022)Chandio et al. (2022) recently reported that climatic and non-climatic factors significantly influence agricultural adaptation in neighboring India, where farming practices in the plain areas are like the agriculture in the plain areas of Pakistan.

Our results revealed that the rise in climatic factors slightly increases the chances of adaptation, which means that a hostile climate can push farmers to take adaptive action. The rise in non-climatic factors lessens the adaptation despite having enough capital. This can be explained because non-climatic factors are similar to a variable that contribute to farmers' capital; higher non-climatic factors mean a lower amount of capital.

The study found that non-climatic factors negatively influence the relationship between capital and adaptation with high significance, while climatic factors influence positively but with weak significance. The results further suggest that the effect of capital on adaptation increases in the absence of climatic and non-climatic factors. Without including factors, the overall model accounts for only 55% of the variance in adaptation. However, when non-climatic factors are introduced as a moderator, this variance increases to 60%, increasing to 62% with the inclusion of climatic factors in the model. This suggests that farmers adapt more effectively in the presence of climatic and non-climatic factors. We propose the same in our third hypothesis that climatic and non-climatic factors moderate the relationship between capital and adaptation, supported by findings. However, it is essential to note that both factors are moderating oppositely.

Despite this valuable insight, it is important to consider the limitations of this study. Conducting fieldwork during the COVID-19 pandemic posed significant challenges. Gathering data from 800 farmers while adhering to safety protocols was a significant task and may have influenced the data collection process. Having focus on the irrigated agricultural regions in Pakistan means that our findings may not universally represent the diverse socio-economic and geographical realities of all Pakistani farmers. The use of structural equation modeling, with its inherent assumption of statistical linearity among variables, might not entirely capture the complex, non-linear relationships that often exist in real-world scenarios. Furthermore, the skewed distribution of farmland in Pakistan, despite our multicriteria-based spatial cluster sampling, might lead to underrepresentation of certain farmer groups. Lastly, the theoretical basis of the VIABLE framework, while effective, might not account fully for the varied and unpredictable nature of human responses to climate change. These limitations, while providing a realistic view of our study's constraints, also open avenues for further research. Future work could focus on broader sampling, incorporation of non-linear relationships, understanding collective decision-making influences, and factoring in the unpredictability of human behavior.

### 5.6. Conclusion

In conclusion, our study explores the relationship between livelihood capital and climate change adaptation with the mediating and moderating variables in irrigated agricultural regions of the Indus plain. Capital is the most significant factor in farmers' adaptation strategies in the Indus plain. Other variables such as water investment, land investment, farming purposes, and farming constraints are less important than capital. Investments in land and water are equally important in farmers' eyes when they make decisions about their investment options. Our research found that maintaining social status emerged as a primary motivation for farming among farmers in our study area. Our model explains approximately two-thirds of the adaptation process, while capital alone accounts for 57%. The model identified 13 statistically significant pathways which explain the role of different mediators in the adaptation process. The study also found that the relationship between capital and adaptation is more significant without mediators. The moderation results suggest that climatic and non-climatic factors significantly influence the relationship between capital and adaptation. Non-climatic factors hinder the adaptation process, while climatic factors play a positive but weak role in the adaptation process. The results suggest that farmers adapt more effectively in the presence of these factors, with the effect of capital on adaptation increasing in their absence. The climatic and non-climatic factors are responsible for increasing the adaptive capacity of farmers. Overall, our findings are consistent with previous studies conducted in developing countries and neighboring countries of Pakistan. Our study helps us learn more about the complex relationship between capital, investments, constraints, farming purpose, factors, and adaptation. It also gives policymakers and people who work in agriculture and rural development useful information. It also gives policymakers and people who work in agriculture and rural development useful information.

**Author contribution statement**

Muhammad Mobeen: Conceived and designed the experiment; Developed the instrument; Performed the experiments in data analysis tool; Analyzed and interpreted the data; Wrote the paper. Khondokar Humayun Kabir: Conceived and designed the experiment; Developed the instrument; Wrote the paper. Uwe A. Schneider: Conceived and designed the experiment; Developed the instrument; Analyzed and interpreted the data; Wrote the paper.

Tauqeer Ahmed: Performed fieldwork; Wrote the paper

Jürgen Scheffran: Conceived and designed the experiment; Developed the instrument; Wrote the paper.

# Chapter 6: Investigating Various Facets of Livelihood Capitals as Necessary Predictors of Climate Adaptation in Pakistan’s Irrigated Farmlands


## Abstract

Farmers’ adaptation strategies depend on climatic factors and various livelihood capitals, such as natural, social, financial, human, and physical capital. The present study explores the sufficiency and necessity of livelihood capital and climatic factors for successful adaptation based on a Sustainable Livelihood Framework (SLF). Employing Partial Least Square Structural Equation Modeling (PLS-SEM) and Necessary Condition Analysis (NCA), we analyzed primary data from 800 farmers in the irrigated Indus plains in Pakistan. Our field survey, conducted from December 2021 to February 2022, utilized a structured questionnaire with a five-point Likert scale. Our results reveal that both climatic factors and all forms of livelihood capital are necessary for a successful adaptation action. The farmer cannot achieve a higher level of adaptation if either component is missing. Natural and social capital are significant predictors of a successful adaptation, with beta values of 0.345 and 0.283, respectively. Specifically, a minimum value of 1.809 for natural capital and 1.621 for social capital is required to achieve basic adaptation levels. Increasing the value of all predictors in our model enhances the adaptation level. Unexpectedly, our findings indicated that financial capital is inversely related to adaptation, with a beta coefficient -0.185. These insights are vital for highlighting the essential nature of all forms of livelihood capital and policy interventions to promote adaptation measures in Pakistan’s irrigated agricultural regions.



**Keywords**: Climate Change, Adaptation, Sustainable Livelihood Framework, Livelihood capital, Agriculture, Pakistan


## 6.1. Introduction

According to an estimate, Pakistan spends between 7 and 14 billion USD annually on measures to curtail the damages of climate change on its economy (Hussain et al., 2020). This financial strain is particularly evident in the agricultural sector, which serves as the foundation of Pakistan’s economy but is severely affected by climate change. Hence, climate change poses a significant threat to agricultural sustainability, particularly in regions reliant on ecosystem stability, such as Pakistan (Singh & Singh, 2017). The country’s heavy reliance on agriculture makes it more vulnerable to climate risks. Farmers in developing regions are particularly vulnerable to threats from climatic disasters, pests, and insect attacks, which push them into a vicious poverty cycle (van den Berg, 2010). These vulnerabilities underscore the need for effective adaptation strategies tailored to these regions' unique socio-economic and environmental contexts. The ongoing climate change triggers multiple stressors, threatening livelihood and agricultural practices (Jezeer et al., 2019). The livelihood of farmers in the developing world is more vulnerable than in other areas (Cao et al., 2016; Fang et al., 2014; Qasim et al., 2015). Pakistan depends on irrigated agriculture, and threats posed by changing climatic conditions necessitate appropriate adaptation strategies for sustaining agricultural productivity and rural livelihoods (Khan et al., 2021). The usual response of farmers to climate change is mitigation or adaptation to cope with adverse effects on their livelihoods (Elum et al., 2017). However, the mitigation measures cannot undo the damage that farmers have already experienced, but on the other hand, adaptation can lessen the adverse impact of climate change (Alam et al., 2016; U. Khanal et al., 2018; Zhai et al., 2018). Adaptation thus emerges as a critical component of sustainable agricultural practices in the face of climate change. Therefore, investigating the factors influencing farmers' adaptation strategies can improve future risk-handling capabilities. Several publications discuss the impact of individual farmer characteristics such as age, gender, family size, education, household income, and cognitive elements (such as perception and understanding of climate change) on their adaptation strategies (Alam et al., 2016; Jin et al., 2015; U. Khanal et al., 2018; Li et al., 2017).

Understanding farmers' adaptation strategies requires a robust theoretical framework, such as the Sustainable Livelihood Framework (SLF), which offers insights into the multifaceted nature of agricultural resilience. SLF has gained widespread use and has established itself as a classic paradigm for investigating household livelihoods (Li et al., 2017; Mobeen et al., 2023; Pandey et al., 2017). This framework views farmers in the context of vulnerability and states they can enhance their livelihoods by utilizing their financial, human, natural, physical, and social assets (Baffoe & Matsuda, 2018; Wu et al., 2017). Despite the proven utility of the SLF in various contexts, its application in the specific socio-economic and climatic conditions of Pakistan's irrigated agriculture remains underexplored. In a recent study, Mobeen et al. (2023) identified that livelihood capital alone is responsible for 57% of adaptation actions, while all other factors are less important. Deploying the SLF (DFID, 1999), we delve into the relative importance of various livelihood capitals, including financial, human, natural, physical, and social, in aiding climate change adaptation. While SLF provides a comprehensive understanding of these capitals, their necessity-specific and relative importance in climate change adaptation within Pakistan's irrigated agriculture are less explored. This gap in the literature highlights the need for context-specific research that can inform targeted policy interventions. Prior research shows that livelihood assets serve not only as the basis for farmers' decisions for cultivation but also as a means of helping farming communities cope with the vulnerability and risks associated with their livelihoods (Fang et al., 2014; García de Jalón et al., 2018; Liu et al., 2018). This study, therefore, seeks to fill this critical gap by applying the SLF in the unique context of Pakistan, thereby contributing to a more tailored understanding of adaptation strategies in the region.

This study proposes an innovative integration of the SLF with PLS-SEM and NCA to bridge these research gaps in Pakistan's irrigated agriculture. Such an integration offers a deeper analysis of the factors influencing adaptation beyond traditional single-factor analyses. The ability to handle many variables and our objective of highlighting the necessary predictors drive us to select PLS-SEM and NCA as the current study methods. This approach examines the relationships between various livelihood capitals and adaptation outcomes. This approach helps to identify the necessary and sufficient conditions for successful adaptation strategies, offering empirical evidence for policy and practice.

Based on the strengths of PLS-SEM and NCA in uncovering complex relationships, this research aims to highlight the role of climatic factors and sub-components of livelihood capitals on climate adaptation. Additionally, it seeks to identify the necessary conditions and adequate levels of various livelihood capitals for an effective adaptation in the irrigated agricultural regions of Pakistan.

## 6.2. Methods & Materials

### 6.2.1. Study Locale

The investigation was conducted through a field survey in the Indus Basin's agriculturally significant and irrigated areas, as depicted in Figure 6.1. This region is crucial for Pakistan's economic and food security, with the Indus River and its tributaries facilitating vital irrigation via an expansive network of canals and dams. The resulting fertile territories are instrumental in producing primary crops such as wheat, rice, and cotton. These lands, benefiting from advanced agricultural techniques, contribute markedly to the country's agricultural output (Steenbergen et al., 2015). The area, characterized by small-scale farming operations, has seen a notable increase in crop yield and productivity, enhancing food security.

In-person, scheduled interviews were conducted with smallholder farmers in the Punjab and Sindh provinces using a structured interview format. The selection of these provinces was strategic, reflecting their considerable contribution to agricultural output and susceptibility to the detrimental effects of climate change. The zone covers an area of 16.85 million hectares and includes important reservoirs and canals, making it the most extensive irrigation system in the world. A sizable portion of this land is under irrigation, accounting for a significant share of Pakistan's crop production. Approximately 40% of the country's land area and three-quarters of its population reside in this region. The fertile alluvial soil, a remnant of ancient river systems, significantly enhances the agricultural capacity of these plains. Pakistan is one of the leading global producers of various crops and fruits, with its primary crops contributing 4.9% to the national GDP. Despite these benefits, water shortages and decreased per capita water supply are major regional issues.

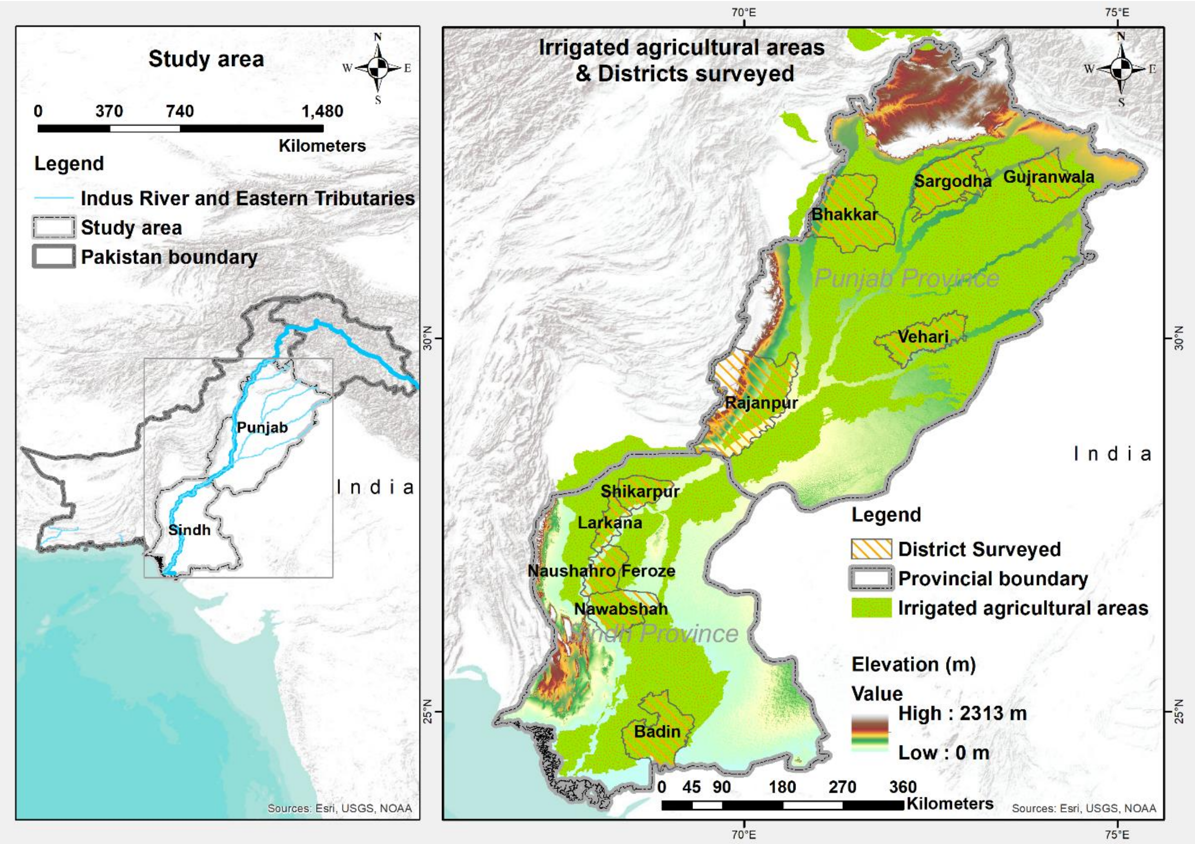


**Figure 6. 1 Map of the study area highlighting the irrigated agricultural districts surveyed for this study**

Climatic conditions, precisely temperature and precipitation patterns, exhibit significant variability across the studied region. In Punjab, there is a notable range in temperature fluctuations, with recorded extremes spanning from a minimum of -2 °C to a maximum of 45 °C. During peak summer periods, temperatures have been observed to rise as high as 50 °C, whereas winter temperatures can drop to as low as −8 °C. In contrast, Sindh experiences more intense heat, particularly from May to August, with temperatures regularly exceeding 46 °C and winter temperatures occasionally descending to 2 °C. A notable climatic event was recorded in 2010, when lower Sindh registered a temperature of 53.5 °C, marking one of the highest temperatures ever recorded in Asia (Abbas et al., 2018; DG Huber & J Gulledge, 2011). Precipitation trends in these provinces also display distinct patterns. Punjab typically receives annual rainfall ranging from 275 to 830 mm, while Sindh, in comparison, receives significantly lower rainfall, averaging about 150–180 mm per year. This pattern indicates a gradual decrease in precipitation levels moving southwards. Recent data from 2021 further corroborates a trend of decreasing precipitation across Pakistan (Ali et al., 2021). The topographical profile of the Indus Plain shows a descent from 300 meters above sea level in northern Punjab to sea level as it nears the Arabian Sea, characterized by a gentle slope gradient (Khan, 2016). These agricultural provinces confront challenges, including insufficient rainfall and the ongoing issue of desertification.

### 6.2.2. Population, Sampling, Instrumentation and Data Collection

Pakistan's farmland distribution is uneven, with 28% of the land cultivated by 80% of the farmers (Mahmood et al., 2020). Pakistan has approximately 7.4 million small farmers who own less than 12 acres of land (Naseer et al., 2016; Shahbaz et al., 2017). This study focuses on small farmers in irrigated Punjab and Sindh areas who cultivate landholdings of ≤16 acres (Ali et al., 2017). All 66 districts of the Punjab and Sindh provinces contain these small farmers. We employed a multicriteria-based spatial cluster sampling strategy to select respondents from these districts. In the first stage, we chose five districts from Punjab province and five from Sindh based on their physiographic settings and irrigation controls.

In the first stage, we selected one district from each interfluve of Punjab and one from the Sagar doab. The selection criteria also included irrigation control of the Punjab plains, with Bhakkar, Vehari, and Rajanpur receiving water from the Terbela reservoir, Sargodha from the Mangla reservoir, and Gujranwala not being directly controlled by any reservoir. We focused on irrigation control as a selection criterion for selecting districts from Sindh. Guddu, Sukkur, and Kotri barrage control the water distribution in Sindh. We picked at least one district from the canal command area of every barrage. As a result, we chose the districts Shikarpur (next to the Guddu barrage), Badin (close to the Kotri barrage), Larkana, Naushahro Feroze, and Shaheed Benazirabad (near Sukkur barrage).

In the second stage, we covered all Tehsils and Talukas in each district and interviewed farmers in 39 tehsils. In the third stage, we randomly selected mauzas based on the best spatial coverage of a Tehsil. Finally, we selected respondents for interviews based on their willingness and our accessibility to their households or farmland. We conducted eight hundred interviews in total

from 10 selected districts. We conducted 80 interviews per district, but the number of respondents from each tehsil varies due to the variable number of tehsil units in every district.
In developing our questionnaire, we operationalized the SLF into a series of questions that probed farmers' levels of agreement and disagreement on various facets of their livelihoods, a similar approach validated in prior research (Bhalerao et al., 2022; Bhalerao et al., 2021). Our questions targeted climatic factors and their crop and form management adaptation actions. We covered the farmers' capital in five dimensions, naming Financial Capital (FC), Human Capital (HC), Natural Capital (NC), Physical Capital (PC), and Social Capital (SC), drawing on a foundation of literature supporting the components that constitute a sustainable livelihood (Chambers & Conway, 1992; Reed et al., 2013). Adaptation strategies were categorized into crop and farm management, reflecting the adaptation paradigm model (Zobeidi et al., 2022).
Respondents assessed each statement using a five-point Likert scale, which spans from strong disagreement to strong agreement, incorporating a neutral midpoint (Akter et al., 2017). This psychometric scale is designed to capture the intensity of their attitudes toward the statement of a question. The field survey for data collection started in December 2021 and concluded in March 2022. Enumerators were assigned for each district to collect the data.
We conducted five online interviews with the farmers located in Gujranwala district as a pretesting of our instrument. This pretesting led us to refine the statement of our questions, which enhanced the clarity and precision of the questionnaire.

### 6.2.3. Data Analysis

In this research, PLS-SEM is employed as a key analytical tool to explore the relationships between various forms of capital and adaptation strategies in Pakistan's irrigated agriculture sector. PLS-SEM is particularly advantageous in exploratory research contexts where theoretical underpinnings are being developed or extended (Richter et al., 2022). This technique helps to handle complex models with multiple predictors and outcome variables (Hair et al., 2019), making it appropriate for our multifaceted research design that involves financial, human, natural, physical, and social capital as well as climatic factors as predictors of adaptation (Ringle et al., 2020).
PLS-SEM estimates path models involving latent variables represented by observed indicators (Firman et al., 2022; Hair et al., 2018). This method focuses on maximizing the explained variance of the dependent variables, offering robustness against deviations from normal distribution and being suitable for smaller sample sizes. In our study, PLS-SEM aids in

understanding the strength and direction of the relationships between several types of capital and the adaptation strategies farmers employ.

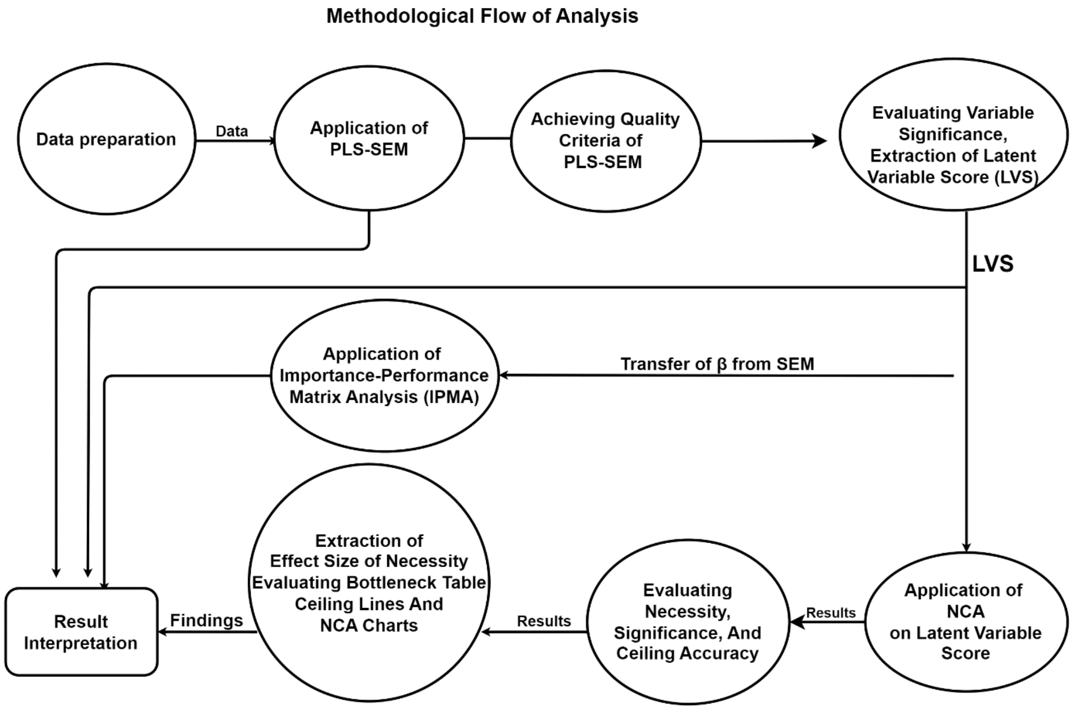


**Figure 6. 2 Flowchart illustrating the integrated methodology of (PLS-SEM) and (NCA) used in the study**

The process of employing PLS-SEM involves several steps. Initially, we developed a measurement model to ensure the reliability and validity of the constructs. Following this, the study formulated a structural model to hypothesize the relationships between the variables involved in our research. The model is then estimated using the SmartPLS 4.0 software (Ringle et al., 2022).

### 6.2.4. Livelihood Capitals through the Yardstick of Necessary Condition Analysis (NCA)

Following the core objective of the research, NCA was utilized to complement PLS-SEM and identify the indispensable levels of each facet of capital required for various degrees of adaptation. Recent advancements in NCA offer a distinct perspective by pinpointing 'must-have' factors or conditions without which a particular level of outcome, in this case, adaptation, is unattainable (Richter et al., 2020). In other words, while PLS-SEM explores how much a predictor contributes to an outcome, NCA investigates whether the absence of a specific condition (such as a certain level of financial capital) completely precludes the achievement of a desired level of adaptation (Dul, 2016; Dul et al., 2023).

NCA operates by examining scatter plots of the dependent and independent variables to identify areas that indicate the presence of necessary conditions or bottlenecks (Dul et al., 2019). It establishes a ceiling line beyond which the outcome cannot be improved, regardless of the presence or enhancement of other factors (Dul et al., 2020; Dul et al., 2021). In our study, NCA is crucial for determining the critical thresholds of various capitals beyond which adaptation efforts may not yield further improvements. This insight is particularly valuable for policy formulation, as it identifies the minimum necessary levels of each capital needed for effective adaptation.

### 6.2.5. Relative Importance of Livelihood Capitals by Integrating PLS-SEM with NCA

While PLS-SEM explains the capitals' predictive relationships and relative importance, NCA delineates the non-compensatory, essential conditions for successful adaptation. This method offers a holistic view of the adaptation process, enabling us to identify crucial components in adaptation strategies and determine multidimensional predictors critical for achieving desired outcomes (Ngoc Su et al., 2023).

## 6.3. Results

### 6.3.1. Demographic profile of the Respondents

The demographic profile of the farmers provides valuable insights for understanding the adaptation strategies. Figure 6.3. shows the farmers' education level, farming experience, and secondary occupation, which correlate with livelihood capital. The respondent reflects a diverse educational background, farming experience, and engagement in secondary occupations. Many farmers possess middle-level education (237), followed by a substantial number with primary education (135), suggesting that most have basic literacy skills. In contrast, a smaller segment has achieved higher education, with the least number holding a master's degree or higher (37), indicating limited access to advanced education within this group. Regarding farming experience, a substantial proportion of the respondents have been farming for more than ten years, with those having 10-20 years (357) and over 20 years (336) of experience.

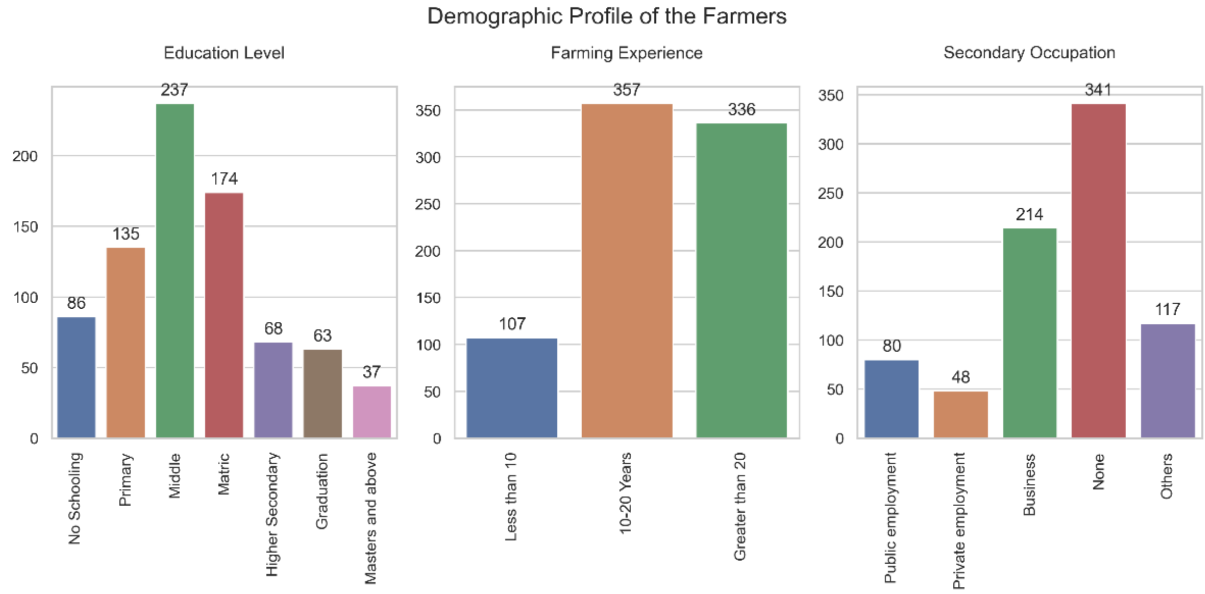


**Figure 6. 3 Demographic profile of the surveyed farmers, including age, education level, and farming experience**

The demographic profile represents our respondents' educational level, farming experience, and secondary occupation. A notable finding in secondary occupations is a substantial number of farmers do not engage in any additional work (341), indicating a firm reliance on agriculture as their primary source of income. Those who do have a secondary occupation are involved in business activities (214), with fewer farmers employed in public (80) or private sectors (48) and a small portion engaging in other unspecified activities (117).

This demographic background, including education, farming experience, and secondary occupation, is crucial for farmers' adaptation strategies. Most farmers have primary education, highlighting the need for an educational intervention plan for the community. The farming experience ranges from new agrarians to experienced farming families, highlighting generational knowledge and experience of adaptation and climate. Most farmers insist on farming as their sole livelihood, underscoring the need to protect their primary livelihood. However, farmers with secondary occupations suggest income diversification and can integrate their adaptation options into other occupation sectors. Our data reveals that most farmers have primary education and varied farming experiences, but farming is their sole livelihood.

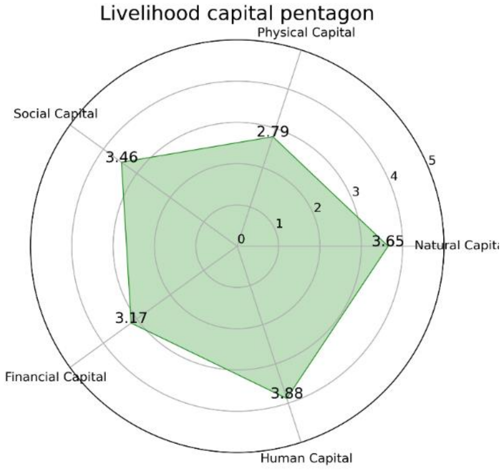


**Figure 6. 4 Status of livelihood capitals analyzed in the study**

Figure 6.4 depicts a Livelihood Capital Pentagon, a framework used to evaluate access to several community capital types. The pentagon visually encapsulates the relative availability of five capitals on a scale where the center represents zero access, and the perimeter indicates maximum access. The values, Natural Capital (3.65), Physical Capital (2.79), Social Capital (3.46), Financial Capital (3.17), and Human Capital (3.88) reveal that the community has the great access to Human Capital, reflecting a solid investment in education, health, and skills. In contrast, Physical Capital is the least accessible, suggesting room for improvement in infrastructure and equipment.

The livelihood capital pentagon indicates a balanced picture of livelihood assets, where natural and human capital is the strongest. This shows farmers have a solid foundation for sustainable agriculture and effective livelihood engagements. However, moderate scores in physical, financial, and social capital indicate areas where the policymakers should plan intervention. Enhancing financial access and physical capital could lead to better climate adaptations. Strengthening these areas can prepare the farming community to be resilient against climate change.

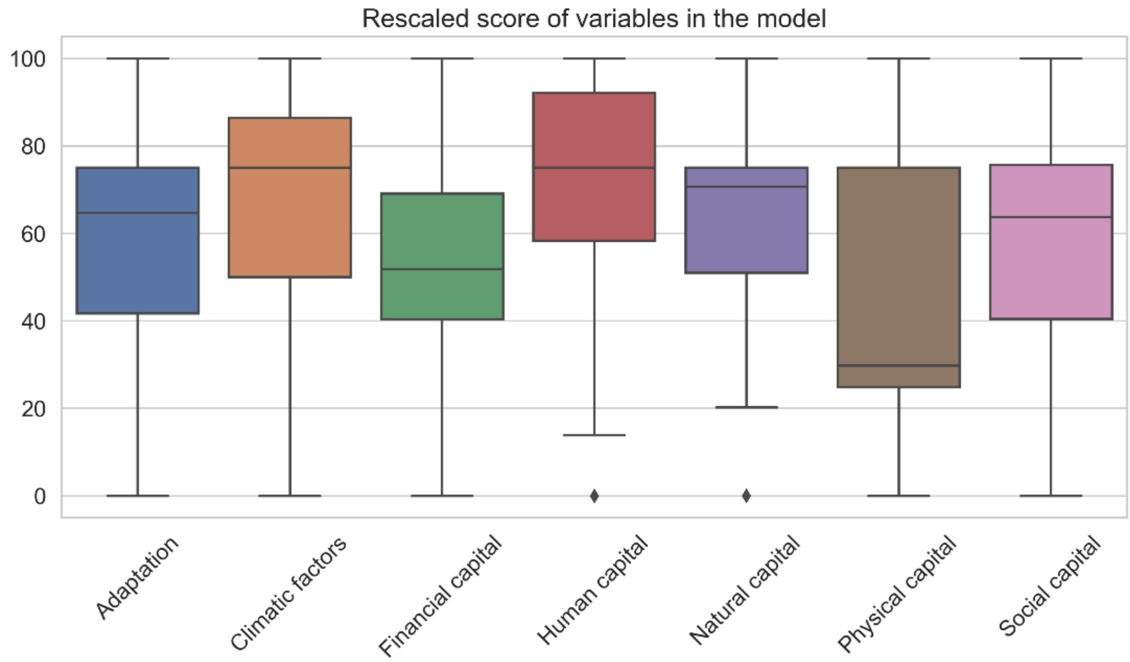


**Figure 6. 5 Trends of empirical data showing different forms of livelihood capital, climatic factors, and adaptation levels**

Figure 6.5 presents the distribution and central tendency of rescaled scores for variables in our model. The median, represented by the line dividing each box, indicates the data's midpoint for each variable. The adaptation, shown in blue, has a median below the 60th percentile, suggesting that the central tendency for adaptation practices is comparatively moderate across the sample. Climatic factors, in orange, display a similar median, yet the wider box indicates a greater interquartile range, reflecting varied responses to climate-related questions.

Financial capital, in green, shows a narrower interquartile range, suggesting a more consistent distribution of financial resources among the participants. Human capital, represented in red, has a broad spread of values, indicating a diversity in the population’s skills and knowledge levels. The natural capital, in purple, also shows a wide interquartile range but with outliers, which are individual values that fall well below the lower quartile, highlighting specific instances where this capital is particularly low. Physical capital, depicted in brown, has a higher median, nearing the 70th percentile, which could imply that infrastructural resources are abundant or valued among the farmers. The social capital, in pink, exhibits a high median as well, suggesting solid social networks and communal ties.

In conclusion, Figure 6.5 shows distinct disparities in livelihood capital and adaptation measures, with more pronounced physical and social capital. These findings underscore the need for targeted strategies to enhance adaptation capacities, particularly in areas lacking human and natural capital.

### 6.3.2. Livelihood Capitals and PLS-SEM

The PLS-SEM model (see Figure 6.6) visualizes the relationships between diverse types of livelihood capitals, climatic factors, and their collective impact on adaptation. It integrates survey items as observable indicators and connects them to latent constructs through factor loadings. The paths linking these constructs display coefficients that measure the strength and direction of their relationships. Notably, the model assigns an $R^2$ value of 0.483 to adaptation, indicating that approximately 48.3% of its variance is explained by the predictors in the model. This graphical representation is pivotal for discerning the key elements that drive adaptation outcomes in the context of livelihood capitals and climatic influences. We put the output of this model in Table 1.

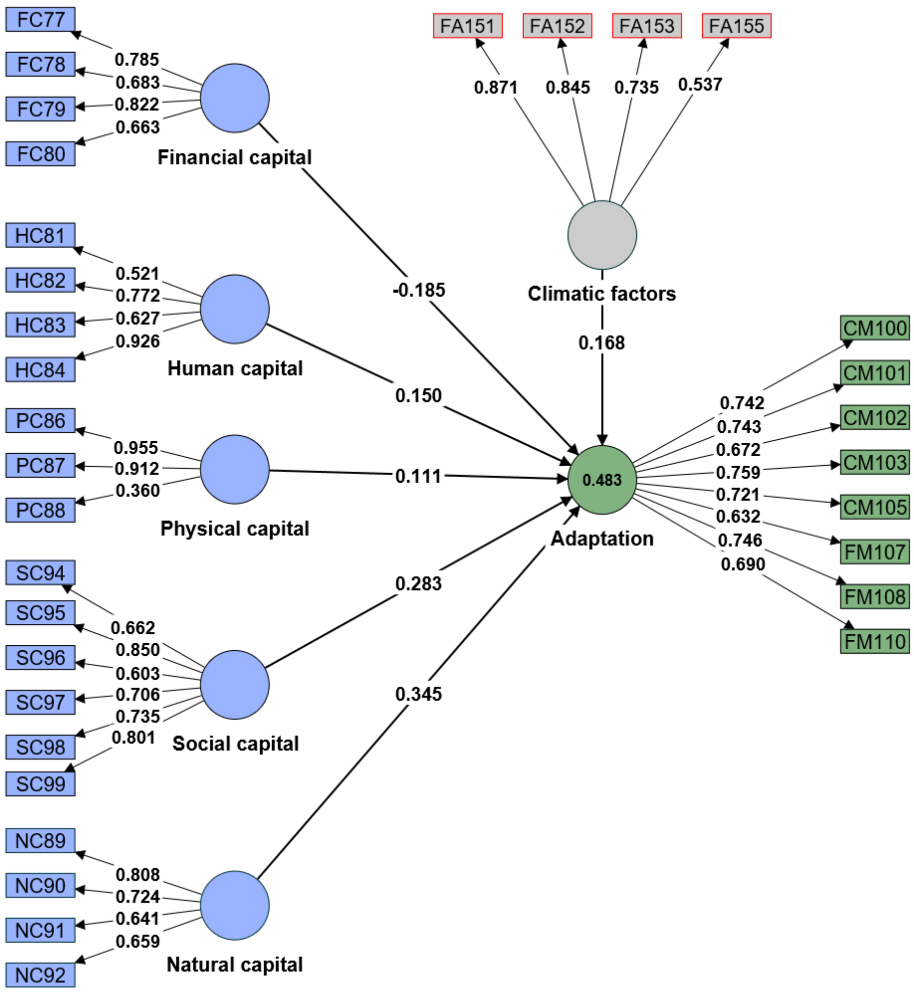


**Figure 6. 6 The proposed PLS-SEM model depicting the relationships between livelihood capitals, climatic factors, and adaptation outcomes**

The PLS-SEM results highlight significant relationships between the predictors and the adaptation outcome. Climatic factors positively influenced adaptation, with a path coefficient of 0.168, which was statistically significant (T stats = 6.358, $p < 0.001$). This underscores the importance of climatic awareness in shaping adaptation strategies.

Conversely, financial capital exhibited a negative relationship with adaptation, as indicated by a path coefficient of -0.185. This was statistically significant (T stats = 3.734, $p < 0.001$), suggesting that financial constraints might hinder the implementation of effective adaptation measures or that financial resources are being allocated in ways that do not contribute to effective adaptation. Human capital positively affected adaptation (path coefficient = 0.150, T stats = 3.645, $p < 0.001$), indicating that investments in education and training are crucial for enhancing adaptive capacity. Natural capital had the most substantial positive impact (path coefficient = 0.345, T stats = 8.994, $p < 0.001$), reflecting the critical dependence of agricultural adaptation on natural resources. Physical capital, although to a lesser extent than natural capital, also positively affected adaptation (path coefficient = 0.111, T stats = 2.232, $p = 0.026$), emphasizing the role of infrastructure and technology. Social capital's positive association with adaptation (path coefficient = 0.283, T stats = 8.096, $p < 0.001$) highlights the significance of social networks and community support systems in facilitating adaptive actions.

**Table 6. 1 Tabulated results combining PLS-SEM outcomes and NCA findings, with beta values, T stats, and predictor influences on the outcome variable**

| PLS-SEM | | | | | NCA | | |
|---|---|---|---|---|---|---|---|
| **Predictors** | **Outcome** | **Beta** | **T stats** | **p-values** | **Effect size** | **Role** | **p-value** |
| Climatic factors | Adaptation | 0.168 | 6.358 | 0.000 | 0.123 | 17% | 0.000 |
| Financial capital | Adaptation | -0.185 | 3.734 | 0.000 | 0.057 | 15% | 0.000 |
| Human capital | Adaptation | 0.150 | 3.645 | 0.000 | 0.144 | 18% | 0.000 |
| Natural capital | Adaptation | 0.345 | 8.994 | 0.000 | 0.266 | 18% | 0.000 |
| Physical capital | Adaptation | 0.111 | 2.232 | 0.026 | 0.038 | 14% | 0.000 |
| Social capital | Adaptation | 0.283 | 8.096 | 0.000 | 0.159 | 18% | 0.000 |

### 6.3.3. Necessary Condition Analysis (NCA)

Figure 6.7 shows Necessary Condition Analysis (NCA) effect sizes, quantifying the influence of various forms of capital necessary for successful adaptation. Each arrow leading to ''Adaptation' represents a different type of capital, with the associated numerical values depicting the strength of each as a precondition for adaptation. Natural capital emerges as the most substantial precondition with an effect size of 0.266, suggesting it is a critical factor for adaptation success. Physical and social capital also demonstrate notable effect sizes, while financial and human capital exhibit more modest but still significant roles. We show the results of our NCA in Table 1 and Table 2.

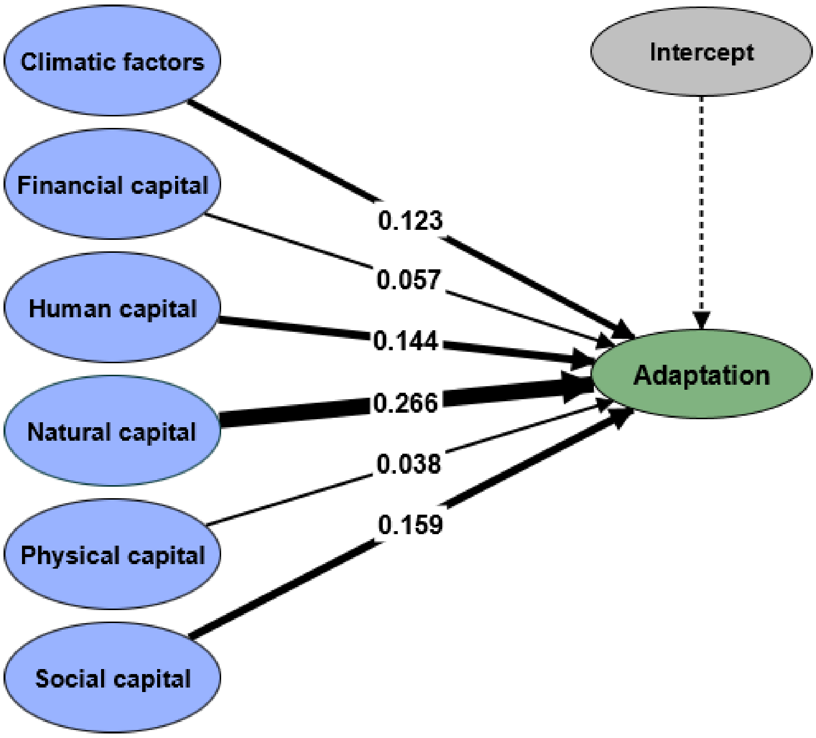


**Figure 6. 7 Visualization of Necessary Condition Analysis (NCA) effect sizes for various forms of capital required for successful adaptation**

The NCA provided additional insights into the indispensability of specific conditions for achieving various levels of adaptation. The effect size indicated that climatic factors (effect size = 0.123, $p < 0.001$) are necessary for adaptation, aligning with the positive path coefficient in PLS-SEM. While negatively associated with adaptation in PLS-SEM, financial capital was also identified as necessary (effect size = 0.057, $p < 0.001$), suggesting that financial resources must surpass a certain threshold to enable adaptation. Human capital's necessity for adaptation was further corroborated (effect size = 0.144, $p < 0.001$), with higher levels being critical for advanced adaptation stages. Natural capital was the most critical condition (effect size = 0.266, $p < 0.001$), essential across all adaptation levels. However, physical capital was necessary with a smaller effect size (effect size = 0.038, $p < 0.001$), particularly at higher adaptation levels. Social capital was necessary throughout (effect size = 0.159, $p < 0.001$), especially critical at the highest adaptation level.

The synthesis of PLS-SEM and NCA findings elucidates a comprehensive landscape of how different livelihood capitals contribute to adaptation. The necessity and sufficiency analysis reveal that while some capitals are instrumental in enhancing adaptation outcomes, others must reach specific thresholds to be effective. These insights are pivotal for stakeholders to prioritize interventions and allocate resources efficiently, considering the magnitude of impact (sufficiency) and the minimum required levels (necessity) for successful climate change adaptation in agricultural practices.

### 6.3.4. Bottleneck analysis and adaptation thresholds

The Bottleneck Table (Table 6.2) and Ceiling chart (Figure 6.8) provide us with value threshold predictors for various levels of adaptation. Table 6.2 shows where each capital becomes necessary for adaptation, revealing that climatic and financial capital is not necessary until adaptation reaches an 80% level. However, their necessity becomes substantial from this point, peaking at 100% adaptation levels, as evidenced by the increasing bottleneck values (climatic capital: from 2.891 to 3.728, financial capital: from NN to 3.308). Human capital is necessary beyond a 50% adaptation level, with its criticality becoming more pronounced at complete adaptation (bottleneck value at 100% adaptation: 4.000).

Natural capital's necessity starts at a 20% adaptation level, emphasizing its importance even at lower levels of adaptation, and becomes most critical at complete adaptation (bottleneck value: 3.829). The threshold of physical capital is observed at an 80% adaptation level (bottleneck value at 100% adaptation: 3.000), underscoring its role in more advanced adaptation stages. Social capital is necessary from the 20% adaptation level onwards, with its role becoming increasingly significant, and it is critical at the highest adaptation level (bottleneck value: 4.000).

**Table 6. 2 Bottleneck analysis showing the necessity thresholds of predictors for various levels of adaptation.**

| | Adaptation | Climatic factors | Financial capital | Human capital | Natural capital | Physical capital | Social capital |
|---|---|---|---|---|---|---|---|
| 0% | 1.000 | NN | NN | NN | NN | NN | NN |
| 10% | 1.300 | NN | NN | NN | NN | NN | NN |
| 20% | 1.600 | NN | NN | NN | 1.809 | NN | 1.621 |
| 30% | 1.900 | NN | NN | NN | 1.809 | NN | 1.621 |
| 40% | 2.200 | NN | NN | NN | 1.809 | NN | 1.621 |
| 50% | 2.500 | NN | NN | 1.555 | 1.809 | NN | 1.621 |
| 60% | 2.800 | NN | NN | 1.555 | 1.809 | NN | 1.621 |
| 70% | 3.100 | NN | NN | 1.555 | 2.109 | NN | 1.621 |
| 80% | 3.400 | 2.891 | NN | 2.000 | 2.934 | 1.019 | 1.621 |
| 90% | 3.700 | 2.891 | 2.208 | 2.100 | 2.934 | 1.616 | 1.621 |
| 100% | 4.000 | 3.728 | 3.308 | 4.000 | 3.829 | 3.000 | 4.000 |

In explaining the influence of various levels of livelihood capital on climate change adaptation in Pakistan's irrigated agriculture, the Bottleneck Table Analysis highlighted the necessity of each form of capital across different adaptation levels. At the foundational 20% adaptation level, only natural capital (NC) and social capital (SC) were necessary, with the requisite minimum levels being 1.809 and 1.621, respectively. This necessity underscores the foundational role of environmental resources and community networks in the initial stages of adaptation.

As adaptation efforts intensified, the necessity for climatic factors became apparent at the 80% level, with a value of 2.891, indicating that beyond this threshold, farmers must consider climatic variations more robustly to sustain agricultural productivity. Financial capital did not exhibit necessity until the 90% adaptation level, suggesting that financial resources alone are insufficient for the most substantial adaptation measures without the support of other capitals. The analysis revealed that human capital (HC) and physical capital (PC) had thresholds of necessity at the intermediate adaptation levels. Human capital became necessary at a 50% adaptation level with a value of 1.555, reflecting the importance of knowledge and skills in implementing effective adaptation strategies. Physical capital showed necessity at the 80% adaptation level with a value of 1.019, indicating its role in more developed adaptation processes.

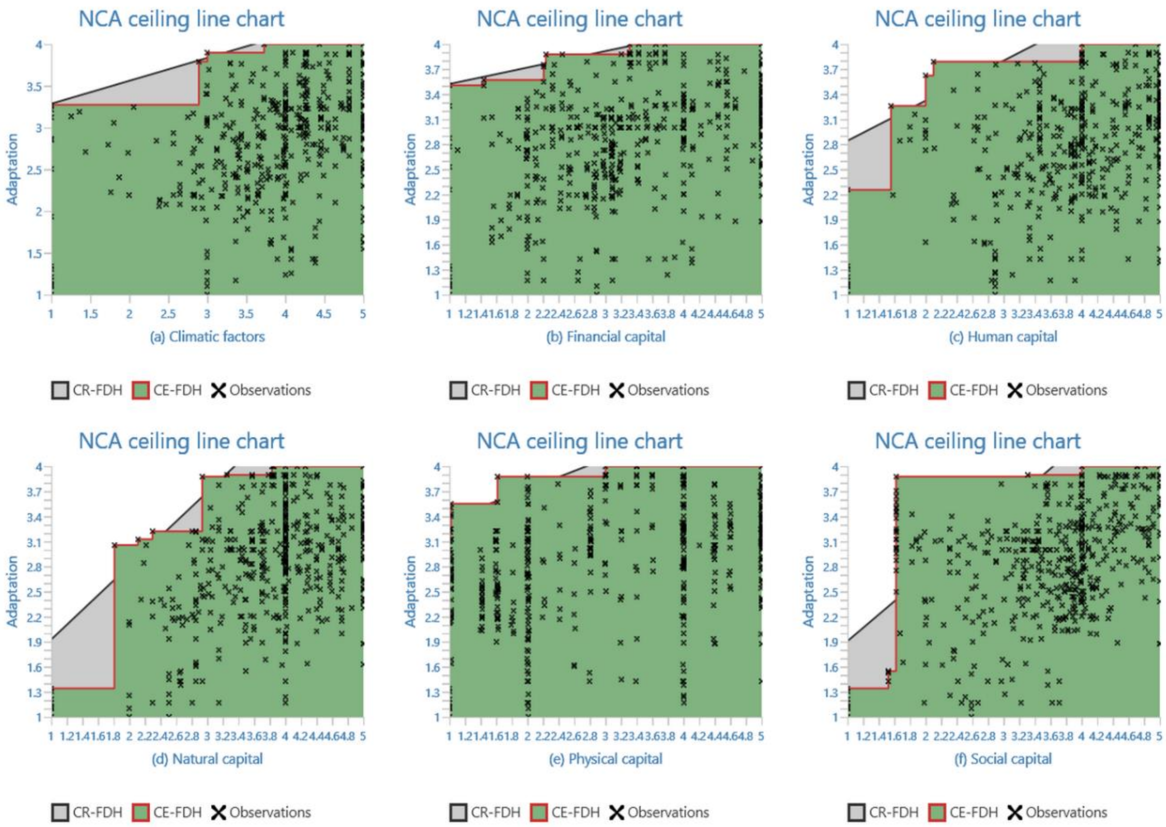


**Figure 6. 8 Bottleneck charts demonstrating the necessity thresholds for different forms of capital across various adaptation levels**

A striking outcome from the Bottleneck Table was the pronounced necessity of all forms of capital for achieving complete adaptation (100%). The required levels for climatic factors, financial, human, natural, physical, and social capital were 3.728, 3.308, 4.000, 3.829, 3.000, and 4.000, respectively. These values represent the minimum levels of each capital that must be available to farmers to achieve complete adaptation to climate change.

The bottleneck analysis illustrates that while certain forms of capital are essential throughout the adaptation process, their necessity varies significantly at different stages. For instance, while natural and social capital is consistently necessary, the importance of human, financial, and physical capital becomes more pronounced only at higher levels of adaptation. This suggests that effective adaptation is contingent not just on the presence of these capitals but on their strategic development and utilization at various stages.

Our results present a complex picture of adaptation in Pakistan's irrigated agricultural sector. While the positive influence of some capitals is in line with expectations, the inverse relationship of financial capital with adaptation and the varying thresholds of necessity identified for different forms of capital offer new insights. These results highlight the critical role of a balanced.

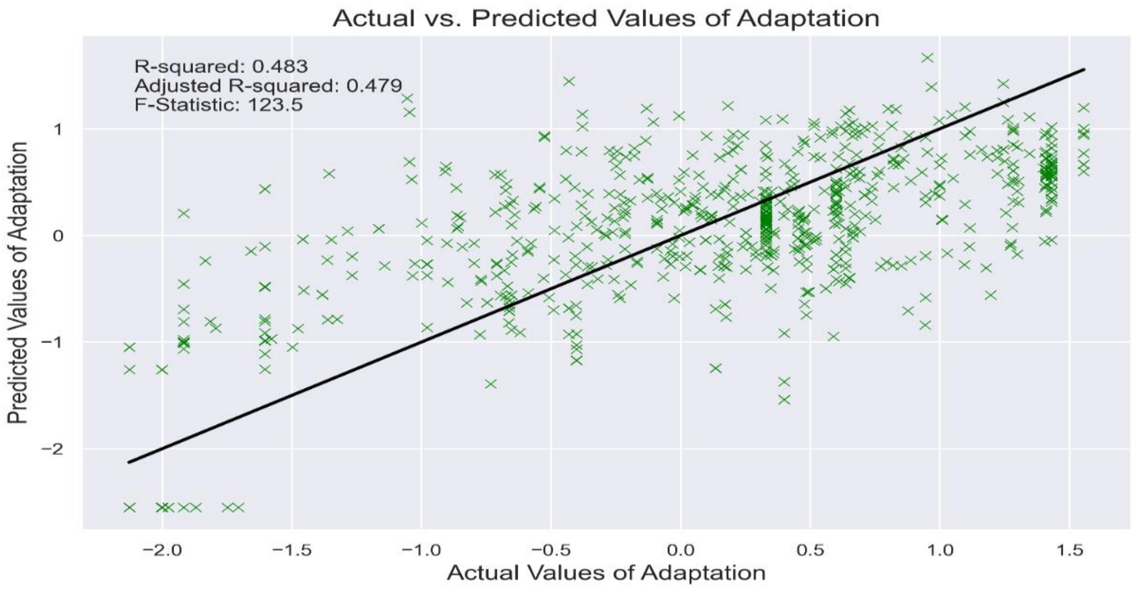


**Figure 6. 9 Regression model showing the statistical relationships and path coefficients between different livelihood capitals and adaptation**

Figure 6.9 presents a regression model delineating the statistical relationships between various livelihood capitals and adaptation. The scatterplot with a fitted line depicts the correlation between actual and predicted adaptation values, suggesting the model's ability to capture the underlying pattern. The R-squared value of 0.483 indicates that the model explains close to half of the variability in adaptation, while the adjusted R-squared value of 0.479 accounts for the model's explanatory power after adjusting for the number of predictors included. The F-statistic of 123.5 further attests to the overall significance of the model.

The distribution of points around the fitted line reflects the precision of the model's predictions relative to actual outcomes, with most data points clustering near the line, indicating a generally accurate model. Some points fall further away, which could signal outliers or instances where the model does not fully capture the nuances of the data.

In sum, the model effectively quantifies the impact of livelihood capital on adaptation, although the scatter of points suggests room for further refinement to enhance predictive accuracy. The model's substantial F-statistic reinforces the robustness of the relationships between the independent variables and adaptation, emphasizing the relevance of these capitals in shaping adaptive responses.

### 6.3.5. Synthesis of PLS-SEM and NCA

The synthesis of PLS-SEM and NCA findings explains a comprehensive landscape of how different livelihood capitals contribute to adaptation. The necessity and sufficiency analysis reveal that while some capitals are instrumental in enhancing adaptation outcomes, others must reach specific thresholds to be effective. These insights are pivotal for stakeholders to prioritize interventions and allocate resources efficiently, considering the magnitude of impact (sufficiency) and the minimum required levels (necessity) for successful climate change adaptation in agricultural practices.

PLS-SEM indicates the direction and strength of relationships between several types of capital and adaptation. At the same time, NCA provides insights into the capital thresholds necessary for achieving various levels of adaptation. Natural capital is a consistent necessity across all levels, whereas other financial and physical capital is only necessary at higher adaptation levels. Human and social capital are critical for a broad range of adaptation levels, with their necessity becoming more pronounced as adaptation levels increase. This suggests that while all forms of capital play a role in adaptation to climate change, their importance and necessity vary at various stages of adaptation. These insights can be crucial for policymakers and practitioners in prioritizing resources and interventions for climate change adaptation strategies.

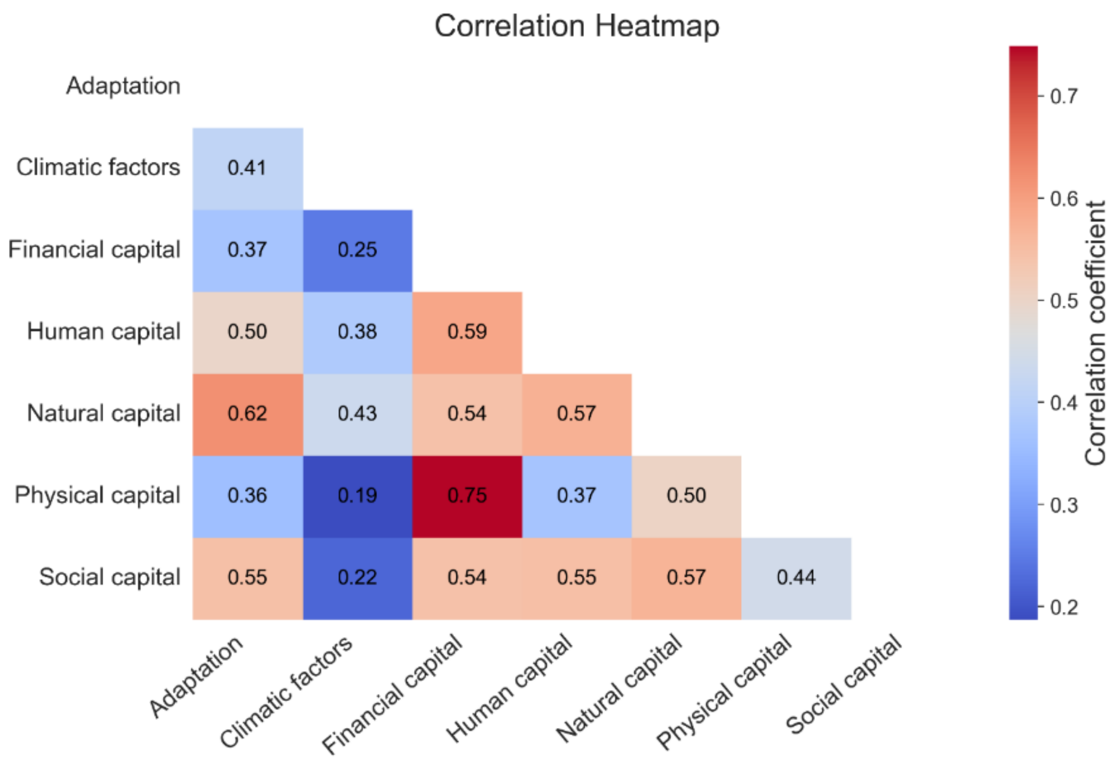


**Figure 6. 10 Heatmap displaying the correlation coefficients between study variables**

Figure 6.10 is a heatmap that elucidates the correlation coefficients among study variables, offering a visual representation of the strength and direction of relationships within the research model. The color-coded matrix ranges from blue (positive correlation) to red (negative correlation), with deeper shades signifying stronger relationships. Natural capital exhibits the strongest positive correlation with adaptation, indicated by a coefficient of 0.62, suggesting a significant role in adaptive processes. Human and social capital also show notable positive correlations with adaptation, with coefficients of 0.50 and 0.55, respectively, underscoring their importance in facilitating adaptive measures.

Conversely, financial and physical capitals demonstrate weaker correlations with adaptation, as reflected by their lower coefficients of 0.37 and 0.36. The inter-correlations among the capital types are also varied, with the highest positive correlation observed between human and natural capitals (0.59), implying a potential interplay between these assets in influencing adaptive capacities.

In conclusion, the heatmap concisely summarizes how climatic factors and several types of capital correlate with adaptation outcomes. The visual depiction through the heatmap enables researchers to quickly identify and focus on the most influential factors, which is crucial for formulating effective adaptation strategies and directing future research inquiries.

### 6.4. Discussion

Our analysis of adaptation strategies among Pakistani farmers in the irrigated Indus plains has produced compelling insights. Our survey data reveals that the demographic landscape of Pakistani irrigated farmers has a primary education, diverse farming experience, and a predominant dependency on farming as their sole livelihood support. This finding aligns with (Mehmood et al., 2022), who reported similar results for Punjab province. The data also show a strong base on natural and physical capital but moderate physical, financial, and social levels, suggesting policy intervention in these areas. Sargani et al. (2022) also argued the similar findings in his empirical research on Sindh province. However, our combined use of PLS-SEM and NCA explains the roles of capitals with different magnitudes needed for successful adaptation.

#### 6.4.1. Climatic Factors

The PLS-SEM results indicate a positive relationship between climatic factors and adaptation, which aligns with the understanding that awareness and experience of climatic changes can trigger adaptive actions. However, the NCA suggests these climatic factors become necessary only at higher adaptation levels. This delay in necessity could imply that initial adaptation efforts may rely less on climatic factors and more on immediate accessible resources (Moser & Ekstrom, 2010). It means that insufficient resources act as a hindrance to starting adaptation planning. Moreover, in the beginning, adaptation strategies are influenced by non-climatic factors, including income diversification and seeking employment outside of farming (Mohamed Esham & Chris Garforth, 2013; Mobeen et al., 2023).

### 6.4.2. Financial Capital

Our study reveals an inverse relationship between financial capital and adaptation. This contradicts most studies that found financial capital positively contributes to adaptation (Ankrah et al., 2023; Berti et al., 2004; Chandio et al., 2022; Sahoo et al., 2017). This counterintuitive finding suggests that increased financial capital does not always correspond to enhanced adaptation. Instead, it often becomes a source of parallel livelihood resilience by transferring the assets to more secure spheres such as bank deposits and investment in livestock. One potential interpretation is that reliance on financial resources might lead to complacency or reduced motivation to seek diverse adaptation strategies. The inverse relationship observed could indicate a unique dynamic in Pakistan's irrigated agricultural sector, where farmers with a higher financial capital may prioritize immediate, more secure investments over longer-term adaptive strategies. This reflects a resource allocation strategy where farmers with more financial resources choose to invest in non-agricultural assets, viewing them as less vulnerable to climate-related risks compared to on-farm adaptive measures. It is plausible for the farmers that abundant financial capital leads to a sense of security that diminishes the urgency to adapt. This also highlights the complexity of adaptation processes, where financial capital might not always directly translate into adaptation, especially when other factors such as knowledge, skills, or institutional support are lacking. Furthermore, the findings indicate a research gap that future research may focus on. Moreover, the NCA findings, which show the necessity of financial capital only at the highest adaptation levels, further support this notion, indicating that financial capital alone is insufficient for initiating adaptation but may be crucial for fully realized adaptation strategies.

### 6.4.3. Natural Capital

The pivotal role of natural capital as a predictor of successful adaptation is underscored by its high path coefficient in PLS-SEM and its early necessity in the NCA analysis. Academia has consensus over the crucial role of natural capital for adaptation (Behara et al., 2022; Kuang et al., 2020; Kuang et al., 2019; Monge & McDonald, 2020; Mubaya & Mafongoya, 2017; Uy & Shaw, 2012). In our findings, the reliance on natural capital for adaptation, with a beta value of 0.345, is consistent with the sustainable livelihood framework, which views natural resources as the bedrock of agricultural resilience. Our findings corroborate the study of Kuang et al. (2019), who also identified the positive role of natural capital in farmers' farming decisions. The necessity for a minimum value of 1.809 to achieve basic adaptation levels is indicative of the threshold beyond which the absence of natural capital can severely restrict the ability of farmers to adapt. This suggests that natural resources such as water availability, soil fertility, and biodiversity are not merely resources to be exploited but fundamental components that underpin the adaptation process. It highlights the need for conservation and sustainable management practices to maintain these resources, ensuring they support adaptation actions.

#### 6.4.4. Human Capital

Human capital, encompassing the knowledge, skills, and health that enable individuals to pursue different livelihood strategies, has a direct and positive relationship with adaptation, supporting the findings of Qi et al. (2022). With a beta coefficient of 0.150, human capital's significance is non-negligible but also suggests a complex interplay with other forms of capital. The findings resonate with the understanding that human capital influences adaptation decision-making and the capacity to implement adaptive measures effectively. Training and education in sustainable practices and climate-smart agriculture can enhance human capital, equipping farmers with the necessary tools to adapt to changing climatic conditions. The positive role of human capital in successful adaptation in agriculture has been widely recognized in the literature (Chandio et al., 2022; Liu et al., 2020; S. H. Shah et al., 2019). However, the necessity analysis indicates that human capital alone, without the support of other forms of capital, may not be sufficient to achieve higher levels of adaptation.

#### 6.4.5. Physical Capital

Physical capital, which includes infrastructure, technology, and tools, presents a nuanced influence on adaptation. With a lower path coefficient in PLS-SEM (0.111) and its necessity emerging only at higher levels of adaptation in the NCA (minimum value of 1.019 at 80% adaptation), its role appears to be more conditional compared to other forms of capital. The weak role of physical capital in successful adaptation in agriculture has been highlighted by Hassan et al. (2023). However, most studies identified this as a promoter of climate adaptation (Kuang et al., 2019; Salam et al., 2021; S. H. Shah et al., 2019). This suggests that while physical capital is essential, its direct influence on adaptation may be overshadowed by the availability of natural resources and strong social networks. Nonetheless, as adaptation efforts intensify, the importance of physical capital becomes more pronounced. Investments in infrastructure such as irrigation systems, storage facilities, and transportation can drastically improve the adaptive capacity of farmers, particularly in the face of extreme climatic events.

### 6.4.6. Social Capital

Social capital, represented by the networks of relationships, trust, and norms that facilitate cooperation, emerges as a strong predictor of adaptation with a path coefficient of 0.283. Social capital's consistent necessity from a 20% adaptation level and its substantial increase at full adaptation highlight its integral role across the entire spectrum of adaptive actions. This aligns with the literature that overwhelmingly states the positive role of social capital in adaptation (Adger, 2003a, 2003b; Chepkoech et al., 2020; Hagedoorn et al., 2019; Jordan, 2015; Kuang et al., 2020; Kuang et al., 2019; Paul et al., 2016; Saptutyningsih et al., 2020; Utami & Cramer, 2020) that emphasizes the importance of collective action and shared knowledge in managing common resources and facing common threats. The NCA indicates that a level of 1.621 is necessary for initiating basic adaptation strategies, reinforcing that social cohesion, community engagement, and mutual aid are vital components of adaptation that can catalyze or constrain adaptation actions.

The intricate relationship between different forms of livelihood capital and adaptation to climate change is evident in this study's findings, which align with. Natural and social capitals are significant predictors across a spectrum of adaptation levels, emphasizing their foundational importance. The inverse relationship of financial capital with adaptation, contrasted with the positive influences of human and physical capital, presents a more complex scenario requiring further exploration. Policy interventions must recognize the multifaceted nature of adaptation and the varied necessity levels of different forms of capital.

## 6.5. Limitations

This research is subject to certain limitations that should be considered when interpreting the findings. Firstly, the findings of this study are specific to the context of Pakistan's irrigated agriculture and may not be directly generalizable to other regions or agricultural contexts. Different geographical, cultural, and socio-economic settings may exhibit varied relationships between livelihood capitals and adaptation strategies. Secondly, the study primarily examines the individual impact of different capitals on adaptation. However, the interactions between these capitals can be complex and nonlinear, which the analysis may not fully capture. Interdependencies and synergistic effects between different forms of capital are areas that warrant further exploration. These limitations highlight areas for future research, including longitudinal studies. One specific area of investigation about financial capital must try to understand the role of financial assets as livelihood resilience and not merely as an asset to deal with poverty. Similarly, regarding the Pakistani irrigated farming community, it was found that farmers have accumulated experience in farming, and their skills and confidence in themselves are important in determining their adaptation.

### 6.6. Conclusion

The integration of PLS-SEM and NCA in this research has provided a nuanced understanding of the adaptation to climate change in Pakistan's irrigated agriculture. The PLS-SEM analysis identified the strength and directionality of the relationships between climatic factors, livelihood capitals, and adaptation. Natural and social capital (with beta 0.345 and 0.283) are the two most significant predictors of climate adaptation. The financial capital exhibits a negative (beta -0.168) relationship with adaptation. Necessary Condition Analysis (NCA) complemented the PLS-SEM findings by identifying threshold levels for each capital needed for successful adaptation. The NCA results highlighted the role of Human, Natural, and Social capital (18% each). It also shows that the increase in the value of all predictors will also increase the adaptation as an outcome.

# Chapter 7: Summary and Conclusion

## 7.1. Summary

This thesis assesses flood risk and its consequences, climate adaptation, and rural livelihoods in Pakistan's irrigated agricultural regions. This research consists of two main parts. The first part consists of Chapters 2 and 3, and the second comprises Chapters 4, 5, and 6. The first part of the thesis analyzes the impact of floods on the Indus Plains using UNITAR's 2022 flood monitoring datasets based on NOAA 20/VIIRS imagery. It assesses the extent of the flood and its effects on the population (Chapter 2). This section also explores how farming communities decide on relocation during floods and investigates the impact on the farmers using the Protection Motivation Theory (PMT) (Chapter 3).

The second part (Chapters 4,5 and 6) of the thesis examines the livelihood capital and adaptation practices in Pakistan's irrigated agricultural areas. Chapter 4 highlights the climate change perception of farmers and their adaptation strategies. Chapter 5 employs the VIABLE framework to assess how livelihood capital contributes to adaptation strategies. This Chapter also considers climatic factors that influence farmers' investment actions. Chapter 6 is an extension of the findings of Chapter 5 that digs further into subcategories of livelihood capital by using the Sustainable Livelihood Framework (SLF) to investigate how individual livelihood capital and climatic factors affect adaptation strategies. This Chapter uses Necessary Condition Analysis to identify necessary elements for climate adaptation (Chapter 6). The subsequent sections elaborate on the salient features of each Chapter based on the objectives and research questions stated in the first chapter.

Chapter 2 addresses the question, "What is the impact of the 2022 flood on irrigated agricultural areas and the extent of the affected population in the lower Indus plains, as analyzed through UNITAR's flood monitoring datasets and NOAA-20/VIIRS observations from August 25 to November 20, with a focus on identifying the most severely affected areas? This Chapter titled "2022 Flood Disaster in Pakistan: Identifying the Regions Most Affected" examines the extraordinary flood catastrophe that devastated the country in 2022. With almost a third of the country submerged, the flood affected 33 million people, displacing 8 million and claiming 1,730 lives. The economic ramifications were enormous, exceeding $30 billion in damages and losses, surpassing the destruction wrought by the 2010 flood. Geostatistical analysis of UNITAR flood monitoring datasets identified the districts most severely affected: Khairpur, Jacobabad, Larkana, Dadu, Naushahro Feroze, Shaheed Benazirabad, Badin, and Thatta. These findings give a quick overview of the flood assessment, help formulate post-flood recovery strategies, and emphasize the need for comprehensive empirical and field research to accurately assess post-disaster damage in these areas.

Chapter 3 investigates how the 2022 flood in the lower Indus plains influenced the immediate displacement of farming communities and what are the dynamics behind their uneven displacement and return patterns, utilizing the Protection Motivation Theory framework. This chapter is a post-flood assessment of implications on the most affected regions of Sindh, Pakistan. It further explains the factors that influence farmers' relocation decisions. Based on Protection Motivation Theory (PMT), the study tested the necessity of PMT's six subcomponents: Severity, Vulnerability, Response Efficacy, Self-Efficacy, Reward, and Fear as predictors of decision of displacement. It further discusses the role of predictors in motivating displacement decisions among farmers in flood-prone districts of Sindh. Using PLS-SEM and NCA, the study analyzed primary field survey data from 195 farmers affected by the 2022 floods. The combined use of PLS-SEM and NCA is appropriate when we have limited datasets. This technique is also helpful when complementing necessity logic with sufficiency logic. It identified that a minimum level of Fear at 3.11 and Response efficacy at 2.32 are necessary for activating sufficient protection motivation to decide on displacement. The combined output of PLS-SEM and NCA shows that Fear and Response efficacy are the two significant predictors (with a p-value of 0.00). Fear is the most significant predictor, with a coefficient of 0.489 accounting for 19%, while Response efficacy, with a coefficient of 0.324, contributed 14% in displacement decisions. Necessary Condition analysis identified the specific threshold values necessary for activating sufficient protection motivation. Increased Fear and Response efficacy significantly boosts displacement motivation, whereas other predictors are insignificant and unnecessary. These insights emphasize the complex interplay of various factors in shaping farmers' protective actions and have profound implications for disaster management policies, highlighting the need for targeted interventions that focus on these necessary predictors to enhance the effectiveness of flood relief efforts.

Chapter 4 explored how farmers perceive the impact of climate change on their agricultural practices and adaptation strategies, emphasizing constraints and factors influencing their decisions. This Chapter explores farmers' perceptions of climate change, their adaptation techniques, and the barriers to implementing these strategies. The study used descriptive statistics to analyze data from a standardized questionnaire from 800 farmers across Punjab and Sindh. The results display a clear awareness among farmers of climatic changes, including extended summers and contracted winters and a decline in crop yields over the past decade due to climate change. The dominant adaptation strategies differ within the irrigated regions. The farmers in Punjab primarily adapted crop and farm management, while farmers in Sindh focused on implementing irrigation measures. The study identifies crucial constraints impacting farming decisions, such as financial limitations, water scarcity, and poor soil fertility. This Chapter offers valuable insights for policymakers, suggesting the need for tailored policy instruments that consider farmers' perceptions, motivations, and constraints to promote sustainable farming practices effectively.

Chapter 5 evaluated how the VIABLE framework elucidates the role of livelihood capital in climate adaptation among farmers, including viable investment pathways and factors influencing adaptation measures. What is the moderating impact of climatic and non-climatic factors on their adaptation actions? This chapter describes the role of sustainable livelihood capital in Pakistan's agricultural sector's climate change adaptation process. By utilizing the Values and Investments for Agent-Based Interaction and Learning in Environmental Systems (VIABLE) framework, this study assesses stakeholders' actions and priorities in adapting to climate change. This Chapter used the PLS-SEM approach to the VIABLE framework. This study used data collected during the first survey. The study found that livelihood capital is the most significant (beta = 0.57, effect size = 0.503) determinant of farmers' adaptation strategies in the Indus Plain, with other factors, such as investment options and farming constraints, having less impact. The VIABLE-SEM identified thirteen viability pathways, highlighting the complex interplay of factors influencing climate change adaptation. Notably, the study discovered that non-climatic factors negatively affected the relationship between capital and adaptation. The model also tested climatic factors as moderators. The results showed that climatic factors positively influence the relationship between capital and adaptation. These findings provide crucial insights for policymakers and researchers to develop effective climate change adaptation strategies in Pakistan's agricultural sector.

Chapter 6 further investigates the most significant determinants of climate adaptation that the VIABLE-SEM model identified in the previous Chapter. These two determinants were Livelihood capital and climatic factors, which were influential. Chapter 6 explores what sub-components of livelihood capital and climatic factors are necessary for climate adaptation. This Chapter explores the critical role that different forms of livelihood capital and climatic factors play in farmers' adaptation strategies. This section used the combination of PLS-SEM and NCA to analyze data from the first survey in which the author collected data from 800 farmers. The study found that both climatic factors and all forms of livelihood capital are necessary for successful adaptation. Natural and social capital emerged (beta values of 0.345 and 0.283) as significant predictors with specific threshold values identified for basic adaptation levels.

Interestingly, financial capital (beta coefficient -1.85) shows an inverse relationship with adaptation, suggesting complex interactions between economic constraints and adaptation strategies. This Chapter provides critical insights into the importance of various forms of livelihood capital and climatic factors in adaptation processes, which are essential for policymakers in Pakistan's irrigated agricultural regions.

### 7.2. Conclusion

In Pakistan, irrigated agriculture is facing severe climate change impacts ranging from climatic extremes to flood disasters. Floods and climate-related catastrophes particularly hit Sindh province in 2022. A region with 23% of Pakistan's population has been experiencing frequent flood breaches near the Indus River, resulting in a significant loss of life and property. This study highlights the critical areas in the irrigated Indus Plains that were worst hit by the 2022 flood. In the particular context of the 2022 flood, Fear and Response efficacy emerge as pivotal and influential predictors in shaping farmers' decisions to displace. Fear and response efficacy need a value of 3.11 and 2.32, respectively. These values are required to instigate sufficient motivation for displacement in a flood disaster. The prominence of Fear as a determinant is underscored by its significant predictive power, evidenced by a coefficient of 0.489, which accounts for 19% of the variation in displacement decisions.

Conversely, Response efficacy, though slightly less impactful with a 14% contribution, marked by a coefficient of 0.324, remains a critical component in this decision-making process. Further highlighting the study's key findings, it is evident that the increase in Fear and Response efficacy significantly enhances the motivation toward displacement. Notably, the study elucidates the relative insignificance of other predictors, affirming that Fear and Response efficacy are necessary for motivating a farmer to displace in case of floods. The contextual backdrop of this study is the irrigated Indus Plain, a region undergoing climatic shifts. Over the past decade, farmers have observed changes in climate extremes, characterized by extended summers and truncated winters.

Consequently, farmers are inclined to adaptation practices, know various adaptation options, and have already implemented specific measures. However, adopting these strategies varies across regions, reflecting the heterogeneity in the agro-ecological agricultural landscape. In Punjab, farmers have primarily adapted crop and farm management practices. In contrast, farmers in Sindh have concentrated on adopting irrigation management, a strategy that aligns with the region's unique hydrological and agronomic conditions. Rainwater harvesting emerges as the least favored adaptation strategy across both provinces. Farmers in the Indus

Plain have several constraints that hinder them to adapt. Foremost among these are the lack of financial resources, water scarcity, and poor soil fertility. These limitations not only deter them from the implementation of adaptive strategies but also exacerbate the vulnerability of agricultural communities to climatic extremes. The study reveals that the availability of financial capital and climatic conditions are the principal drivers of farming decisions.

The comprehensive analysis of farmers’ adaptation strategies in the Indus Plain reveals several critical determinants and their respective influences, painting a complex picture of the adaptation process. The study confirms the importance of livelihood capital as the most significant determinant for adaptation strategies, with a beta value of 0.57 and an effect size of 0.503. This finding underscores the central role of livelihood capital in shaping farmers’ adaptive responses to climate change. In contrast, other variables, such as the principal purpose of farming, available investment options, and natural and human constraints, are comparatively less influential in this context. The study further delineates 13 significant viability pathways, elucidating the farmers’ investment priorities, farming purposes, and constraints encountered in climate change adaptation. These pathways provide a nuanced understanding of the diverse strategies employed by farmers in the face of climatic and non-climatic challenges. Notably, non-climatic factors negatively influence the relationship between capital and adaptation, as indicated by a beta value of -0.156. Conversely, climatic factors positively influence this relationship, with a beta value of 0.050. Interestingly, the presence of these influencing factors, both climatic and non-climatic, is found to increase the adaptive capacity of farmers, suggesting a dynamic interplay between various elements that shape adaptation.

Further, the study highlights the significance of Natural and Social capital based on their beta values of 0.345 and 0.283, respectively. The bottleneck table analysis identified the minimum value of 1.809 for Natural capital and 1.621 for Social capital, which are crucial for attaining basic levels of adaptation. This finding emphasizes the critical need for Natural and Social capital to facilitate effective adaptation strategies. Moreover, enhancing the values of all predictors in the model correlates with improved adaptation levels. This result indicates a cumulative effect of various factors contributing to the adaptation process. Surprisingly, the study reveals an inverse relationship between Financial capital and adaptation, with a beta coefficient of -1.85. This counterintuitive finding suggests that increased Financial capital does not necessarily translate to better adaptation, challenging conventional assumptions and inviting further exploration into the complexities of adaptation dynamics in agricultural contexts

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# Appendix

## (Questionnaire used in Chapter 3)

## Flood Response of farmers in the lower Indus plains, Pakistan-

**Purpose:** Evaluating farmers' flood response and likelihood of relocation in flooding: A case of 2022 floods in Sindh

**PART-1** **1-Basic Information**

| No. | Questions | Answers | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 01 | Name of surveyor | | | | | | | | | | | |
| 02 | Date of survey | | | | | | | | | | | |
| 03 | District name | | | | | | | | | | | |
| 04 | Taluka name | | | | | | | | | | | |
| 05 | Village/Mauza name | | | | | | | | | | | |
| 06 | Name of respondent | | | | | | | | | | | |
| 07 | Age of respondent | | | | | | | | | | | |
| 08 | Flood condition around household (up to 50m) | ① Dried ② Soil Wet ③ Water stagnant (puddles) ④ Still flooded | | | | | | | | | | |
| 09 | Water stagnated around household until | ① Jun 2022 | ② Jul 2022 | ③ Aug 2022 | ④ Sep 2022 | ⑤ Oct 2022 | ⑥ Nov 2022 | ⑦ Dec 2022 | ⑧ Jan 2023 | ⑨ Feb 2023 | ⑩ Mar 2023 | ⑪ Apr 2023 |

**2-Socio demographic information**

| No. | Questions | Answers |
|---|---|---|
| 1 | **Total monthly income** ① up to 50,000 ② 50 to 100,000 ③ Above 100,000 | ①②③ |
| 2 | **Education:** ① No schooling, ② up to Matric ③ HSSC and above | ①②③ |
| 3 | **Family size:** ① Small (up to 4 people), ② Medium (5-6), ③ Above 7 | ①②③ |
| 4 | **House ownership:** ① Owner ② rented ③ Mixed | ①②③ |
| 5 | **House type:** ① Cemented ② Mud ③ Mixed | ①②③ |
| 6 | **Farmland ownership:** ① Owner ② rented ③ Mixed (rented + owner) | ①②③ |
| 7 | **Number of cattle:** ① No Cattles ② for less than 5 ③ for more than 5 | ①②③ |
| 8 | **Personal Vehicle ownership** ①Car, Tractor Truck ②Donkey cart ③ Motorbike ④ None | ①②③④ |
| 9 | **Farm size in Acres** ① 0 - 8.0 ② 8 .1 to 15.9 ③ 16 and above | ①②③ |

**3-Damage and relocation**

| No. | Questions | Answers |
|---|---|---|
| 10 | **Received flood warning from government before flood** ① Yes ② No | ①② |
| 11 | **Life damage in your household** ① No life damage ② Injured ③ Sick ④ Any one died | ①②③④ |
| 12 | **House damage:** ① No Damage ② for 25% Damage ③ for 50% Damage ④ for 75% Damage ⑤ for 100% Damage | ①②③④⑤ |
| 13 | **Crop damage:** ① No crop damage ② Less than half Damage ③ Half damage ④ More than Half Damage ⑤ Total Crop Damage | ①②③④⑤ |
| 14 | **Cattle loss:** ① No cattle damage ② Less than half Damage ③ Half damage ④ More than Half Damage ⑤ Total cattle Damage | ①②③④⑤ |
| 15 | **Relocated:** ① Yes ② No | ①② |
| 16 | **Relocated at** ① Nearby settlement ② Relief Camps ③ Spontaneous Camps | ①②③ |
| 17 | **Previous experience of relocation:** ① Yes ② No | ①② |
| 18 | **Relocated** ① on Personal capacity or ② Government assisted ③ NGO assisted | ①② |
| 19 | **Returned home / rehabilitated** ① Yes ② No | ①② |
| 20 | **Returned** ① on Personal capacity or ② Government assisted ③ NGO assisted | ①② |

**PART-2 (Protection Motivation Theory)**

| | Tick the option that applies to you<br>①Not at all ②Low ③Medium ④High, ⑤Very High | Answers |
|---|---|---|
| | **1-Threat appraisal (Risk Perception)** | |
| | **Severity** | |
| 21 | How do you rate the intensity of flood in summer 2022? | ①②③④⑤ |
| 22 | How serious do you believe the consequences of this hazard can be. | ①②③④⑤ |
| 23 | To what extent do you think this hazard could harm your health or property? | ①②③④⑤ |
| 24 | To what extent do you think flood in summer 2022 has greater intensity than any other flood in the past? | ①②③④⑤ |
| | **Vulnerability** | |
| 25 | To what extent do you feel your community is exposed to flood? | ①②③④⑤ |
| 26 | To what extent you are susceptible to the negative consequences of floods? | ①②③④⑤ |
| 27 | To what extent do you feel your community is at risk from future floods? | ①②③④⑤ |
| 28 | To what extent do you feel that you can recover from the impacts of floods? | ①②③④⑤ |
| | **2-Coping Appraisal** | |
| | **Response efficacy** | |
| 29 | How much effective do you think relocation would be in reducing the threat of flood? | ①②③④⑤ |
| 30 | How confident are you that relocation would be able to mitigate the harm of this hazard? | ①②③④⑤ |
| 31 | How successful do you rate relocation as compare to other flood responses strategies? | ①②③④⑤ |
| 32 | How effectively did you relocate as compare to others in your community? | ①②③④⑤ |
| | **Self-efficacy** | |
| 33 | How capable do you feel yourself to successfully relocate/evacuate? | ①②③④⑤ |
| 34 | To what extent do you believe that you have the necessary skills to carry out relocation? | ①②③④⑤ |
| 35 | To what extent do you believe that you have the resources to carry out relocation? | ①②③④⑤ |
| 36 | How much do you think you would be able to accomplish if you relocated? | ①②③④⑤ |
| | **Perceived Protective Response Cost** | |
| 37 | How much time and effort would it take for you to relocated | ①②③④⑤ |
| 38 | How much would you have to sacrifice in order to relocate? *how much left behind | ①②③④⑤ |
| 39 | To what extent would this coping relocation would be a burden on you in future? | ①②③④⑤ |
| 40 | How much resources (money and others) did you invest in relocation? | ①②③④⑤ |

| | **Tick the option that applies to you**<br>①Not at all ②Low, ③Medium ④High, ⑤Very High | **Answers** |
|---|---|---|
| | **Protective response** | |
| 41 | How likely are you to act for protection before flood in case of emergency call? | ①②③④⑤ |
| 42 | How motivated are you to coordinate with neighbours to mitigate the effects of floods? | ①②③④⑤ |
| 43 | How likely are you to take preventive measures (e.g. sandbags, flood barriers for doors and windows, for mitigating flood effects? | ①②③④⑤ |
| 44 | How committed are you prepare necessary arrangements before flood for your emergency stay in case of flooding? | ①②③④⑤ |
| | **Non-Protective response** | |
| 45 | To what extent do you believe that this threat is not real or not a concern for you? | ①②③④⑤ |
| 46 | How likely are you to adopt a "wait and see" attitude towards this threat? | ①②③④⑤ |
| 47 | How much do you rely on faith or destiny to deal with this threat? | ①②③④⑤ |
| 48 | How pro-actively will you act for relocation arrangements in case of future flooding? | ①②③④⑤ |
| | **Fear** | |
| 49 | How afraid are you of the potential harm that flood could cause to your and your property? | ①②③④⑤ |
| 50 | How worried are you about the potential consequences of a flood in your area | ①②③④⑤ |
| 51 | How anxious do you feel about the possibility of a flood happening in your community? | ①②③④⑤ |
| 52 | How stressed do you feel about the potential impact of a flood on your daily life? | ①②③④⑤ |
| | **Reward (Intrinsic/ Extrinsic)** | |
| 53 | How much secure do you feel if you relocated to prevent the harm of flood? | ①②③④⑤ |
| 54 | How satisfied are you with your decision of relocation during floods? | ①②③④⑤ |
| 55 | How important is this for you that others should also positively approve your relocation? | ①②③④⑤ |
| 56 | How much would you value the approval of your friends and family if decide to relocate in case of flood? | ①②③④⑤ |
| | **Protection motivation (PM)** | |
| 57 | To what extent do you feel that migrating to a safer location is an effective way to protect yourself from flood damage? | ①②③④⑤ |
| 58 | To what degree are you confident to relocate in case of future flooding | ①②③④⑤ |
| 59 | To what extent will you act before time for the arrangements of relocation. | ①②③④⑤ |
| 60 | How much would you advice others to relocate in case of flooding in future? | ①②③④⑤ |

## (Questionnaire used in Chapter 4)

**Climate change perception, adaptation, and constraints in irrigated agriculture in Punjab and Sindh, Pakistan.**

| Code | Questions | Answers | |
|---|---|---|---|
| | Name of surveyor | | |
| | Date of survey | | |
| | Time | | |
| | Location (Latitude/Longitude) | X or Lat: | Y or Long: |
| | Mean Sea Level Hight (m) | | |
| | Temperature in ◦C | | |

**1-Basic information**

| | Questions | Answers |
|---|---|---|
| **Code** | **Geographic information** | |
| | Province name ① for Punjab and ② for Sindh | ①② |
| | District name Punjab<br>① Gujranwala ② Sargodha ③ Bhakkar<br>④ Vehari ⑤ Rajabpur | ①②③④⑤ |
| | District name Sindh<br>① Shikarpur ② Larkana ③ Nausharo Feroze<br>④ Nawabshah/SBA ⑤ Badin | ①②③④⑤ |
| | Tehsil/Taluka name | |
| | Village name | |
| | **Demographic information** | |
| | Education:<br>① No schooling, ② Primary, ③ Middle ④ Matric<br>⑤ HSSC, ⑥ Graduation, ⑦ Masters and above | ①②③④<br>⑤⑥⑦ |
| | Farming experience in years: ① less than 10, ② 10-20, ③ Above 20 | ①②③ |
| | Secondary occupation other than farming<br>① Public employment, ② Private employment ③ Own business ④ Others ⑤ None | ①②③④⑤ |

**2-Perception on climate change**

| Code | Tick the option that applies to you<br>①Strongly Disagree, ②Disagree, ③Neutral, ④Agree, ⑤Strongly agree | Answers |
|---|---|---|
| | **Perception on climate change (within the last 10 years in your area)** | |
| | The summer season has become longer | ①②③④⑤ |
| | The winter season has become shorter | ①②③④⑤ |
| | A rise in the summer temperature has been observed | ①②③④⑤ |
| | A decline in the winter temperature has been observed | ①②③④⑤ |
| | The frequency of rainy days in a year has declined | ①②③④⑤ |
| | The frequency of rainy days in a year has increased | ①②③④⑤ |
| | Soil salinity has increased | ①②③④⑤ |
| | Soil fertility has declined | ①②③④⑤ |
| | Soil fertility has improved | ①②③④⑤ |
| | Soil erosion has been observed | ①②③④⑤ |
| | Frequent Droughts have been observed | ①②③④⑤ |
| | Frequent Floods have been observed | ①②③④⑤ |
| | No heat waves have been observed | ①②③④⑤ |
| | **Perception on impacts of climate change** | |
| | Rabi crop sowing has been delayed | ①②③④⑤ |
| | Rabi crop harvesting has been delayed | ①②③④⑤ |
| | Kharif crop sowing has been delayed | ①②③④⑤ |
| | Kharif crop harvesting has been delayed | ①②③④⑤ |
| | Climate change has deteriorated the quality of irrigated water at your farm | ①②③④⑤ |
| | Climate change has changed the taste of groundwater at your farm | ①②③④⑤ |

**3-Adaptation strategies**

| Code | Statements | Answers |
|---|---|---|
| | What is your take on the given adaptation practices under the changing climate and water conflicts? Mark<br>① I am not aware of this practice<br>② I know about this practice but I am not applying it<br>③ I know about this practice and applying it<br>④ I know about this practice and have a plan to apply in future<br>⑤ I know about this practice and do not have a plan to apply in future | |
| | **Crop Management** | |
| | Cultivation of early cultivars | ①②③④⑤ |
| | Cultivation of drought and water scarcity tolerant crops | ①②③④⑤ |
| | Cultivation of salt-tolerant crops | ①②③④⑤ |
| | Cultivation of crops that can produce more revenue | ①②③④⑤ |
| | Adding tree plantations with the main crop (Agroforestry) | ①②③④⑤ |
| | Cultivating legume cropping (Soybean, Chickpea etc.) | ①②③④⑤ |
| | **Farm Management** | |
| | Re-scheduling the land preparation | ①②③④⑤ |
| | Changing the methods and techniques of cultivation | ①②③④⑤ |
| | Land consolidation or de-fragmentation of farmlands | ①②③④⑤ |
| | Reducing the area under cultivation | ①②③④⑤ |
| | Changing the fertilizers | ①②③④⑤ |
| | Weeds management | ①②③④⑤ |
| | Tree plantation | ①②③④⑤ |
| | Tillage application | ①②③④⑤ |
| | **Irrigation Management** | |
| | Irrigation re-scheduling | ①②③④⑤ |
| | Change method of irrigation (Shifting to drip, sprinkle irrigation) | ①②③④⑤ |
| | Cementation of watercourse | ①②③④⑤ |
| | Canal dredging or canal clearing | ①②③④⑤ |
| | Weeds removal from irrigation channels | ①②③④⑤ |
| | Modification of water allocation rules between individual farmers | ①②③④⑤ |
| | Rainwater harvesting for future irrigation | ①②③④⑤ |
| | New tube-well installation | |

### 4-Constraints

| Code | To what extent are the following factors responsible for not changing your farming practice during the last ten years. Mark ① for **Not at all**, ② for **Low,** ③ for **Medium,** ④ for **High,** ⑤ for **Very high** | |
|---|---|---|
| | Lack of money | ①②③④⑤ |
| | Lack of information | ①②③④⑤ |
| | Lack of motivation | ①②③④⑤ |
| | Lack of farming skills | ①②③④⑤ |
| | Lack of knowledge | ①②③④⑤ |
| | Water scarcity | ①②③④⑤ |
| | Poor soil fertility | ①②③④⑤ |
| | Insufficient size of land | ①②③④⑤ |
| | Lack of manpower needed for making any change | ①②③④⑤ |

### 5-Factors

| Code | Statement | Answers |
|---|---|---|
| | If you get profit from your crop, how would you allocate it?<br>Rate the amount of investment from ① to ⑤, ① for the lowest and ⑤ for the highest | |
| | Changes in temperature | ①②③④⑤ |
| | Changes in rainfall | ①②③④⑤ |
| | Water availability | ①②③④⑤ |
| | Amount of money/capital | ①②③④⑤ |
| | Pest/insect attack | ①②③④⑤ |
| | The market price of your crop | ①②③④⑤ |
| | Government decisions and policies about farmers | ①②③④⑤ |
| | Peers’ advice | ①②③④⑤ |
| | Advice from agricultural extension services | ①②③④⑤ |

## (Questionnaire used in Chapter 5 and 6)

### Famers' Capabilities and their climate change adaptation strategies in irrigated farmland in Sindh and Punjab, Pakistan.

| | Questions | Answers | |
|---|---|---|---|
| 1 | Location (Latitude/Longitude) | Y or Lat: | X or Long: |
| 2 | Date of survey | | |
| 3 | Name and contact of respondent | | |
| 4 | Age of the respondent | | |
| 5 | District, Tehsil, Village (Chak no. etc) | | |

**Socio-demographic profile of respondents**

| | | |
|---|---|---|
| 17 | Education<br>① No schooling, ② Primary, ③ Middle ④ Matric<br>⑤ HSSC, ⑥ Graduation, ⑦ Masters and above | ①②③④<br>⑤⑥⑦ |
| 19 | Farming experience in years ① less than 10, ② 10-20, ③ Above 20 | ①②③ |
| 20 | Secondary occupation other than farming ① Public employment, ② Private employment ③ Own business ④ Others ⑤ None | ①②③④⑤ |

**Part-2 VIABLE Model**
**Farming Purpose**

| | **Tick the option that applies to you, Mark**① for Strongly Disagree, ② for Disagree, ③ for Neutral, ④ for Agree, ⑤ for Strongly agree | **Answers** |
|---|---|---|
| | **Purpose of farming (45-48)** | |
| 45 | The purpose of my farming is to compete with other farmers | ①②③④⑤ |
| 46 | The purpose of my farming is revenue maximization | ①②③④⑤ |
| 47 | The purpose of my farming is to raise my social status | ①②③④⑤ |
| 48 | The purpose of my farming is subsistence (meeting the daily livelihood) | ①②③④⑤ |

**Capital of the farmer**

| | Statement | Answers |
|---|---|---|
| | Tick the option that applies to you, Mark<br>① for Strongly Disagree, ② for Disagree, ③ for Neutral, ④ for Agree, ⑤ for Strongly agree | |
| | **Financial capital** | |
| 77 | I have an adequate size of my farmland | ①②③④⑤ |
| 78 | I have sufficient livestock at my farm | ①②③④⑤ |
| 79 | I have all the machinery needed for farming | ①②③④⑤ |
| 80 | I have sufficient capital at hand for the next year's investment | ①②③④⑤ |
| | **Human capital** | |
| 81 | I have an adequate number of labours at my farm | ①②③④⑤ |
| 82 | My labour has good farming skills | ①②③④⑤ |
| 83 | My farmworkers have good physical fitness | ①②③④⑤ |
| 84 | I have good knowledge about agriculture | ①②③④⑤ |
| | **Natural capital** | |
| 89 | The level of fertility of my farm is good | ①②③④⑤ |
| 90 | I am farming close to transportation networks (roads, rail etc.) | ①②③④⑤ |
| 91 | My farmland can support multiple crops | ①②③④⑤ |
| 92 | My farm is closer to the irrigation channel | ①②③④⑤ |
| | **Social capital** | |
| 93 | I have a good relationship with my neighbouring farmer | ①②③④⑤ |

| | | |
|---|---|---|
| 94 | I have good relations with farmers' associations | ①②③④⑤ |
| 95 | I have good networking and links to all experts of farming in my area | ①②③④⑤ |
| 96 | I trust in my social connections for solving my problems | ①②③④⑤ |
| 97 | I trust in the government agricultural institutions for solving my problems | ①②③④⑤ |
| 98 | I trust in the non-governmental organizations (NGOs) working for farmers | ①②③④⑤ |
| 99 | I trust in my networking about the farming community for my problem solving | ①②③④⑤ |

**Adaptation actions**

| | **Statements** | Answers |
|---|---|---|
| | What is your take on the given adaptation practices under the changing climate and water conflicts? Mark<br>① I am not aware of this practice<br>② I know about this practice but I am not applying it<br>③ I know about this practice and applying it<br>④ I know about this practice and have a plan to apply in future<br>⑤ I know about this practice and do not have a plan to apply in future | |
| | **Crop Management** | |
| 100 | Cultivation of early cultivars | ①②③④⑤ |
| 101 | Cultivation of drought and water scarcity tolerant crops | ①②③④⑤ |
| 102 | Cultivation of salt-tolerant crops | ①②③④⑤ |
| 103 | Cultivation of crops that can produce more revenue | ①②③④⑤ |
| 104 | Adding tree plantations with the main crop (Agroforestry) | ①②③④⑤ |
| 105 | Cultivating legume cropping (Soybean, Chickpea etc.) | ①②③④⑤ |
| | **Farm Management** | |
| 106 | Changing the methods and techniques of cultivation | ①②③④⑤ |
| 107 | Re-sheduling the land preparation | ①②③④⑤ |
| 108 | Changing the fertilizers | ①②③④⑤ |
| 109 | Tree plantation | ①②③④⑤ |
| 110 | Modification of tillage system | ①②③④⑤ |
| | **Irrigation Management** | |
| 111 | Irrigation re-scheduling | ①②③④⑤ |
| 112 | Change method of irrigation (Shifting to drip, sprinkle irrigation) | ①②③④⑤ |
| 113 | Cementation of watercourse | ①②③④⑤ |
| 114 | Canal dredging or canal clearing | ①②③④⑤ |
| 115 | Modification of water allocation rules between individual farmers | ①②③④⑤ |
| 116 | Rainwater harvesting for future irrigation | ①②③④⑤ |
| 117 | New tube-well installation | |
| | **Economic Management** | |
| 118 | Addition of livestock | ①②③④⑤ |
| 119 | Reduction of livestock | ①②③④⑤ |
| 120 | Migrating to the urban centre | ①②③④⑤ |
| 121 | Land renting | ①②③④⑤ |
| 122 | Land selling | ①②③④⑤ |
| 123 | Getting loans from banks | ①②③④⑤ |
| 124 | Change in number of farmworkers | ①②③④⑤ |
| | **Social Network and Knowledge management** | |
| 125 | Use of meteorological information | ①②③④⑤ |
| 126 | Taking advisory from the agricultural department | ①②③④⑤ |
| 127 | Contacting and talking with other farmers | ①②③④⑤ |
| 128 | Using local knowledge and wisdom/ taking advice from elder farmers sages etc. | ①②③④⑤ |
| 129 | Using TV or newspaper for taking information for farming | ①②③④⑤ |
| | **Constraints:** To what extent are the following factors responsible for not changing your farming practice during the last ten years. Mark<br>① for **Not at all**, ② for **Low,** ③ for **Medium,** ④ for **High,** ⑤ for **Very high** | |
| 130 | Lack of money | ①②③④⑤ |

| | | |
|---|---|---|
| 131 | Lack of information | ①②③④⑤ |
| 132 | Lack of motivation | ①②③④⑤ |
| 133 | Lack of farming skills | ①②③④⑤ |
| 134 | Water scarcity | ①②③④⑤ |
| 135 | Poor soil fertility | ①②③④⑤ |
| 136 | Insufficient size of land | ①②③④⑤ |
| 137 | Lack of manpower needed for making any change | ①②③④⑤ |

**Priorities of Investment options**

| | **Statement** | Answers |
|---|---|---|
| | The answer is Yes or No ①for Yes for ②No | |
| 138 | Do you ask for help from your neighbouring farmer if your harvest fails? | ①② |
| 139 | Do you get into conflict with your neighbouring farmer if your harvest fails? | ①② |
| | If you get profit from your crop, how would you allocate it?<br>Rate the amount of investment from ① to ⑤, ① for the lowest and ⑤ for the highest | |
| 140 | Investment in changing in cultivating a more (climatologically) suitable crop | ①②③④⑤ |
| 141 | Investment in expanding the area under the main crop with reference to farm | ①②③④⑤ |
| 142 | Investment in extending the farm size two-fold | ①②③④⑤ |
| 143 | Investment in buying more land for your farm | ①②③④⑤ |
| 144 | Investment in farm size de-fragmentation | ①②③④⑤ |
| 145 | Investment in the installation of your tube well | ①②③④⑤ |
| 146 | Investment in constructing a small water reservoir on the farm | ①②③④⑤ |
| 147 | Investment in livestock. | ①②③④⑤ |
| 148 | Investment in starting any alternative source of earning | ①②③④⑤ |
| 149 | Investment in increasing the labour force on the farm | ①②③④⑤ |
| 150 | Investment in learning new methods farming | ①②③④⑤ |
| | **Rate the factors controlling the decision of your farming** | |
| 151 | Changes in temperature | ①②③④⑤ |
| 152 | Changes in rainfall | ①②③④⑤ |
| 153 | Water availability | ①②③④⑤ |
| 154 | Amount of money/capital | ①②③④⑤ |
| 155 | Pest/insect attack | ①②③④⑤ |
| 156 | The market price of your crop | ①②③④⑤ |
| 157 | Government decisions and policies about farmers | ①②③④⑤ |
| 158 | Peers' advice | ①②③④⑤ |
| 159 | Advice from agricultural extension services | ①②③④⑤ |

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