Climate Change and Agriculture in Pakistan: Impacts and Adaptation Strategies

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Abstract

This thesis presents three self-contained essays, each addressing a salient aspect of climate change impact and adaptation on Pakistan's agricultural sector. The first essay estimates how rising temperatures and anomalous rainfall patterns affect agricultural output, particularly focusing on wheat yields over time. The second essay explores the input side, analysing how changes in land allocation serves as an adaptation strategy in response to past temperature shocks amid government support. The final essay explores how agricultural households respond to past temperature shocks through off-farm labour participation, showing income diversification as a key adaptation strategy in the face of climate change.

Wheat yield response to climate change: A district-level analysis in Pakistan

This study examines the impact of daytime and nighttime warming, along with excess rainfall, on various stages of wheat development—planting, growing, and harvesting—in the province of Khyber Pakhtunkhwa (KP), Pakistan. We quantify excess heat and rainfall at each developmental stage by comparing current climate variables (maximum temperature, minimum temperature, and rainfall) with their respective long-run averages at the district level. Using panel data methods, we analyse the effects of these climate conditions on wheat yields across districts in KP from 2000 to 2019.

The findings indicate that wheat is highly sensitive to high temperatures in KP province. Excess heat affects wheat yields negatively across all the districts. The impact is particularly severe in hotter districts, adversely affecting both

the growing and harvesting stages. While, excess rainfall during the planting stage benefits wheat yields, while rainfall at later stages has a negative impact, potentially delaying the ripening of wheat. Moreover, the results also show that districts adjust their input choices amid hot climate. Irrigation emerges as a crucial strategy for mitigating the negative effects of high temperatures across all districts. In contrast, fertiliser application does not appear to be an effective adaptation strategy during hot climate conditions. This study concludes that wheat is highly sensitive to high temperatures in the province, necessitating improved adaptive practices to safeguard yields.

Adaptation to extreme temperature: Evidence from land allocation in agricultural sector of Pakistan

This chapter investigates the impact of past temperature shocks on different land-use types—total agricultural land, other cropland, and wheat land—in Khyber Pakhtunkhwa, Pakistan, over the period 1981 to 2019. Using a log-linear regression model, it estimates how land allocation responds to past temperature shocks and examines whether these effects vary across the climatic regions. The analysis is framed within the context of a government policy supporting wheat production. This policy refers to the government's Minimum Support Price (MSP) for wheat, which aims to encourage wheat production by guaranteeing farmers a fixed price for their crop. The study compares two sub-periods: 1981–2006, characterised by relatively low government support for wheat production, and 2007–2019, when support was relatively higher. The findings show that during the low support period, land allocated to wheat declined in the aftermath of temperature shocks, resulting in a contraction of total cultivated land across the province. The effects, however, vary across climatic regions. During the low support period, southern districts employed resilience-building strategies by shifting to heat-resilient crops. This adaptive response resulted in an expansion of total cultivated land. While, other regions experienced reductions in both the share of land allocated to wheat and total agricultural land. Their limited capacity to transition to alternative crops constrained their responses, forcing them to focus on minimising potential losses from climatic risks. During the high support period (2007–2019), the findings suggests that government support has prevented a decline in the land allocated to wheat. The results show no evidence of a reduction in wheat land across the province, instead, an increase was observed, particularly in the southern and northern regions. In these regions, land allocation towards government-supported wheat increased in response to previous year's temperature shocks, often at the expense of other crops. In particular, the northern region, which is poorer and more resource-constrained, shifted away from growing heat-resistant crops and instead devoted more land to wheat cultivation. While the government support provides a sense of security in the face of climatic risks, it may also inadvertently increase reliance on a vulnerable crop.

Extreme temperature, labour supply, and subsistence farming: Evidence from Pakistan

This chapter focuses on how off-farm labour response have changed among agricultural households over the the past two decades (2001-2018). Utilising survey data from about 21200 agricultural households across 107 districts and high-resolution gridded temperature and rainfall data over time, our analysis indicates changes in off-farm labour responses among agricultural households in the aftermath of temperature shocks. We find no significant impact of one-year lagged temperature shock on off-farm labour participation over the first decade (2001-2011) and a positive association between a lagged-year temperature shock and off-farm labour supply in the second decade (last two survey years 2015 and 2018). We, empirically examine three potential mechanisms underlying observed responses in off-farm labour supply. We show that the increase reliance on off-farm labour is not driven by 1) worsening of temperature shocks over time, nor by 2) learning from repeated exposure, but can be linked to 3) improvements in local development conditions. This chapter highlights that local development conditions have significantly improved and derive off-farm responses among agricultural households, which partly explains the recent increase in the off-farm labour supply response.

Lay summary

This thesis comprises three empirical chapters that provide a comprehensive analysis of the impact of and adaptation to climate change in Pakistan's agriculture.

Wheat yield response to climate change: A district-level analysis in Pakistan

The first chapter focuses on the output side, examining how deviations in district-level average temperature and rainfall impact wheat yields over two decades in Khyber Pakhtunkhwa (KP) province. The results show that higher-than-average temperatures during critical stages of wheat development significantly reduce yields across all districts. While excess rainfall is beneficial during the planting stage, it becomes harmful to yields in later stages. Furthermore, the findings identify input adjustments as potential adaptive responses to heat stress. For instance, enhanced irrigation proves to be an effective coping mechanism, mitigating the adverse effects on wheat yields. In contrast, adjustments in fertiliser application, whether increased or decreased, seem to be less effective under these conditions. This chapter estimates the vulnerability of wheat yields to climatic variability and the role of input adjustments in reducing the negative impacts of climate change.

Adaptation to extreme temperature: Evidence from land allocation in agricultural sector of Pakistan

This chapter examines how temperature shocks in the past have influenced the use of agricultural land in Khyber Pakhtunkhwa, Pakistan, from 1981 to

2019. It looks at three main types of land use: total agricultural land, other cropland, and wheat land. The study also considers the role of government support for wheat production through the Minimum Support Price (MSP), which guarantees farmers a fixed price to encourage wheat farming and stabilise incomes. The research focuses on two periods: 1981–2006, when government support was relatively low, and 2007–2019, when support increased. During the low-support period, temperature shocks caused a decline in the land allocated to wheat, leading to a reduction in total cultivated land across the province. Southern districts adapted by switching to heat-resistant crops, which increased total cultivated land. However, other regions, with fewer resources and limited options, reduced both wheat land and overall agricultural land in an effort to minimise losses. In the high-support period, government policies helped prevent declines in wheat land, and wheat cultivation even increased in southern and northern regions. In these areas, in response to past temperature shocks land allocated to wheat expands, often reducing land for other crops. Particularly, poorer northern regions shifted away from heat-resistant crops to focus more on wheat, relying on government support to mitigate climate risks. While this policy provided stability, it also increased dependency on wheat, a crop vulnerable to future temperature shocks.

Extreme temperature, labour supply, and subsistence farming: Evidence from Pakistan

This chapter examines how agricultural households' off-farm labour responses have changed over the past two decades (2001-2018) in relation to past temperature shocks. Using survey data from around 21,200 households across 107 districts, alongside detailed temperature and rainfall data, the study finds a growing reliance on off-farm work, especially in the more recent years. The analysis shows that, while temperature shocks didn't significantly affect off-farm labour participation in the early period (2001-2011), there was a clear increase in off-farm work in response to temperature shocks in the later years (2015 and 2018). The study also investigates three possible reasons for this change and finds that the increased reliance on off-farm labour is not due to worsening temperature shocks or farmers learning from past events. Instead, it is linked to improvements in local development conditions, such as better infrastructure or access to services.

This chapter highlights that as local development conditions have improved, off-farm labour responses among agricultural households have also increased, partly explaining the recent rise in off-farm labour participation.

By connecting district-level responses in wheat yields and land allocation with household-level labour allocation, these chapters collectively highlight the impacts of climate change and the presence of adaptation strategies in Pakistan. By examining both macro-level (district) and micro-level (household) responses, the analysis offers a more holistic view of how different stakeholders adapt to climate shocks. The findings from this thesis can help design policies that improve resilience, ensure food security, and support sustainable livelihoods in vulnerable farming communities across Pakistan.

Declaration

I hereby declare that this thesis has not been and will not be submitted in whole or in part to another University for the award of any other degree.

Signature:

Sonia Jan Alam

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Embarking on a PhD is not unlike setting sail on uncharted waters—challenging, transformative, and occasionally overwhelming. The crew I was fortunate enough to have on this voyage made all the difference, and it's time to thank them.

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Dedication

To my beloved mother, Fatima Batool (Late),

As I stand here, having reached this milestone, I feel your spirit with me in every moment of this journey. This achievement is as much yours as it is mine. I know that you are watching with pride, and I carry you with me in everything I do.

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Chapter 1

Introduction

This thesis consists of three self-contained essays devoted to analysing the impact of climate change and its adaptation in Pakistan's agricultural sector. Each chapter addresses a specific aspect of climate variability, focusing on its effects on crop yields and adaptation strategies, including input choices, land and labour allocation, at both the district and household levels. The three chapters interlink by exploring different yet interconnected dimensions of adaptation to climate change, collectively highlighting the impacts of these mechanisms in shaping agricultural resilience in Pakistan.

1.1 Motivation

The focus on Pakistan is motivated by the growing threat of climate change, which increasingly strains the agricultural sector—a mainstay of the country's economy. Climate change is one of major threats to Pakistan's economy making it among top five vulnerable countries in the world (Ahmad et al., 2015). The vulnerability is due to the extreme weather events such as extreme temperatures, drought and floods, primarily driven by climate change (Chaudhry, 2017). According to World Meteorological Organization (WMO), Pakistan experienced an extreme temperature of 53.7°C in 2017, making it the fourth-highest temperature ever recorded in the world. More recently, Pakistan regularly experiences some of the highest maximum temperatures in the world, with a yearly average ranging between 38 to 40°C (WBG and ADB, 2021). Given these extreme conditions, the Intergovernmental Panel on Climate Change (IPCC) projects a significant temperature rise of 5.3°C by 2081-2100 , which is higher than the projected global average increase of 3.7°C (IPCC, 2019). In addition, rainfall patterns have become increasingly erratic in recent years and are expected to intensify in the future (Mani et al., 2018). For instance, floods have become more frequent and severe, particularly during th monsoon months (July to September), while for the rest of the year, the country receives less than 250 mm of annual rainfall (indicating a dry climate), placing additional pressure on water resources needed for agriculture (Syed et al., 2022). According to FAO (2023), Pakistan is the 15th most water-stressed country in the world, and is predicted to become water scarce by 2035.

Climate change poses significant challenges to the agricultural sector globally (Dell et al., 2014; Birkmann et al., 2022), impacting crop yields (Schlenker and Roberts, 2009; Mendelsohn and Massetti, 2017), farming practices (Kurukulasuriya and Mendelsohn, 2008; Gautier et al., 2016; Aragón et al., 2018) and food security (WFP, 2018; ADB, 2022). In Pakistan, agriculture is particularly vulnerable to these changes, with shifting climate patterns, increasing temperatures, and erratic rainfall threatening both the productivity and sustainability of this crucial industry (Ghanem, 2010; Miller et al., 2021). One of the primary reasons for this vulnerability is that agriculture is the largest employer in the country, providing approximately 45% of the workforce (Chaudhry, 2017). Additionally, climate change directly affects major food crops, raising significant concerns for food security and livelihoods (Siddiqui et al., 2012; Gov-KP, 2018). The country's key food crops are highly sensitive to fluctuations in temperature and water availability. Specifically, when temperatures rise by 0.5°C to 2°C coupled with low water availability, it can result in an estimated 8 to 10% decline in major food crop yields (Dehlavi et al., 2015; Mani et al., 2018). Wheat, in particular, is highly sensitive to high temperatures. When exposed to temperatures above 28−30°C, the crop is severely damaged, leading to reduced or even zero yields (Hertel and Lobell, 2014; Heil et al., 2020). According to agronomic literature, the reduction in yields can vary significantly depending on the growth stages of the wheat crop. During critical reproductive phases, where most reproductive activities occur, temperatures exceeding 20°C can drastically reduce yields by up to 57% (Kosina et al., 2007; Asseng et al., 2011).

Pakistan faces a significant challenge, as over 80% of its population relies on wheat as a staple food, with wheat flour accounting for 72% of daily caloric intake (FAO,, 2018). Nearly 20% of the population is already undernourished (Mani et al., 2018). This issue is further worsened at the sub-national level, where geographical and socioeconomic disparities intensify the problem. Khyber Pakhtunkhwa (KP) province is particularly vulnerable due to its diverse topography and low levels of socioeconomic development. The province's unique landscape—ranging from high-altitude mountains in the north to lowland plains in the south—exposes it to extreme climate risk such as heatwaves, droughts, and floods (Kreft et al., 2016). The province is consistently vulnerable to these climate risks, as farming serves as the primary economic activity, employing nearly 80% of its workforce—significantly higher than in other provinces (BPS, 2018). Moreover, development constraints, including limited infrastructure, low economic investment, and inadequate access to resources, further exacerbate food insecurity (EPA, 2016). According to the National Nutrition Survey (2018), only 54.6% of KP's residents are food secure, while 22% experience mild food insecurity and 24% face severe food insecurity. Given this scenario, climate change is anticipated to further complicate the situation in Khyber Pakhtunkhwa (KP) province specifically, and more generally across the country.

1.2 Research objectives

The first two chapters of this thesis provide district level analysis for KP province. The first chapter examines how extreme climate conditions, such as excessive heat and rainfall, affect wheat yield over time. The second chapter explores how land allocation serves as an adaptation strategy to past temperature shocks, focusing on government support for wheat production through the Minimum Support Price (MSP), a fixed price established by the government. The final chapter explores how agricultural households across Pakistan respond to past temperature shocks through off-farm labour participation, highlighting income diversification as a key adaptation strategy in the face of climate change.

Each chapter develops a line of argument based on standard agricultural household model in the development literature (Benjamin, 1992; Taylor and Adelman, 2003). We consider this framework in the context of incomplete markets where consumption and production decisions can not be separated. In such circumstances, a negative productivity shock and the resulting reduction in agricultural output could potentially push household consumption below subsistence levels. Without access to adaptive measures such as savings, credit, crop insurance, or off-farm opportunities (e.g., non-farm employment or migration), the only viable option to offset the reduction in output and maintain consumption would be to increase reliance on available resources, such input choices, land or household labour.

While all chapters stem from this agricultural household theory, each one concentrates on a different aspect of productive adjustment in response to climate change and utilises empirical strategies specific to the research questions to be addressed. The first two chapters use district-level data for KP province over time. The first chapter focuses on the output side, using data on wheat yield and production inputs from 2000 to 2019. The second chapter focuses on the input side, particularly on land use changes in response to past temperature shocks within the framework of government policy, specifically the minimum support price (MSP) for wheat. The data used in this chapter provides information on total agricultural land, land under wheat, and land allocated to major summer crops over time (1981-2019). The third chapter shifts to household level labour allocation, utilising survey data from agricultural households collected during six survey years (waves) between 2000/2001 and 2018/2019 across Pakistan. It explores how off-farm labour responses have changed over the past two decades(2001-2018). The survey used in this chapter provides comprehensive information on household income and employment conditions, including socio−economic characteristics. Therefore, each chapter has its own data section, theoretical framework, and empirical methodology.

The first chapter examines the impact of warming and excessive rainfall on district-level wheat yields through a production model, employing a fixed effects framework and panel data approach. Warming and excessive rainfall are measured using deviations from long-run district-level climate averages. To assess robustness, this chapter also considers ideal climate conditions, using deviations from optimal climate ranges. Given the sensitivity of specific growth phases to temperature and rainfall, the empirical analysis focuses on three critical stages of wheat development: planting, growing, and harvesting. The results indicate that the growing stage is particularly sensitive to warming, as it is a critical phase where major reproductive processes occur. High temperature during this stage can significantly reduce grain numbers by increasing floret mortality and sterility, ultimately leading to lower yield (Kumar et al., 2016; Khan et al., 2020). In contrast, increased rainfall benefits wheat, particularly during the planting stage, enhancing germination and resulting in higher yields. The empirical model also tests heterogeneous effects across districts, categorised into milder, moderate, and hotter districts based on temperature quartiles. The results are consistent across all specifications, showing that warming negatively impacts all districts. However, the hotter districts in the southern part of the province are more severely affected, experiencing negative production shocks at both the growing and harvesting stages. The analysis also reveals that changes in input use, such as irrigation and fertiliser application, can help mitigate heat stress during the wheat growing season. Specifically, better irrigation has a positive effect on yields in the face of heat stress, highlighting its effectiveness as a coping strategy across districts in the province. In contrast, applying either low or high levels of fertiliser does not effectively mitigate the adverse effects during the hot season.

The second chapter examines how land allocation changes in response to past temperature shock, with a focus on the role of government policy in form of a minimum support price (MSP) for wheat from 1981 to 2019. This analysis seeks to understand how the minimum support price (MSP) policy influences adaptation through land use changes following a temperature shock by comparing two periods. The first period (1981–2006) represents a time of relatively low support prices for wheat, while the second period (post−2006) is characterised by a substantial increase in support prices. The results show a decline in land allocated to wheat in response to the previous year's temperature shock during the low-support period, leading to an overall reduction in total cultivated land across the province. However, the empirical analysis highlights heterogeneous land allocation responses to temperature shocks across the climatic regions. During the period of low government support (pre−2006 period), southern region adopted resilience-building strategies by shifting from wheat, a temperature-sensitive crop, to more heat-resilient alternatives. This adaptation resulted in an increase in total cultivated land. In contrast, other regions reduced both the land allocated to wheat and the total agricultural area, resulting in a contraction of total cultivated land. This finding suggests that these regions face limited capacity to transition to alternative crops, relying instead on reduced land use as an adaptation strategy to minimise potential losses from climatic risks. During the high-support period (post−2006), there was no significant reduction in the share of land allocated to wheat across all climatic regions in the province. Instead, both the southern and northern regions observed an increase in wheat cultivation, contributing to an overall expansion in land use following a temperature shock. In particular, the resource-poor northern region allocated more land to wheat at the expense of more heat-resilient crops. These findings suggest that high government support prevented a reduction in land allocated to the temperature-sensitive crop, wheat, which is also a government-supported crop, following a temperature shock. While government support has mitigated climate change-induced yield losses, it has also increased reliance on wheat—a crop that remains vulnerable to climate change—potentially exposing regions to greater risks in the future. At the same time, it limits their ability to shift to more heat-resistant crops, which could serve as a more effective adaptation strategy to climatic risks.

The final chapter focuses on how off-farm labour responses have changed among agricultural households over the past two decades (2001-2018). The empirical analysis reveals that lagged temperature shocks had a null effect on off-farm labour supply choices during the first decade (2001-2011). However, these effects became positive and significant in the most recent survey years (2015 and 2018), indicating that income diversification has become a more prominent adaptation strategy in more recent years, with respect to the past decade. The chapter also investigates the mechanisms behind this transition toward off-farm labour and considers factors that either facilitate or hinder households' ability to diversify their income. To support the analysis, a conceptual framework is developed that links off-farm labour productivity choices to farmers' expectations regarding future climate risks, contributing to the existing literature on adaptation strategies in agricultural contexts. Three possible mechanisms are explored based on this framework. First, the chapter empirically tests whether households have become more responsive to off-farm labour opportunities due to the increasing severity of temperature shocks over time. Second, it examines whether improvements in local development conditions have enhanced the availability of off-farm opportunities. Third, it investigates whether households have engaged in a learning process, shaped by their experiences with multiple past temperature shocks, which may influence their off-farm labour choices. The empirical strategy tests these three mechanisms, with results indicating that changes in off-farm labour responses over time are not driven by the increasing severity of temperature shocks or by learning from accumulated past shocks. Instead, the findings show that local development conditions have significantly improved, driving farmers' off-farm responses, which partly explains the recent increase in labour supply.

1.3 Contribution of the study

Broadly, this thesis contributes to the current debate on climate change impacts and adaptation in the agricultural sector. It provides a snapshot of how climate variability—particularly rising temperature and excessive rainfall—impacts wheat yields, a major component of food security for marginalised communities living in vulnerable regions. The analysis also provides an overview of how input adjustments (e.g., irrigation) and shifts in land and labour allocation serve as adaptive mechanisms amid climate change. Moreover, by exploring these strategies, the research contributes to the broader literature on risk management, adaptation, and coping strategies in agriculture, demonstrating how farmers respond to environmental risks by adjusting inputs and reallocating resources such as land and labour.

Each chapter, however, makes a significant contribution to the literature on climate change impacts and adaptation in agriculture, based on the set research objectives.

The first chapter is unique in its consideration of deviations in climate variables from both long-run averages and optimal conditions to assess their effects on wheat yields. It specifically considers robustness with ideal temperature conditions at each stage of wheat development, including planting, growing, and harvesting. While several studies in Pakistan have addressed crop growth stages, they often focus on average or seasonal climate variables in different districts or provinces (Ahmed et al., 2011; Afzal et al., 2016; Ahmad et al., 2017). Additionally, this chapter explores the heterogeneity in wheat yields across different district categories within the province, enhancing our understanding of local responses to climate variability and the necessary adjustments in input use amid climate shocks.

The second chapter makes a key contribution to the existing literature by being the first study to examine land allocation in response to lagged temperature shocks over time within Pakistan's agricultural sector. This chapter explores this relationship in the context of government support prices, capturing both autonomous and planned adaptation strategies. To the best of our knowledge, no prior research has explicitly investigated the impact of lagged temperature shocks on land allocation decisions in this specific context.

The last chapter contributes to the literature by examining the dynamics of rural adaptation strategies over two decades, in response to changing local climate and economic conditions. Many previous adaptation studies have been limited by short-term temporal coverage and have neglected fluctuations in local market conditions (see (Hussain et al., 2020; Shahid et al., 2021)). We build on the understanding that adaptation to climate change is a dynamic, long-term process. This chapter presents a conceptual framework that incorporates changes in both local market conditions and farmer's expectations over time, testing the hypotheses (derived from the conceptual framework) by comparing off-farm responses across six waves of household-level data. Additionally, this chapter is the first to explore off-farm labour supply as an adaptation strategy in Pakistan. While existing research has largely concentrated on on-farm adaptation strategies, often focusing on specific districts or short time periods, for example, (Abid et al., 2015; Ali and Erenstein, 2017; Gorst et al., 2018)). Also, studies that consider mixed adaptation strategies, including off-farm labour, have been restricted to small farmer samples (Ali et al., 2017; Ahmad et al., 2024).

Chapter 2

Wheat yield response to climate change: A district-level analysis in Pakistan

2.1 Introduction

Climate change is a significant driver of hunger in Pakistan, exerting substantial pressure on its agricultural sector. With over 80% of its population relying predominantly on agriculture for their livelihoods, the country is exposed to adverse effects of climate variability (ADB, 2022). These effects include frequent crop failures and reduced yields, which undermine economic stability and food security in the country. Studies show that climate change is adversely affecting crop yields (Welch et al., 2010; Khan et al., 2020; Miller et al., 2021). For instance, over the past five decades, temperature has risen by 0.9 to 1.1°C in Pakistan (World Bank, 2022), leading to a decrease in yields by approximately 3–10% (Chaudhry, 2017). "Pakistan Vision 2025" identifies climate variability as a critical factor contributing to the current lag in agricultural productivity, which poses a significant threat to national food security (WFP, 2018).

Over the last 20 years, Pakistan has remained in the top 10 most vulnerable countries on the Climate Risk Index (CRI), due to climate related risks (Eckstein et al., 2021). This vulnerability stems from its geographical location, high dependency on the agricultural sector, and low adaptive capacity. Even at the sub-national level, the vulnerability scale is not evenly distributed. For example, Khyber Pakhtunkhwa (KP) province is more susceptible to adverse Climate patterns than other provinces, primarily due to three key factors. First, KP's diverse landscape makes it particularly vulnerable to climate change. The northern and eastern regions, with high mountains, experience extremely cold and dry climate with heavy rainfall. The central plains, with their lower elevation and fertile land, have a temperate climate with moderate rainfall. The southern regions are hot and arid, experiencing high temperature and low rainfall. This topographical diversity results in varied climate impacts across KP, making it more susceptible to changing Climate patterns than other provinces in the country (EPA, 2016). key characteristics of each climate region are presented in the appendix Table A.1. Second, KP has a higher proportion of people in poverty than other provinces of Pakistan. According to the latest assessments of Millennium Development Goals (MDG) outcomes, 49.2% of KP's population lives below the poverty line, which is higher than the national average (40%)(Miller et al., 2021). Poverty, combined with a lack of financial, institutional, and technical support within the province, increases vulnerability to climate change (Nizami et al., 2020). Third, for the majority of households in KP, crop production is primarily for subsistence, focusing on staple crops, with a significant land dedicated to wheat cultivation. About 60% of population is highly depend on wheat. That's why more than 82% of farmers in KP grow wheat on small landholdings (less than 2 hectares) (WFP, 2018), thereby exposing them significantly to climate change (ADB, 2022).

Given wheat's critical role in food security and economic self-sufficiency, it is essential to address the significant adverse impacts of climate change on its production. High temperatures are currently reducing wheat yields by up to 30% in Pakistan (Siddiqui et al., 2012; Hussain and Bangash, 2017), and projections suggest that a 3°C temperature increase by 2040 could cut yields by an average of 50% (Ghanem, 2010). This poses increasing pressure on the agricultural sector. However, the extent of these negative effects varies significantly at the sub-national level. KP experiences particularly high Climate-induced wheat losses due to its extreme climatic conditions: a colder northern region near the mountains and a hotter southern region. These extremes have led to substantial losses. For instance, Climate-induced wheat losses are notably higher in southern region, compared to other regions. This is primarily due to temperature in the southern region already exceeding the ideal threshold required for optimal wheat growth (Ghalib et al., 2017). Research indicates that a 2°C rise in annual mean temperature could lead to a substantial 37% reduction in net returns for wheat growers, disproportionately affecting the southern region of the province (Ghalib et al., 2017).

In the northern part of KP, temperatures, while not inherently high compared to optimal wheat growth requirements, have consistently exceeded their long-run averages over the past two decades, mimicking the conditions observed in the southern regions. This has been accompanied by a noticeable warming trend, particularly during the winter season when wheat is grown. This recent trend poses significant risks for wheat yield losses in the province (Zomer et al., 2016; Nizami et al., 2020). Rainfall has been found to positively impact wheat production especially at early development phase. For instance, Ghalib et al. (2017) find that increased rainfall leads to a 6% rise in net returns for wheat growers in the province.

The existing agronomic literature highlights that the adverse effects of climate change vary not only across climatic regions but also across the different growth stages of crops (Farooq et al., 2011; Heil et al., 2020; Harkness et al., 2020). These effects vary throughout the crop growth stages, including from sowing to emergence (planting), emergence to flowering (growing), and flowering to maturity (harvesting). Each stage is crucial for determining the final crop yield. High temperatures during the emergence to flowering stage reduce the number of viable florets, leading to a reduced yield (Masters et al., 2010; Harkness et al., 2020). For example, Liu et al. (2023) show that when temperature exceeds 27°C during growing stage, wheat yields reduce by 60%. During the planting stage, wheat is relatively resilient to temperature increases. In fact, moderately warmer temperatures during this phase can enhance soil microbial activity and promote quicker germination and root establishment, resulting in good harvest (Porter and Gawith, 1999; Kahlown et al., 2003). However, adequate moisture is crucial, excess rainfall at this stage maintains soil moisture and improves germination rates, leading to stronger crop stands (Tack et al., 2017).

Among these stages, the growing stage is particularly critical for wheat development (Lobell and Ortiz-Monasterio, 2007; Wassmann et al., 2009; Hertel and Lobell, 2014) because most of the reproductive growth occurs at this stage (Khan et al., 2020). Exposure to high temperature at this stage reduces grain number by inducing sterility, resulting in low yields (Harkness et al., 2020). Excessive rainfall during the ripening stage can delay the maturation process and reduce grain quality (Masters et al., 2010; Siddiqui et al., 2012). This implies that the impact on yields is not only influenced by the local climate but also by the specific growth stage of the wheat crop. Each stage such as planting, growing, and ripening, responds differently to variations in temperature and rainfall, making it crucial to consider the timing of these climatic variables when assessing their overall effect on wheat yields.

In this chapter, we examine the impact of climatic variables—maximum temperature, minimum temperature, and rainfall—on wheat yield across the KP province over the past two decades (2000–2019). Our primary objective is to estimate the effects of warming and excessive rainfall during three critical stages of wheat development: planting, growing, and harvesting. By focusing on these stages, we aim to provide a detailed understanding of how climatic variations influence wheat yields over time. Additionally, we empirically analyse how wheat yields vary across districts, categorised based on temperature ranges into milder, moderate, and hotter districts within the province.

To achieve this, we utilise high-resolution, gridded monthly data on maximum temperature, minimum temperature, and rainfall from the Climate Research Unit (CRU) at the University of East Anglia, UK, covering the years 1960 to 2019. By using this dataset, we first calculate long-run district-level climate averages for each stage during wheat development. In our analysis, we use 40-year long averages, which are obtained by averaging district-level monthly maximum temperature, minimum temperature, and rainfall at each stage from 1960 to 2000. Then, to capture the effects of warming and excess rainfall (climate anomalies) on wheat yield, we utilise a binary indicator to determine the existence of excess heat and rainfall if standardised climate variables at each stage are 1.5 standard deviations above the district-level long-run climate averages. By merging climate data with geo-referenced, district-level agricultural data for the province from 2000 to 2019, we construct our final dataset for analysis.

Our empirical framework employs panel data methods to investigate the impact of excess heat and rainfall on yields over time. Our findings indicate that wheat is particularly sensitive to high temperatures during the growing and harvesting stages within the province, while excess rainfall is positively associated with yields during the planting stage. The impact on yields varies across district categories. In milder and moderate districts, yields decline when temperatures exceed long-run averages during the growing phase. In hotter southern districts, both growing and harvesting stages are affected. Excess rainfall during planting benefits yields, but it harms them during later stages. The results remain consistent under alternative warming measures, such as a 1.5°C rise above ideal temperatures. From the input side, the findings show that increased irrigation proves to be an effective adaptation strategy during hot climate.

A key contribution of this study lies in its combined use of deviations from long-term climate averages and stage-specific ideal temperature thresholds for wheat—covering the planting, growing, and harvesting phases. Most existing studies in Pakistan rely solely on historical climate deviations to estimate impacts on crop yields (Janjua et al., 2010; Hanif et al., 2010; Siddiqui et al., 2012; Abbas, 2022), potentially overlooking the importance of ideal climatic conditions required at different growth stages. This study addresses that gap by incorporating deviations from optimal temperature ranges specific to each phase of wheat development. To our knowledge, this approach has not yet been applied in the context of Pakistan. Its relevance is particularly evident in southern districts, where growing-season temperatures often exceed the optimal range for wheat cultivation.

The rest of this chapter is organised as follow. Section 2.2 presents the contextual background of the study area. Section 2.3 describes the background and motivational evidence. Section 2.4 outlines some of the related literature. Section 2.5 describes the empirical strategy. Section 2.6 discusses the data. Section 2.7

presents our main results and Section 2.7.3 outlines some heterogeneous tests. Section 2.8 concludes.

2.2 Contextual Background of KP province

KP province is characterised by its rich traditions, strong cultural identity, and distinct social and political factors that collectively impact province's economic and social life. Traditions in the province are rooted into old customs and practices that continue to guide socio-economic behaviour. For example, women are often considered as the honor of the household, and therefore they are not allowed to work outside of home. This restrict their participation in socio-economic development. Moreover, this province has the lowest literacy rates in the country—for both men and women—compared to provinces such as Punjab and Sindh (UNDP, 2024). Gender roles are conservative, and household decisions are made by elder male members. Majority of household heads have no formal education, and farming is the dominant occupation across the province (BPS, 2018). The population is predominantly rural, and agricultural practices are often rooted in old traditions.

From a political standpoint, while Pakistan in general faces political instability, the situation is particularly fragile in KP. This instability is further compounded by the province's proximity to the former Federally Administered Tribal Areas (FATA) and the border with Afghanistan—regions affected by years of conflict, military operations, and large-scale migration. These conditions have disrupted local security, mobility, and development priorities. According to recent estimates, such conflict has contributed to more than 50% of school-aged children being out of school in KP (Khalid et al., 2025). In response to these challenges, several non-government organisations, including the Food and Agriculture Organization (FAO) are working in collaboration with the government and local extension workers to support agricultural development and improve community resilience.

Together, these traditional norms, social structures, and political situations in the KP provides a general context for development challenges faced by rural communities in the province.

2.3 Background and motivational evidence

Growing wheat is one of the major agricultural activities in the province of Khyber Pakhtunkhwa (KP), engaging more than 82% of farmers and cultivating almost 79% of cropped areas (EPA (2016)). Despite its prominence, KP has been facing food deficits. According to a recent report by the Government of KP (Gov-KP, 2018), the province produces an average of 1.40 million tons of wheat annually. However, compared to the estimated consumption of 3.95 million tons, there is a net deficit of 1.69 million tons, representing a 55% shortfall. Projections suggest that if the current population growth rate persists at 2%, by 2030, wheat production will only reach 2.59 million tons, leaving a deficit of 1.67 million tons, equivalent to 39%. However, according to the most recent population census (2023), the growth rate is 2.38%, and this is expected to increase over time. With ongoing population growth and shifting dietary preferences favouring greater cereal consumption, the demand for wheat is expected to increase, placing additional presssure on the agricultural sector (Miller et al., 2021).

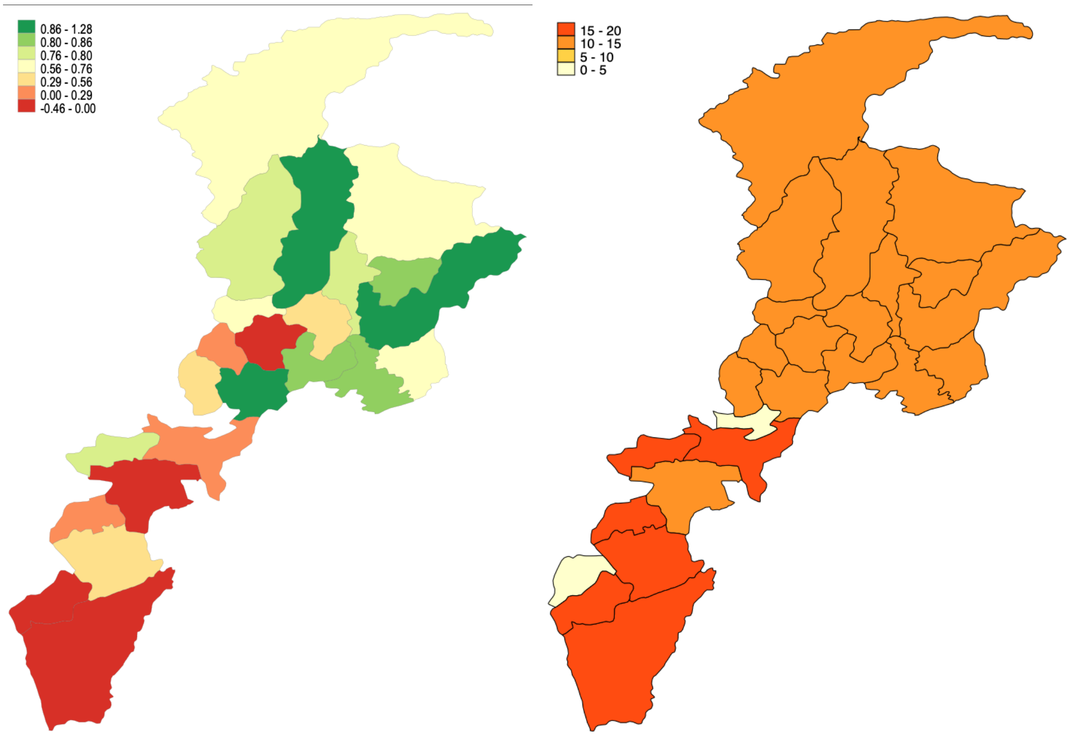
With the agricultural sector being central to the province's economy and the livelihoods of its population, a significant portion of the population remains vulnerable to various climatic conditions. This vulnerability is because of the province's unique landscape and climatic conditions, ranging from the Himalayan mountains in the north to the hot plains in the south. These diverse geographical and climatic factors have adversely affected wheat production in the province. According to a projection study by Nizami et al. (2020), the warming trend during the wheat season is particularly significant in the northern region, experiencing a temperature increase of 1.9°C. This is closely followed by the central region with an increase of 1.8°C, and the already heat-stressed southern region with 1.6°C. Although the warming trend is lower in the south, temperatures there already surpass optimal thresholds. Rising temperatures not only disrupt wheat production but also compel many farmers to abandon cultivating the crop altogether. For instance, during an interview with a local Dawn news channel, a farmer from the southern region explained that he decided to quit wheat farming due to consecutive seasons of poor yields, worsened by extreme Climate conditions, especially high temperatures. [1]

Using our data, we show the prevalence of the decline in wheat yield in Figure 4.1, where panel (a) shows the change in wheat yield, which is measured by subtracting the yield of the last year (2019) from that of the initial year (2004). The lower, green shaded regions denote the southern part of the province, where negative yields indicate a concerning decline over time. The topmost yellow shaded area represents the northern part, which exhibits yields below the mean but comparatively higher than those in the southern region. The middle area displays the central and western regions, where yields display a mixed distribution. This spatial distribution highlights the variability of wheat yields across different agro-climatic zones.

Panel (b) of Figure 4.1 shows that, on average, each district experiences between 10 and 15 hot growing seasons over the 20-year period. The number of times each district faced temperatures exceeding the long-run average during the wheat season is presented in Table A.2 in the appendix. A hot growing season is defined as a period during which a district experiences average temperatures exceeding one standard deviation from the historical district-level mean temperature during the wheat season. Although the distribution of hot growing seasons is relatively uniform across the province, yield impacts are more significant in the extreme regions of the province.

Given the heavy reliance on wheat yield, the agricultural performance in KP is poor, necessitating dependence on other provinces to fulfill consumption needs. Under such circumstances, rather than diversifying agricultural support, the government is predominantly focusing on wheat, thereby locking farmers into growing a crop that is increasingly sensitive to extreme climatic events. This narrow support strategy not only increases the vulnerability of wheat farmers to climate variability but also threatens the overall food security in the province.

[1] Source: link



(a) Change in wheat yield (b) Number of hot events during wheat season

Figure 2.1: Prevalence of wheat yield and high temperature over time (2000-2019)

Note: Change in wheat yield is calculated based on the difference between the yields at starting point (2000) and the endpoint (2019) yields in our analysis. Panel b, refers to districts experiencing average temperatures above 1.5 standard deviations from the long-run district-level average temperature during the wheat season.

2.4 Related Literature

In the climate change and agriculture domain, two main econometric approaches are widely used to assess the impact of climate change on agricultural output. The first is the cross-sectional approach, which examines how long-term climate conditions, typically averaged over multiple years, influence land values or firms' net revenues across different regions. The second is the panel approach, which analyses how temporal deviations in climate affect agricultural yields or profits. In the following sections, we review studies employing both approaches.

2.4.1 Impact of climate change on land values

These studies employ statistical methods, such as regressions, to estimate the association between cross-sectional climate data and measures of agricultural productivity, often proxied by land value. These studies use the Ricardian approach, which is based on the ideas of Ricardo (1817), who was the first to discover that land value reflects the net revenue from farmland, which in turn represents the net productivity of crops in the agricultural sector.

The Ricardian cross-sectional method, introduced by Mendelsohn et al. (1994), is a foundational econometric technique for evaluating the effects of climate change on farmland productivity. It assumes that farmers, as profit-maximising agents, adjust their production and crop choices based on environmental factors such as soil quality, land slope, and climate averages. By analysing the relationship between land values and climate variables, this method reveals how different climatic conditions affect land profitability.

One of the major benefits of this framework is that it allows the estimation of adaptation using cross-sectional data from farmers operating under different climate conditions, enabling predictions of how cooler regions might respond to warming based on practices in hotter regions (Mendelsohn et al., 2001; Massetti and Mendelsohn, 2011). For example, farmers in cooler climates may grow crops suited to lower temperatures, while those in warmer regions might select heat- or drought-adapted crops. This approach applies to both developed and developing countries, as it accounts for farmers' ability to adapt to climate change by adjusting crop choices or modifying farming practices (Auffhammer, 2018).

Empirical results from the Ricardian method, based on data from over 50 countries, highlight the importance of adaptation in mitigating the adverse effects of climate change on agriculture (Mendelsohn and Massetti (2017)). Warming generally lowers farm revenues, but developed countries experience less significant losses as compared to the developed countries. The is because developed countries have access to advanced mechanisation and farm technologies, which act as effective adaptation strategies (Mendelsohn et al., 2001; Wimmer et al., 2024). In contrast, developing countries face more severe climate change risks, as as farmers often lack access to financial and technological resources, needed for adaptation (Kurukulasuriya and Ajwad, 2007; Kurukulasuriya et al., 2011) For instance, Mendelsohn et al. (2001) and Kumar and Parikh (2001) find that even slight warming significantly affects agriculture in India and Brazil. In India, temperature changes lower farm revenues, while in Brazil, they cause a significant decline in land values. The severity of these impacts depends on the effectiveness of farm-level adaptation strategies. Moreover, using data from 11 African countries, Kurukulasuriya et al. (2006) demonstrate that irrigated farms are more resilient to warming than drylands. Irrigation mitigates the effects of high temperatures, reducing losses. These studies also show that increased rainfall generally has a positive effect on farm productivity.

Crop switching is widely recognised as an effective adaptation strategy in many developing countries. Wang et al. (2010) show that Chinese farmers in hotter regions often select heat-tolerant crops such as maize and cotton, while those in colder regions typically grow soybeans and vegetables. When rainfall increases, farmers are more likely to cultivate wheat and less likely to grow potatoes and vegetables. Similarly, studies by Sadiq et al. (2017) and Khan et al. (2018) indicate that rising temperatures negatively affect net farm revenue among Pakistani farmers. To adapt, farmers often adjust planting schedules. For instance, shifting planting to cooler periods of the year helps mitigate the effects of rising temperatures. Adjusting planting schedules based on seasonal rain patterns, such as planting earlier or later, can also be beneficial. However, the effects of rainfall on agriculture in Pakistan show mixed outcomes. For instance, Hanif et al. (2010) using Ricardian model, find that higher winter rainfall reduces farmland value, whereas increased summer rainfall enhances net farm revenue (Guiteras, 2009; Sadiq et al., 2017).

This method has been widely applied. However, over time, concerns about omitted key variables have raised doubts regarding its accuracy. Schlenker et al. (2005) showed that including some variables in the model could change the final results. For example, including irrigation in the analysis conducted by Mendelsohn et al. (1994) changed the estimated impacts of climate change from slightly beneficial to strongly negative. Moreover, the method assumes that adaptation to climate change occurs without costs, an assumption that is unrealistic. Crop switching often comes with significant costs, including investments in new equipment and technical training, which can bias estimates of climate change impacts (Deschênes and Greenstone, 2007).

Furthermore, applying the Ricardian method in developing countries necessitates more careful and rigorous estimation (Guiteras, 2009; Ahmad et al., 2014). In Pakistan, the lack of detailed agricultural land value records and inefficient land markets can result in biased estimates.

2.4.2 Impact of climate change on crop yields

Considering the methodological limitations of Ricardian model, Auffhammer et al. (2006) and Deschênes and Greenstone (2007) proposed an alternative approach based on year-to-year weather fluctuations. Instead of relying on cross-sectional data and long-run cliamte averages, the authors used year to year variation in temperature and rainfall to study short term effects on crop yields. By controlling for both region and time-specific factors using panel data, this method helps mitigate concerns over omitted variable bias, a major limitation in Ricardian method.

These panel based studies use statistical methods typically estimate profit or production functions to measure effects of weather change. Because weather largely being random or unpredictable, as a natural experiment for identifying causal impacts on agricultural outcomes (Massetti and Mendelsohn, 2018). The use of panel model allows researchers to exploit within-region variations over time, avoiding biases that arise when comparing across regions with different, unobserved characteristics.

Building on this framework, Schlenker and Roberts (2009) used panel model that employed temperature bins to estimate impacts on crop yields in the United States. Their findings revealed a critical temperature threshold for crop output, typically between 29 to 32 degrees Celsius, varying by crop type. Temperatures below this threshold are moderately beneficial, while those exceeding it negatively affect agricultural yields. A growing body of panel-based literature has found similar results in the context of developed countries, where adverse weather shocks continue to negatively impact agricultural yields (Schlenker and Lobell, 2010; Billé and Rogna, 2022). However, these negative effects can be mitigated in advanced countries through adaptive responses, such as using better crop varieties and advanced irrigation systems. For example, Butler and Huybers (2013) found that by using high-yield crop varieties in hotter regions, U.S. farmers could reduce crop losses from 14% to 6%.

While such studies focus on advanced economies, a growing body of research examines climate impacts in developing countries, where adaptive capacity is often more constrained. For example, Schlenker and Lobell (2010) reported adverse yield effects from temperature and rainfall shocks in Sub-Saharan Africa. Using a multi-country panel, Welch et al. (2010) documented negative impacts of higher temperatures on rice and other staple crops across Asia, forecasting accelerated yield declines even under moderate warming. Similarly, Guiteras (2009) projected that medium-run climate change could reduce crop yields by up to 9While in developing countries, the impact of climate variability on crop yields presents a more serious challenge, where adaptive capacity is often more constrained. For instance, Schlenker and Lobell (2010) show adverse effect of temperature and rainfall on crop yield in Sub-Saharan Africa. Similarly, utilising a panel model across multiple Asian countries, Welch et al. (2010) find adverse effects of higher temperatures on major food crops. They predict that even under moderate warming scenarios, yields would decline at a faster rate as compared to the developed countries. These findings suggest that negative impacts on yields in developing countries are worsening over time. For example, Guiteras (2009) projects that medium-run climate change could reduce crop yields by up to 9% in India, increasing to 25% in longer-run scenarios across 200 districts. similar findings are reported in Indonesia (Levine and Yang, 2006), Mexico (Feng et al., 2010), Africa (Blanc, 2012), Bangladesh (Sarker et al., 2012), and China (Zhang et al., 2022).

In Pakistan, where agriculture is highly climate-sensitive, several panel studies reveal serious yield losses associated with temperature extremes. A study by Siddiqui et al. (2012) find that rising temperatures reduce the yields of major crops such as wheat, rice, and maize, potentially posing risk to national food security. Ahmad et al. (2014) report an average decrease of 7.6% in wheat yield with higher temperatures, and yields drop further with each additional degree Celsius above the optimal level. Conversely, rainfall generally benefits crop production. Abbas (2022) finds a positive impact of rainfall on major crop yields in

Pakistan. Rainfall helps during the planting stage and can boost yields, though excessive rainfall later in the growing season can be harmful (Gul et al., 2022). Overall, panel-based studies conclude that high temperature have adverse effects on the agricultural sector, while rainfall generally has a positive impact on crop yields

In conclusion, while both econometric approaches are widely used, panel data studies offer clear advantages over Ricardian models. Panel data models use fixed effects to control for time-invariant factors like climate and soil quality, isolating the impact of climate changes more effectively. In contrast, Ricardian studies may suffer biased in settings with imperfect land markets such as Pakistan, where land values are not well-documented. As a result, these models often rely on proxies like profits or revenues, which may not accurately estimate changes in productivity. Therefore, panel data approaches provide a more robust framework for analysing the impact of climate variability on agricultural outcomes in Pakistan and other similarly economies with less developed land markets.

While numerous studies in Pakistan utilise panel methods to estimate the impacts of climate change on crop yields (Farooq et al., 2011; Abid et al., 2015; Ahmad et al., 2017; Saqib et al., 2024), our research differs in three key ways. First, instead of relying on station-level weather variables, we utilise fine-scale cliamte data from the Climate Research Unit (CRU) for the period 1960 to 2019. This dataset provides high-resolution data on a 0.5° latitude by 0.5° longitude grid, offering greater spatial granularity. Second, rather than using average monthly, seasonal, or annual weather variables, we employ deviations from long-run climate averages, which are calculated over a 40-year period. Additionally, we consider robustness with respect to ideal temperature conditions. Finally, our analysis integrates both phenological aspects, such as planting, flowering, and maturity stages of the crop, and economic factors, including yields and production inputs, to examine the relationship between yield and climate variables. Based on the extant literature, we anticipate a negative association between climate variables, particularly high temperatures, and wheat yields.

2.5 Empirical framework

Generally, a production function includes inputs such as land, labour, and capital. However, applying this standard production function directly in an agricultural context overlooks the significant influence of weather as an exogenous factor (Oury, 1965). Therefore, to measure the economic effect of climate change, panel models commonly use crop yields as the output of the production function and weather is taken as key input into a crop production function (Schlenker and Lobell, 2010). Numerous studies investigating the effects of climate change on crop yields typically include temperature and rainfall as key weather inputs in the production function (Dell et al., 2014). Our primary estimating equation is as follows:

$$y_{dt} = \sum_{g=1}^{3} \beta_g (Tmax)_{dt} + \sum_{g=1}^{3} \alpha_g (Tmin)_{dt} + \sum_{g=1}^{3} \gamma_g (Rain)_{dt} + \mathrm{X}_{id} + \lambda_d + \theta_t + \Omega_d t + \epsilon_{cidt} \tag{2.1}$$

Where (y_{dt}) represents the natural log of wheat yield in district d during wheat growing season t. The summation ($\sum_{g=1}^{3}$), index by g from 1 to 3, indicates the three growth stages such as planting (Nov-Dec), growing (Jan-Mar) and harvesting (Apr-May) stages during wheat season. The variables of interest, $(Tmax)_{dt}$, $(Tmin)_{dt}$, and $(Rain)_{dt}$ are binary indicators that take on the value 1 if the standardised weather variables are 1.5 standard deviation above the long-run averages at the three distinct growth stages, and zero otherwise (more discussion on the constriction of the these weather variables is in the Section 2.6.2.1). Note that standardised weather variables and the long-run averages are specific to each stage such planting, growing and harvesting during wheat cropping season.

The coefficients, (β_g) and (α_g) show the impacts of heat during daytime,$(Tmax)_{dt}$ and nighttime, $(Tmin)_{dt}$ respectively, while (γ_g) shows excess rainfall,$(Rain)_{dt}$, at all three stages during wheat season.

(X_{id}) is a set of district level controls such as total agricultural land (in hectares) , proportion of irrigated land, proportion of population working in agricultural sector, number of tractors, fertiliser application (in kilogram per hectare) and number of tube wells installed.

We include district fixed effects, (λ_d) to control for unobserved time-invariant, district specific factors that may affect yield, such as soil quality. The term (θ_t) is a year fixed effect to control for year-specific unobserved shocks, such a trade shocks, that may affect all districts in a given year. $(\Omega_d t)$ is district specific time trend to control for varying district effects such as agricultural technology, that may be changing over time and may vary by district. (ϵ_{cidt}) is the stochastic error term and we cluster the standard error at district level to account for spatial and serial correlation in the error terms.

2.6 Data

Our empirical analysis uses data from two different sources; district-level agricultural data for the province from Bureau of Statistics of Khyber Pakhtunkhwa, Pakistan and climate data on maximum temperature, minimum temperature and rainfall at grid level from the Climatic Research Unit Time Series version 4.07 (CRU TS v. 4.07), University of East Anglia, UK.

2.6.1 Agricultural data

We utilise agricultural data from the Bureau of Statistics of Khyber Pakhtunkhwa, Pakistan. The dataset provides information on crop production, harvested area, and production inputs at district-level for the years 2000-2019. There are a total of 34 districts in the province. However, we exclude 10 districts from our final analysis due to data unavailability. Because, according to the 25$^{\text{th}}$ Amendment to the Constitution of Pakistan, these districts are recently merged into KP province.

Our dependent variable is the annual wheat yield for each district, measured in output per hectare. Input variables include total agricultural land (in hectares), the proportion of irrigated land under wheat, fertiliser application (in kilograms per hectare), the proportion of labour engaged in farming, number of tractors and the number of tube wells installed at district level.

The descriptive summary of agricultural data is presented in panel (a) of Table

2.1. On average, the district-level wheat yield is 1.60 tons per hectare. However, there is considerable variation in yields across different climatic regions. The southern region has the lowest average yield at 1.29 tons per hectare, while the highest yields are predominantly concentrated in the central region, followed by the eastern region. High temperature and low rainfall are likely major contributing factors to the lower yield in the southern region. For instance, during the critical growing stage, the average maximum temperature reaches 24°C, which is significantly higher than the optimal range of 16–20°C, as shown in Panel (b) of Table 2.1. Additionally, rainfall in this region is scarce compared to other regions and falls well below the optimal requirements. For example, during the planting stage, the region receives approximately 10mm of rainfall, whereas the optimal water requirement is between 65 and 120mm, on average. In other regions, temperature often falls below the ideal range for wheat and warming may actually benefit wheat growth contributing better wheat yields. The variability in yield across different climatic regions could be explained by the prevailing weather conditions within the province. This geographical variability in yields also aligns with the motivational evidence presented in Figure 2.1.

In terms of input use, the southern region particularly stands out with higher fertiliser application (121.41 kg/ha) and a greater number of tube-wells (except the central region). Despite higher input use, the region still lags in wheat production as compared to other regions (see Panel (a) of Table 2.1).

2.6.2 Climate data

We use gridded monthly data on maximum and minimum temperatures, as well as rainfall, from 1901 to 2019. This data, produced by the Climate Research Unit (CRU, Time-Series version 4.06) at the University of East Anglia, offers a spatial resolution of $0.5° \times 0.5°$, derived from over 4,000 weather stations globally. To analyse climate patterns at the district level within Khyber Pakhtunkhwa (KP) province, Pakistan, we utilised an administrative district boundary shapefile. Using QGIS software, we overlaid the CRU gridded climate data with the district shapefile and spatially intersected the climate grids with district polygons. This process enabled us to calculate district-level averages of temperature and rainfall over time, by aggregating values from all grid cells contained within each district during wheat growing season across the study period.

The descriptive statistics of weather variables across all three stages of the wheat season, at both district and climatic regional levels, are presented in Panel (b) of Table 2.1. The southern region, followed by the central region, experiences higher maximum and minimum temperatures and lower rainfall compared to other regions during the wheat season. For instance, during the critical growing stage, where the ideal maximum temperature range is 16-20°C (column 11), the southern region consistently exceeds this range by an average of 4°C over the study period (column 9). While the central region exceeds by around 2°C. In contrast, the northern and eastern regions experience lower temperatures and higher rainfall, showing significant climatic variability across regions during the wheat season in the province.

We also present deviations from long-run averages (using 1960-2000 as the base period) at each stage in parentheses (see Table 2.1) to highlight how current weather conditions differ from the long-run average across each region. Overall, current weather consistently exceeds long-run averages across all stages at both the district and regional levels. However, the deviations are more pronounced during the growing and harvesting stages, particularly for maximum temperature (with minimum temperature showing significant deviation only at the harvesting stage). An interesting pattern emerges in the southern and central regions. For example, in the southern region, the long-run average temperature during the growing stage (23°C) is already higher than the optimal maximum temperature, while at the harvesting stage, it is almost within the ideal range. In the central region, the long-run averages during both the growing and harvesting stages are nearly equal to the optimal temperature range for both maximum and minimum temperatures.

Regarding rainfall, the situation is quite interesting. During the growing stage, all regions experience a surplus, with rainfall levels exceeding long-run averages. Even when considering ideal water availability, all regions—except the southern region—surpass the ideal requirement of 75-120 mm. However, the northern, eastern, and southern regions face rainfall deficits during both the planting and harvesting stages. The central region also shows a deficit, but only during the harvesting stage. Despite this, the central region's rainfall of 52.34 mm (as shown in column (7)) falls within the ideal water requirement range of 50-100 mm, indicating sufficient water availability for wheat growth in that region.

2.6.2.1 Construction of climate measures

We are interested to estimate the impact of excess heat and rainfall on crop yield over time. To identify meaningful impacts on crop yields due to climate variation, many studies focus on growing seasons or years with unusually high or low climate variation relative to what is normally experienced in a particular locality. The most common approach is to measure the deviation from the local average in a growing season or year, using either percentages (Dercon, 2004), levels (Schlenker and Roberts, 2009; Mayorga, Villacis, and Mishra, Mayorga et al.; Manohar, 2022), or standard deviations (Hidalgo et al., 2010; Michler et al., 2019; Makate et al., 2022). Unfortunately, the literature lacks a universal benchmark that defines the threshold at which climate variations significantly impact yields (Burke et al., 2015). However, studies differ in their methodologies and criteria for identifying significant effects due to climate change. We adopt a methodology similar to Michler et al. (2019) and Makate et al. (2022), defining excess heat and rainfall as standardised deviations—i.e., the difference between the current year's values and their long-run averages. However, unlike these studies, which use standardised deviations as continuous variables (e.g., z-scores), we employ binary indicators. Continuous measures, while useful, can be problematic when aggregating climate shocks over multiple years because periods of high deviations (e.g., extreme heat) can offset periods of low deviations (e.g., cooler conditions), thereby masking the cumulative impact of extreme events (Burke et al., 2015). To address this issue, we follow Burke et al. (2015) and use binary indicators to classify a given year or crop season as a "shock" based on the occurrence of excess heat or rainfall. This approach ensures a clearer and more consistent measure of climate-related impacts on crop yields over time.

Both types of heat variables (derived from maximum and minimum temperatures) are constructed using the following relationship:

i) $\text{Heat}_{dt} = \frac{\text{Temp}_{vt} - \text{Temp}_d}{\sigma_{\text{temp}_d}}$, where Heat_{dt} is a excess heat measure for a district d, in the growing season, t. Temp_{vt} is the observed temperature for the current growing season, Temp_d is the average seasonal temperature for district, d over 40 years (1960–2000), and σ_{temp_d} is the district-level standard deviation of temperature during the same period.

To define excess rainfall, we use the following method:

ii) $\text{Rain}_{dt} = \frac{\text{Rain}_{vt} - \text{Rain}_d}{\sigma_{\text{rain}_d}}$, where Rain_{dt} is excess rainfall measure for a district, d, in the growing season, t. Rain_{vt} is the observed amount of rainfall for the current growing season. Rain_d is the average seasonal rainfall for district, d over 40 years($1960-2000$), and $\sigma_{\text{rain}_d}$is the standard deviation of rainfall during the same period.

Our measures of excess heat and rainfall are binary indicators. They take a value of one if the standardised temperature (Heat_{dt}) and rainfall (Rain_{dt}) exceed 1.5 standard deviations above the long-run averages, and zero otherwise. Although the literature does not provide definitive estimates for the thresholds at which climate variations become significant, studies differ in their methodologies and criteria for defining the impact of climate conditions, as we discussed at the start of this section. Most studies measure climate shocks at points where they could potentially lead to negative productivity impacts, as highlighted in research by Hidalgo et al. (2010), Burke et al. (2015), and Burke and Emerick (2016). Our selection of climate shocks—excessive heat and rainfall—has the potential to induce negative productivity shocks. We test our measures using an alternative threshold of one standard deviation, which does not show any negative productivity effects (see Table A.3 in the appendix). Additionally, we estimate the effects of excess heat and rainfall as continuous variables and find no significant impacts. Continuous measures, while useful, can be problematic when aggregating climate shocks over multiple years because periods of high deviations (e.g., extreme heat) can offset periods of low deviations (e.g., cooler conditions), thereby masking the cumulative impact of extreme events (Burke et al., 2015; Burke and Emerick, 2016). The results are reported in Table A.4 in the appendix.

Given the importance of various growth stages in wheat cycle—from planting to growing and harvesting—we construct binary indicator measures separately for each stage. This approach allows us to estimate the effect of excess heat and rainfall on each phase during wheat development.

Table 2.1: Descriptive summary

Panel (a): Agricultural data

	All districts	North	East	Centre	South
	(1)	(2)	(3)	(4)	(5)
Wheat yield (output/hectare)	1.60	1.52	1.71	1.81	1.29
Number of tractors	800.00	931.00	353.00	992.00	797.00
Number of tube-wells	573.00	330.00	76.00	1229.00	491.00
Fertiliser use (kg/hectare)	98.17	107.40	60.98	98.99	121.41
Total agricultural land (ha)	51.97	59.16	51.98	60.19	30.41
Irrigated share (%)	22.20	13.23	52.75	11.61	19.05
Observations	480	140	100	140	100

Panel (b): Climate variables and ideal climate conditions by wheat growth stage

	All districts		North		East		Centre		South		Ideal range
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mean	Long-run	Mean	Long-run	Mean	Long-run	Mean	Long-run	Mean	Long-run	Mean	
Maximum temperature (T_{max}) in °C											
T_{max} at planting stage	19.68	19.58	16.41	16.39	15.68	15.49	22.55	22.49	24.27	24.07	20−24
		(0.10)		(0.02)		(0.19)		(0.06)		(0.19)	
T_{max} at growing stage	18.73	17.72	14.93	13.94	14.30	13.28	21.87	20.87	24.09	23.04	16−20
		(1.01)		(0.99)		(1.02)		(1.00)		(1.05)	
T_{max} at harvesting stage	30.07	29.10	25.83	24.96	25.03	24.11	33.42	32.45	36.34	35.19	30−35
		(0.97)		(0.87)		(0.92)		(0.97)		(1.15)	
Minimum temperature (T_{min}) in °C											
T_{min} at planting stage	4.35	4.06	1.35	1.13	1.84	1.51	6.83	6.54	7.59	7.23	5−10
		(0.29)		(0.22)		(0.33)		(0.29)		(0.36)	
T_{min} at growing stage	11.90	11.33	8.08	7.50	8.37	7.78	15.09	14.56	16.30	15.71	12−15
		(0.57)		(0.59)		(0.59)		(0.54)		(0.59)	
T_{min} at harvesting stage	14.99	13.99	10.45	9.49	11.12	10.10	18.43	17.49	20.38	19.28	17−20
		(1.00)		(0.96)		(1.02)		(1.09)		(1.00)	
Rainfall (in mm)											
Rainfall at planting stage	24.74	25.57	34.60	35.25	30.77	32.28	21.98	20.75	9.79	10.34	65−120
		(0.84)		(0.65)		(1.50)		(0.75)		(0.55)	
Rainfall at growing stage	87.70	83.61	110.90	106.10	130.80	100.65	81.06	76.86	48.41	44.51	75−120
		(4.04)		(4.79)		(3.15)		(4.20)		(3.90)	
Rainfall at harvesting stage	59.66	62.70	76.72	81.08	73.12	76.81	52.34	54.82	32.56	33.48	50−100
		(3.04)		(4.36)		(3.39)		(2.48)		(3.04)	
Observations	480		140		100		140		100		

Note: Authors' calculations using data from the Bureau of Statistics: Khyber Pakhtunkhwa (KP) and the Climate Research Unit (CRU). In panel (b), the average deviations are shown in parentheses, which indicate the deviation from the long-run average (1960-2000) for each stage during the study period (2000-2019). The ideal ranges shown in column (11) are based on findings from various agronomic studies, which are detailed in Table A.6 in the appendix.

2.7 Results

This section is divided into two main parts. First, we investigate the effects of daytime and nighttime warming, along with excess rainfall, on wheat yield at both the district and climatic region levels. Second, we explore heterogeneity in the temperature-yield relationships across districts, grouping them into milder, moderate, and hotter categories based on temperature ranges. Additionally, we explore how input choices, specifically irrigation and fertiliser application, interact with temperature variations within each district category. To do this, we divide the sample into sub-samples based on irrigation and fertiliser levels, distinguishing between districts with better versus poorer irrigation and higher versus lower fertiliser use in each category.

2.7.1 Climate effects on wheat yield: Overall estimates

Table 2.2 presents the coefficients of binary climate variables at planting, growing and harvesting stages during wheat development at district level within the KP province. We consider both maximum and minimum temperatures, so we have two types of heat variable at all three stages of wheat growth.

The first type, constructed from the average maximum temperature, indicates a value greater than the long-run district-level average maximum temperature during the day and is termed daytime warming. Similarly, the second type is calculated from the average minimum temperature, and it shows the existence of warming at night if the current stage's minimum temperature is greater than its respective long-run district-level average minimum temperature.

We estimate five regression models, each incorporating different sets of fixed effects to isolate the impact of excess heat and rainfall during key stages of wheat development. The models progressively account for district-specific and time-specific effects, as well as trends and other factors that might affect the results. In column (1), we estimate the effect of day-time warming across the three wheat growth stages, controlling for growing season and district fixed effects. In column (2), we include night-time warming, acknowledging that temperature variations between day and night can have distinct effects on crop growth. In column (3), we add a rainfall shock variable to account for excess rainfall during the wheat season. In columns (4) and (5), we introduce district-specific time trends and district-level controls, capturing unobserved, time-varying factors that could influence wheat yields. These specifications control for factors like local economic conditions, agricultural practices, or policy changes that evolve over time. By including these controls, we ensure that our estimates accurately reflect the impact of heat and rainfall variability on wheat production.

Our estimates suggest that daytime warming has a significant adverse impact on wheat yields during both the growing and harvesting stages. Specifically, an increase in temperature beyond the long-run average during the growing stage reduces wheat yield by approximately 12-13% on average. At the harvesting stage, yield reductions range from 3.6% (column (2)) to 8.4% (column (5)). These effects remain consistent across all specifications, even after accounting for control variables, district fixed effects, and district-time trends. Nighttime warming shows no significant effect on yields, except for a positive impact at the harvesting stage, which is not robust across all specifications. These findings indicate that higher temperatures during the growing and harvesting stages can cause heat stress on the growth and ripening of wheat, a heat-sensitive crop, potentially resulting in lower yields.

Our findings align with existing evidence. Studies such as Kumar and Parikh (2001), Hertel and Lobell (2014), Kumar et al. (2016), and Khan et al. (2020) find that the growing stage is particularly sensitive to higher temperature, as it is a critical phase where major reproductive processes occur. High temperature during this stage can significantly reduce grain numbers by increasing floret mortality and/or sterility, leading to lower yields. Additionally, Pask et al. (2014) find that temperature-induced wheat yield losses in South Asian countries are notably higher compared to other regions, averaging between 3% and 17%.

Excess rainfall has a positive impact during the planting stage, with 1.5 standard deviations above the long-run district-level average rainfall increasing wheat yield by 9.3-12.8%. This result is logical for two reasons. Firstly, wheat, unlike other winter crops, has higher water requirements, especially during its initial growth phase. Adequate soil moisture at planting time significantly benefits the crop, facilitating better seed germination. Studies indicate that farmers prefer to sow wheat following a wet season or year, which aids better seed germination and leads to a good harvest (Siddiqui et al., 2012; Taraz, 2017; Khan et al., 2020). Secondly, Pakistan's winter season is very dry, with limited water availability. During planting time, around 60% of farmers rely heavily on water from melting Himalayan glaciers (Wassmann et al., 2009). In this context, excess rainfall during this period provides sufficient water for the crop, enhancing seed germination and resulting in positive yield effects. Our results are robust to the alternative measures of rainfall. For example, we also define deficit rainfall using a method analogous to that used for excess rainfall, incorporating it into our regression analysis as an alternative measure of rainfall. We find no significant impact at the district level. The results are in the appendix, in Table A.5.

In summary, wheat yields are negatively impacted by daytime warming, as higher temperatures lead to reduced yields. In contrast, excess rainfall, especially during the planting stage, enhances yields.

Table 2.2: Effects on wheat yields at district level (2000-2019)

Dep var: Yield(output/area)	(1)	(2)	(3)	(4)	(5)
T_{max} at planting stage	0.102	0.170	0.169	0.171	0.159
	(0.382)	(0.286)	(0.290)	(0.291)	(0.342)
T_{max} at growing stage	-0.117**	-0.123**	-0.123**	-0.127***	-0.130**
	(0.017)	(0.012)	(0.013)	(0.007)	(0.010)
T_{max} at harvesting stage	-0.036	-0.036*	-0.035*	-0.036*	-0.084*
	(0.113)	(0.092)	(0.086)	(0.086)	(0.078)
T_{min} at planting stage		-0.171	-0.169	-0.167	-0.164
		(0.251)	(0.260)	(0.275)	(0.294)
T_{min} at growing stage		-0.083	-0.084	-0.086	-0.079
		(0.155)	(0.149)	(0.141)	(0.161)
T_{min} at harvesting stage		0.077*	0.075	0.075	0.030
		(0.099)	(0.101)	(0.109)	(0.182)
Rain at planting stage			0.093**	0.095**	0.128***
			(0.029)	(0.025)	(0.006)
Rain at growing stage			0.037	0.037	0.034
			(0.471)	(0.483)	(0.521)
Rain at harvesting stage			-0.021	-0.023	-0.019
			(0.717)	(0.700)	(0.758)
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
District-time trend	No	No	No	Yes	Yes
District Controls	No	No	No	No	Yes
Districts	480	480	480	480	480

Note: The dependent variable is the natural log of wheat yield. Climate variables are specific to three stages (planting, growing and harvesting) during wheat season. Climate variable at each stage is a binary indicator taking value 1 when the standardised Climate variables exceed 1.5 standard deviation from their respective long-run district−level averages. District−level controls include total agricultural land, proportion of irrigated land for wheat, fertiliser application (in kg/ha) and share of population engaged in agriculture. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

2.7.2 Climate effects on wheat yield: Region level estimates

Next, we separate the analysis for the four climatic regions of the KP province: northern, eastern, central, and southern. The rationale for conducting regional-level estimations stems from the considerable climate variability observed across these regions. For instance, the southern region consistently experiences temperatures exceeding the optimal range for wheat cultivation. During the growing and harvesting stages, the average maximum temperatures are 24°C and 36°C, respectively (see Panel (b) and column (9) of Table 2.1), both of which exceed the optimal temperature range for wheat growth. Specifically, the ideal maximum temperature is 16–20°C during the growing stage and 30–35°C during the harvesting stage (see column (11) of Table 2.1).

In contrast, in other regions, temperatures generally fall below the optimal ranges, except in the central region, where they remain close to the ideal range. A detailed comparison of the ideal temperature ranges for each growth stage is provided in Table A.6 in the appendix.

When examining rainfall patterns, the southern region faces a further disadvantage, receiving the lowest rainfall during the wheat season, ranging from 10–35 mm (see column (10) of Table 2.1). The combination of these suboptimal conditions—low rainfall and high temperatures—makes wheat cultivation increasingly challenging in the southern part of the province compared to other regions.

Table 2.3 presents the region-level results for wheat yield, with two sets of estimates. Columns (1) to (7) estimate the impact of excessive heat and rainfall, measured as 1.5 standard deviations above the long-run average for Climate variables at each stage of wheat development. In column (8), we analyse deviations from ideal Climate conditions, particularly in the southern region, where temperatures consistently exceed the optimal range. Both measures of excessive heat indicate a negative impact on yields in this region. Specifically, yields decline by approximately 14% at the harvesting stage when temperatures are 1.5 standard deviations above the long-run average. A 1.5°C increase above the ideal temperature results in yield reductions of approximately 9% during the growing stage and 20% during the harvesting stage. Our findings remain robust under the alternative measure of excessive heat, confirming that wheat yields in the southern region are particularly vulnerable to warming. These findings are consistent with previous studies, such as those by Ghalib et al. (2017), Hussain and Bangash (2017), and Gul et al. (2022), which also conclude that wheat in the southern regions of the country is more susceptible to the direct impact of heat stress, leading to significant yield reductions.

In the central region, daytime warming adversely affects wheat yields during the growing stage. When the current temperature during this stage exceeds the long-run maximum temperature, yields decline by 32% (see columns (5) and (6)). In contrast, no significant effects of warming are observed in the northern and eastern regions, except for a positive impact noted in the eastern region during the planting stage, as shown in columns (3) and (4) of Table 2.3.

We find no detectable effect of nighttime warming at the region level, except in the eastern region. Specifically, there is a negative effect on yields in this region during the planting stage, as shown in columns (3)-(4). This is likely due to the fact that nighttime temperatures are increasing more rapidly than daytime temperatures, particularly in the northeastern highlands. During the wheat season, the average deviation from the long-run temperature is 0.60°C during the day, while it rises to 0.63°C at night (as indicated at the end of the table). These findings are consistent with projections by Screen (2014) and Pepin et al. (2022), which show that fluctuations in minimum temperatures have become more frequent and intense in high mountainous regions compared to lowlands. This is further supported by a recent study in Pakistan by Nizami et al. (2020), which demonstrates that the increase in minimum temperatures in highlands is occurring at a much faster rate, particularly during the wheat season. Our results align with this evidence, indicating negative effects on wheat yields when minimum temperatures exceed their long-run averages.

Our analysis reveals significant regional variability in the effects of rainfall on wheat yields. In the southern region, excessive rainfall during the planting stage has a positive impact on yields. Specifically, rainfall that is 1.5 standard deviations above the long-run average increases yields by about 39% (see column (7)). This positive effect persists even when considering rainfall that is 1.5 mm above the optimal range (see columns (8). This can be attributed to the generally lower levels of rainfall in the southern region than other regions, where surplus rainfall during planting enhances crop growth. These findings are consistent with prior studies in the KP province, which have also documented a positive relationship between higher rainfall and wheat yields (Afzal et al., 2016; Hussain and Bangash, 2017; Gul et al., 2022). Conversely, excessive rainfall has negative effects in the eastern region during the growing stage and in the central region during the harvesting stage. In the eastern mountains, where rainfall often exceeds the optimal water availability (130 mm compared to the ideal 120 mm), additional precipitation negatively impacts yields (Musick et al., 1994). In the central region, excess rainfall during the harvesting stage can delay the ripening process, as the maturity stage of wheat requires less water (Rasul, 1993).This concludes that rainfall above the long-run average benefits wheat during the planting stage,but excessive rainfall during other stages can potentially reduce yields.

Table 2.3: Effects on wheat yields at climatic region level (2000-2019)

	Northern		Eastern		Central		Southern (1.5 sd above)	Southern (1.5°C above)
Dep: Wheat Yield (output/area)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T_{max} at planting stage	0.000	0.000	0.552**	0.490***	0.091	0.081	0.123	0.161**
	(0.000)	(0.000)	(0.010)	(0.002)	(0.813)	(0.829)	(0.399)	(0.044)
T_{max} at growing stage	-0.107	-0.105	0.037	0.043	-0.321***	-0.321**	0.217	-0.090**
	(0.285)	(0.235)	(0.554)	(0.350)	(0.005)	(0.012)	(0.406)	(0.019)
T_{max} at harvesting stage	-0.030	-0.036	-0.089	-0.046	-0.009	-0.008	-0.139*	-0.195**
	(0.556)	(0.489)	(0.411)	(0.631)	(0.940)	(0.953)	(0.065)	(0.041)
T_{min} at planting stage	-0.055	0.062	-0.426***	-0.434***	-0.256	-0.277	-0.456	0.039
	(0.632)	(0.642)	(0.007)	(0.004)	(0.212)	(0.234)	(0.139)	(0.656)
T_{min} at growing stage	-0.031	-0.026	-0.024	-0.024	0.605**	0.523	-0.191	0.000
	(0.846)	(0.866)	(0.708)	(0.693)	(0.027)	(0.182)	(0.287)	(0.000)
T_{min} at harvesting stage	0.158	0.119	0.053	0.028	0.021	0.040	0.307	0.000
	(0.273)	(0.211)	(0.733)	(0.842)	(0.883)	(0.761)	(0.195)	(0.000)
Rainfall at planting stage	0.157	0.172	0.000	0.000	0.134	0.135	0.387*	0.413*
	(0.241)	(0.221)	(0.000)	(0.000)	(0.147)	(0.187)	(0.061)	(0.072)
Rainfall at growing stage	-0.091	-0.068	-0.129**	-0.121**	-0.029	-0.038	0.002	-0.113
	(0.351)	(0.462)	(0.029)	(0.050)	(0.561)	(0.535)	(0.990)	(0.288)
Rainfall at harvesting stage	0.087	0.006	-0.113	-0.087	-0.325***	-0.366***	0.181	0.114
	(0.345)	(0.940)	(0.353)	(0.430)	(0.003)	(0.003)	(0.633)	(0.434)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	Yes	Yes
Region-Year EF	No	Yes	No	Yes	No	Yes	Yes	Yes
Average T_{max} above historical (°C)		0.55		0.60		0.57	0.66	4.04
Average T_{min} above historical (°C)		0.61		0.63		0.57	0.61	0.38
Average rainfall above historical (mm)		3.89		1.91		3.43	2.31	12.83
Observation	140	140	100	100	140	140	100	100

Note: The dependent variable is the natural log of wheat yield. Climate variables are specific to three stages (planting, growing and harvesting) during wheat season. Climate variables in columns (1)−(7) at each stage is a binary indicator taking value 1 when the standardised values exceed 1.5 standard deviations from the specific growing season long-run average for a given district. In column (8), we include a binary indicator taking values 1 when current Climate variables are 1.5 ^{0}C above than the ideal ranges at each stage for southern region. Controls include total agricultural land (ha), proportion of irrigated land for wheat, fertiliser application (in kg/ha) and share of population engaged in agriculture. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

2.7.3 Heterogeneous effects on wheat yields

In this section, we analyse the varying effects on wheat yields across different district categories—milder, moderate, and hotter—based on temperature quartiles during the wheat growing season. Milder districts represent the bottom 25% of the temperature distribution, while hotter districts are in the top 25%. Moderate districts fall between these extremes.

Next, we empirically test how the effects of climate shocks vary based on two key input choices: irrigation and fertiliser application. This analysis is conducted on sub-samples for each district category, accounting for differences in irrigation quality (better and poor) and fertiliser application levels (high and low). We posit that exposure to higher temperatures may indicate the presence of on-farm adaptation strategies employed by farmers, which could mitigate the adverse effects of warming. For example, farmers might adjust irrigation practices and fertiliser application during the wheat growing stage in response to high temperatures, potentially affecting yields differently across district categories.

2.7.3.1 Heterogeneous effects by district category

To examine how the impact of warming during the wheat season varies across districts, we classified them into three categories based on average temperature ranges. The first category, mild districts, includes those in the bottom 25^{th} percentile of the temperature distribution, with an average temperature of 13°C in our study sample. Hotter districts represent the top 25^{th} percentile, with a mean temperature of 26°C. The moderate districts fall between these extremes, with a mean temperature of 23°C, capturing the middle range between the bottom and top 25th percentiles. We also show how these districts are geographically distributed across the province and how they differ climatically using district-level maps. These are presented in appendix Figure A.1.

We conducted separate regressions for each of the three district categories by estimating equation (2.1) and the results are presented in Table 2.4. Column (1) corresponds to the milder districts, column (2) to the moderate districts, and columns (3) and (4) focus on the hotter districts, each examining two distinct measures of heat: 1.5 standard deviations above the long-term averages and 1.5 degrees Celsius above the optimal temperature conditions.

Our findings indicate that daytime warming reduces crop yields across all district categories, with the growing stage being particularly sensitive to heat. In milder and moderate districts, yield reductions occur when temperatures during the growing season exceed the long-run average, while in hotter districts, the impact is seen when temperatures surpass the ideal range (since the long-run average is already above the optimal temperature for wheat). For example, in milder districts (column (1)), yield reductions are approximately 23% when growing-stage temperatures exceed 1.5 standard deviations above the long-run average. Similarly, in moderate districts (column (2)), the reduction is about 56%.

In hotter districts, while no significant impact on yields is observed when temperatures exceed the long-run average (column (3)), yield losses of around 8% are evident when growing-stage temperatures exceed the ideal temperature of 20°C by 1.5°C (column (4)). At the harvesting stage, there is a significant negative effect of heat in both cases: when temperatures exceed the long-run average (column (3)) and when they surpass the optimal temperature (column (4)). This is likely because the long-run average and optimal temperatures are nearly equal, at approximately 35°C.

These results align with those observed at the region level, especially regarding daytime warming and excess rainfall in the central and southern regions (see columns (5)–(8) in Table 2.3). Southern districts, along with some in the central region, fall into the hotter category, making them more sensitive to daytime warming. However, earlier regional analyses did not show significant effects for northern districts. But negative impacts on yields at the growing stage are evident when these districts are classified as milder in column (1) of Table 2.4. The lack of significant effects at the regional level could be attributed to the varying local conditions within regions, which may obscure overall trends. A more detailed analysis of temperature quartiles, as presented in Table 2.4, highlights negative effects that are not immediately apparent in the broader regional analysis shown in Table 2.3. This suggests that the impact on yields is more strongly associated with specific temperature thresholds rather than general regional classifications.

This concludes that the effects on wheat yields are not solely determined by location but are influenced by temperature ranges and the specific growth stages of wheat. For instance, the growing stage is sensitive to high temperatures in both milder and moderate districts. In contrast, in hotter regions, excessive heat adversely affects both the growing and harvesting stages. These findings highlight that all district categories experienced negative productivity shocks due to high temperatures, with the impact being particularly severe in the hotter districts.

Table 2.4: Heterogeneous effects on wheat yields by district category (2000-2019)

	Milder districts	Moderate districts	Hotter districts	
	(Bottom 25%)	(25−75%)	(1.5 sd above long-run)	(1.5^{0}C above ideal)
Dep. Var:Wheat yield	(1)	(2)	(3)	(4)
T_{max} at planting stage	0.000	0.000	-0.038	0.147
	(0.000)	(0.000)	(0.840)	(0.070)
T_{max} at growing stage	-0.227***	-0.560***	-0.017	-0.079*
	(0.005)	(0.001)	(0.942)	(0.076)
T_{max} at harvesting stage	-0.032	-0.190**	-0.149**	-0.200*
	(0.605)	(0.034)	(0.019)	(0.080)
T_{min} at planting stage	-0.165	-0.066	-0.164	0.155
	(0.391)	(0.394)	(0.264)	(0.708)
T_{min} at growing stage	0.114	0.166	-0.095	-0.001
	(0.525)	(0.239)	(0.563)	(0.969)
T_{min} at harvesting stage	0.171	-0.281	0.221*	-0.042
	(0.107)	(0.103)	(0.099)	(0.566)
Rainfall at planting stage	0.585*	0.387***	0.326**	0.522**
	(0.098)	(0.001)	(0.034)	(0.025)
Rainfall at growing stage	-0.154**	0.021	0.001	-0.199*
	(0.042)	(0.771)	(0.997)	(0.081)
Rainfall at harvesting stage	0.134	0.002	-0.246**	0.118
	(0.476)	(0.970)	(0.022)	(0.460)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
District-time trend	Yes	Yes	Yes	Yes
Average temperature deviation (^{0}C)	0.68	0.72	0.63	3.20
Average rainfall deviation (mm)	1.13	1.60	1.19	1.19
No. of obs.	140	220	120	120

Note: The dependent variable is the natural log of wheat yield. Climate variables are specific to three stages (planting, growing and harvesting) during wheat season. Climate variable at each stage is a binary indicator taking value 1 when the standardised Climate variables are 1.5 standard deviations above their respective long-run averages for a given district. In column (4), we include a binary indicator taking value 1 when current Climate variables are 1.5 ^{0}C above their respective ideal ranges at each stage for the hotter districts. Controls include total agricultural land (ha), proportion of irrigated land for wheat, number of tractors, number of tube-wells, fertiliser application (in kg/ha) and share of population engaged in agriculture. All specifications include district-time trend, district and growing season fixed effects. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

2.7.4 Effects by input use

Crop yields are influenced not only by environmental factors affecting plant growth but also by farmers' adaptive responses to climate change, primarily through adjustments in input use (Aragón et al., 2018; Grote et al., 2021; Wheeler and Lobley, 2021). Among the inputs, improved seed varieties are one of the major inputs that help in mitigating temperature induced yield losses. Evidence show that traditional wheat varieties, for example, landraces generally considered more resilient to climatic shocks and stresses (Khan et al., 2020; Arif et al., 2025). However, according to the recent report by Agricultural Research Institute Tarnab (ARIT) (2025), in case of KP province, traditional varieties are no longer efficient among farming community in the past few years. In response to current climate challenges, three new wheat varieties have recently been developed, and it is predicted that they could yield up to three times more than existing varieties.

In addition, agricultural extension services play a crucial role in enhancing crop productivity by providing farmers with timely knowledge, training, and access to agricultural innovations. Evidence from Pakistan shows that farmers who engage with extension agents achieve significantly higher yields—20–25% more on average, compared to those without such support (Abid et al., 2017; Ahmad et al., 2017, 2020). However, access remains limited; only about 40% of farmers across the country benefit from these services, largely due to weak infrastructure and limited internet connectivity (PBS, 2023).

Effective pest management is another key factor in boosting crop yields. Studies indicate that progressive farmers, particularly in more developed regions like Punjab, are more likely to adopt improved pest control practices. In contrast, farmers in KP and rural Sindh often rely on conventional synthetic pesticides, due to a lack of awareness and training. Research suggests that these traditional methods are not only less effective but also poorly suited to managing pest pressures under changing climatic conditions (Khan et al., 2021; Syed et al., 2022).

Despite the importance of these inputs, our analysis is constrained by the lack of consistent, time-series data on wheat varieties, extension services, and pest management practices. Consequently, we focus on irrigation and fertiliser use, inputs for which reliable district-level panel data are available over time.

2.7.4.1 Effect of irrigation

Previous studies have shown that irrigation plays a crucial role in protecting crops from heat stress, making it a key margin of adjustment to climate change (Kurukulasuriya et al., 2011; Taraz, 2017, 2018). Depending on the climatic and local conditions, farmers choose to irrigate more in order to avoid heat induced yield losses. In countries like Pakistan, where extensive publicly funded canal systems that deliver water over long distances to farmers are lacking, irrigation is often solely decided by farmers. Deciding whether or not to irrigate one's crops is a choice that can be influenced by other factors such as climate, locality, wealth of farmers etc. Kurukulasuriya et al. (2011) finds that irrigation is an endogenous choice, often sensitive to climatic conditions. Therefore interacting high temperature with each district's irrigated area or/and share of irrigated land would produce biased estimates of irrigation effects on yield-temperature relationship. For instance, districts experiencing higher level of temperature may tend to use irrigation more extensively and vice versa. In this scenario, a regression model based on irrigated area (or share of irrigated land) could either overestimate or underestimate the impact of irrigation in protecting yields from high temperatures.

To solve this problem, we are using number of tube wells installed at district level as proxy for irrigation. Tube wells are stable over time and independent of short-term shocks, reflecting local water availability at the district. Their installation is driven by factors such as geological features and long-term investment, making them exogenous to climate. please note that the tube wells used in this analysis include both privately and government-installed systems. While some tube wells may experience drying up over time, but they provide the closest available measure for irrigation in KP Province.

To estimate the impact of high temperature in the presence of irrigation, we created a dummy variable that equals one if a district has a higher number of tube wells than the provincial median, and zero otherwise. We then estimate equation (2.1) separately for each district category, dividing the sample into subgroups based on tube well installations. Districts with more tube wells than the provincial median are classified as having better irrigation, while those with fewer are identified as having poor irrigation.

Results are shown in Table 2.5. Columns (1) and (3) show the sub-samples where the number of tube wells installed is greater than the provincial median, indicating better irrigation for the milder and moderate districts, respectively. Columns (2) and (4) represent poor irrigation for both milder and moderate districts. For the hotter district category, we do not include a separate sub-category for poor irrigation, as only one district falls into that group. As a result, the number of observations is 100 instead of 120. Columns (5) and (6) focus on hotter districts with relatively better irrigation, defined as having a number of tube wells above the provincial median. These columns use two alternative measures of heat: Column (5) is based on temperatures 1.5 standard deviations above the long-term average, while Column (6) applies a threshold of 1.5°C above the optimal temperature during the wheat season.

The most striking finding is that irrigation significantly reduces the negative impact of daytime warming in districts with better irrigation systems. In milder districts (column 1 and moderate districts (column 3), as well as in hotter districts (columns 5 and and 6), improved irrigation shows a positive effect during the hot season. In contrast, for poorly irrigated districts (column 4), especially in moderate district category, the results indicate a negative effect of high temperature on yields. This shows that better irrigation substantially mitigates the harmful effects of rising temperature on wheat yields. These results are consistent with previous research, including studies by Lobell et al. (2008), Ahmad et al. (2014), Tack et al. (2017), Taraz (2017), and Benonnier et al. (2022), which have found that irrigation can reduce average maximum temperature by up to 2 °C during dry and hot conditions.

Table 2.5: Effects of better vs. poor irrigation on wheat yields by district category

	Milder districts (Bottom 25%)		Moderate districts (25-75%)		Hotter districts (1.5 sd above long-run)	(1.5°C above ideal)
	Better irrigation	Poor irrigation	Better irrigation	Poor irrigation	Better irrigation	Better irrigation
Dep. Var: Wheat yield	(1)	(2)	(3)	(4)	(5)	(6)
T_{max} at planting stage	0.000	0.000	-0.187	-0.103	-0.105	0.936***
	(0.000)	(0.000)	(0.101)	(0.123)	(0.485)	(0.000)
T_{max} at growing stage	0.480*	-0.067	0.906***	-0.217***	-0.012	0.790***
	(0.097)	(0.804)	(0.009)	(0.006)	(0.949)	(0.000)
T_{max} at harvesting stage	-0.016	0.054	-0.033	-0.016	0.214**	0.417***
	(0.938)	(0.611)	(0.445)	(0.699)	(0.032)	(0.001)
T_{min} at planting stage	-0.117	0.000	0.044	-0.141	-0.117	0.070
	(0.154)	(0.000)	(0.764)	(0.804)	(0.253)	(0.831)
T_{min} at growing stage	0.157	1.768	0.290*	-0.043	0.064	0.137*
	(0.300)	(0.444)	(0.092)	(0.388)	(0.650)	(0.063)
T_{min} at harvesting stage	0.084	0.287	0.109	-0.024	0.142**	0.302
	(0.422)	(0.235)	(0.176)	(0.755)	(0.042)	(0.115)
Rainfall at planting stage	-0.072	-0.258	0.031	0.143*	0.297**	0.459***
	(0.594)	(0.376)	(0.827)	(0.078)	(0.014)	(0.002)
Rainfall at growing stage	-0.202	-0.238*	-0.195**	-0.072	-0.049	0.000
	(0.291)	(0.055)	(0.017)	(0.536)	(0.659)	(0.000)
Rainfall at harvesting stage	-0.057	0.166	-0.021	-0.007	-0.260**	-0.343***
	(0.528)	(0.751)	(0.623)	(0.895)	(0.011)	(0.009)
Irrigation	-0.093	0.054	0.295	0.793*	0.556*	0.929*
	(0.831)	(0.1160	(0.496)	(0.057)	(0.066)	(0.077)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
District-time trend	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	86	54	124	96	100	100

Note: The dependent variable is the natural log of wheat yield. Climate variables are specific to three stages of the wheat season (planting, growing, and harvesting). At each stage, Climate variables are represented by a binary indicator, taking a value of 1 when the standardised Climate variables exceed 1.5 standard deviations above their respective long-run averages for a given district (columns (1)-(5)). In column (6), we include a binary indicator that takes a value of 1 when current Climate variables are 1.5°C above their respective ideal ranges at each stage for hotter districts. Better irrigation is represented in columns (1), (3), (5), and (6), indicating districts with a higher number of installed tube wells than the provincial median. Districts with fewer installations are classified as having poor irrigation in columns (2) and (4). Controls include total agricultural land (ha), proportion of irrigated land for wheat, number of tractors, number of tube wells, fertiliser application (in kg/ha), and the share of the population engaged in agriculture. All specifications include district-time trends, district fixed effects, and growing season fixed effects. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

2.7.4.2 Effect of fertilisers

Secondly, we estimate how adjusting fertiliser application affect yields across the district categories given the different heat levels.

In developing countries, farmers frequently rely on fertilisers to enhance crop yields, as it is one of the most accessible coping mechanisms. Research shows that, in the absence of more advanced farming techniques, poorer farmers often adjust fertiliser application to safeguard their crops from losses, particularly when experiencing high temperature during the growing season (Ali and Erenstein, 2017; Jagnani et al., 2021).

To estimate the impact of fertiliser application, we constructed a binary variable indicating whether fertiliser use per hectare exceeded the provincial median. This variable takes a value of 1 if fertiliser use is above the median, and 0 if it is below. We then estimated the same equation as before (equation 2.1) for subsamples of high and low fertiliser application, separately for each district category: milder, moderate, and hotter.

Our findings, as presented in Table 2.6, outline the relationship between fertiliser application intensity and district-level temperature classifications. Columns (1) and (2) report results for districts characterised by milder temperatures, corresponding to low and high levels of fertiliser application, respectively. For districts with moderate temperatures, columns (3) and (4) provide analogous results for low and high fertiliser use. Similarly, columns (5) and (6) present the outcomes for hotter districts under low and high fertiliser application intensities.

The results show no significant effect of applying either low (below the median) or high (above the median) fertiliser on yields during the growing stage across all district categories. This suggests that changes in fertiliser application, whether increased or decreased, do not offset the negative impact of high temperatures on yields. One possible explanation is that local farmers may struggle to adapt optimal agronomic practices in response to climate shocks, either due to a lack of technical skills or insufficient resources. This is supported by a recent study by Billé and Rogna (2022), who find that in Southeast Asian countries, extreme Climate conditions seem to have little influence on farmers' fertilisation decisions. This means that farmers in these regions do not substantially adjust their fertiliser use in response to changing Climate patterns, likely due to limited access to accurate Climate information, insufficient knowledge, or economic constraints. Majority of poor farmers are in the northern belts of Pakistan, where they have limited access to resources such as heat resistant wheat varieties and climate information. These factors reduce the adaptability of farmers to high temperature, resulting in higher wheat losses (Ali et al., 2017).

Our findings remain robust even when alternative measures of climate shocks, such as drought conditions, are considered. The results are largely consistent with those observed in our primary analysis of temperature shocks. The results are reported in Table A.7 of the appendix, which are largely consistent, supporting the validity of our analysis.

2.8 Conclusions

This study provides a comprehensive analysis of the impact of climate variables—such as maximum and minimum temperatures, along with rainfall—on wheat yields in Khyber Pakhtunkhwa (KP), Pakistan, from 2000 to 2019. By examining the effects of excess heat and rainfall during critical stages of wheat development, planting, growing, and harvesting, we offer valuable insights into how climate outcomes influence wheat yield over time.

Our findings show that wheat yields are highly sensitive to maximum temperatures during both the growing and harvesting stages across the study period in KP. Specifically, when maximum temperatures exceed the long-run average, wheat yields are negatively affected. In contrast, surplus rainfall during the planting stage benefits wheat yields. However, we found no significant adverse impact of minimum temperatures on yields in the province.

These effects remain consistent even when categorising districts into three groups, milder, moderate, and hotter, based on average temperature ranges during the wheat season. In milder and moderate districts, high temperatures during the growing stage negatively impact yields. However, in hotter districts, both the growing and harvesting stages are more severely affected, indicating greater vul-

Table 2.6: Effects of high vs. low fertiliser application on wheat yields by district category

	Milder districts		Moderate districts		Hotter districts	
	Low	High	Low	High	Low	High
Dep. Var:Wheat yield	(1)	(2)	(3)	(4)	(5)	(6)
T_{max} at planting stage	0.000	0.000	-0.330	0.030	1.276**	0.200*
	(0.000)	(0.000)	(0.345)	(0.228)	(0.554)	(0.052)
T_{max} at growing stage	-0.355**	-0.688**	-0.371**	-0.570****	-0.946*	-0.257**
	(0.034)	(0.034)	(0.035)	(0.004)	(0.060)	(0.048)
T_{max} at harvesting stage	0.083	-0.082	0.036	0.022	-0.401	-0.027
	(0.116)	(0.507)	(0.625)	(0.664)	(0.123)	(0.720)
T_{min} at planting stage	-0.131	0.000	-0.039	0.020	0.011	-0.261
	(0.522)	(0.000)	(0.835)	(0.786)	(0.950)	(0.106)
T_{min} at growing stage	0.282**	-0.609	0.696*	0.092***	0.925*	0.265
	(0.018)	(0.447)	(0.084)	(0.007)	(0.091)	(0.186)
T_{min} at harvesting stage	0.106	-0.049	-0.067	0.050	0.445*	0.217
	(0.350)	(0.547)	(0.618)	(0.614)	(0.053)	(0.184)
Rainfall at planting stage	-0.177	-0.017	-0.226**	0.085**	0.247*	0.350*
	(0.313)	(0.951)	(0.005)	(0.014)	(0.085)	(0.075)
Rainfall at growing stage	-0.000	-0.238***	-0.086	-0.087	-0.358	0.068
	(0.997)	(0.006)	(0.466)	(0.196)	(0.146)	(0.624)
Rainfall at harvesting stage	0.175	-0.390**	-0.032	0.084***	0.007	-0.276**
	(0.413)	(0.019)	(0.420)	(0.002)	(0.980)	(0.017)
Fertiliser use (kg/ha)	0.229	1.217	0.658	0.112	0.053	-0.123
	(0.458)	(0.324)	(0.241)	(0.495)	(0.874)	(0.226)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
District-time trend	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	83	57	62	158	54	66

Note: he dependent variable is the natural log of wheat yield. Climate variables are specific to three stages of the wheat season (planting, growing, and harvesting). At each stage, the Climate variable is represented by a binary indicator that takes a value of 1 when the standardised Climate variables exceed 1.5 standard deviations above their respective long-run averages for a given district. The columns labeled 'Low' and 'High' represent sub-samples where fertiliser application is below and above the provincial median, respectively. Controls include total agricultural land (ha), proportion of irrigated land for wheat, number of tractors, number of tube wells, and the share of the rural population at the district level. All specifications include district-time trends, as well as district and growing season fixed effects. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

nerability of wheat to heat stress. We also tested our findings using deviations from ideal temperature conditions in hotter regions, where temperatures consistently exceed optimal levels, further confirming the heightened vulnerability of these districts. Excessive rainfall during the growing and harvesting stages negatively affects yields, while surplus rainfall during planting supports wheat growth.

In terms of coping strategies, our analysis reveals that improved irrigation is essential for mitigating the adverse effects of high temperatures across all district categories. Enhanced irrigation practices can significantly reduce yield losses under hot conditions. In contrast, fertiliser application, whether high or low, does not appear to offer substantial protection against temperature stress, suggesting that its role in adaptation is limited.

These findings have significant policy implications. The persistent damage from high temperatures across districts highlights the difficulties of adapting to these conditions with the current financial and technical resources, as well as existing adaptation strategies and policies in KP. This underscores the need for greater involvement from both the government and the private sector to drive technological innovations and develop policy frameworks that enhance the capacity for adaptation to extreme temperatures.

Chapter 3

Adaptation to extreme temperature: Evidence from land allocation in agricultural sector of Pakistan

In the previous chapter, we showed that wheat yields are sensitive to high temperatures across all districts in KP province, Pakistan. However, these districts often implement coping strategies to mitigate losses from climate change. For example, we showed that during periods of extreme heat, improved irrigation could offset adverse temperature effects on yields, potentially reducing the negative impact on yield. In this chapter, we explore how land use changes serve as an adaptation strategy in response to past temperature shocks, given wheat's sensitivity to high temperatures. The chapter specifically analyses this within the context of government policy in the form of a minimum price for wheat, the only crop receiving support in Pakistan.

The Pakistani government has long supported wheat production through a Minimum Support Price (MSP), purchasing directly from farmers at prices above the market rate. This policy has evolved significantly over time, with a sharp increase in MSP after 2006, creating two distinct periods. Between 1981 and 2006, the MSP remained relatively low, reflecting limited financial relief to farmers.

However, from 2007 to 2019, the MSP rose substantially, reaching approximately five times the average market price by the end of this period. This increase potentially enhanced the MSP's role as a financial safety net, encouraging farmers to sustain wheat cultivation despite environmental challenges.

Wheat, a staple crop in Pakistan, is highly sensitive to elevated temperatures, as demonstrated in the first chapter. While the MSP helps offset potential income losses caused by climate-induced yield reductions and encourages farmers to continue wheat cultivation despite environmental challenges, the crop remains vulnerable to rising temperatures. This vulnerability presents significant risks to its long-term sustainability. The limited adoption of hybrid wheat varieties exacerbates this sensitivity, which is further worsened by farming strategies limited by financial and technical constraints.

Existing literature suggests that farmers are increasingly aware of climate-related risks and are adopting a range of adaptive strategies. The adaptive measures are proactive steps to mitigate potential future impacts (Salazar-Espinoza et al., 2015; Damania et al., 2017). Evidence in the climate change adaptation literature indicates that adaptation strategies are categorised into two types. First, there are short-term adjustments, such as changing planting times, altering the amount of inputs (like fertiliser), and using water-saving techniques like better irrigation or reducing tillage (Hertel and Lobell, 2014; Huang et al., 2015; Kindu et al., 2015; Saddique et al., 2022). Second, there are long-term adaptations, which involve bigger changes, like reallocating land or moving away from certain crops. For example, switching from growing crops with high production variability to those with more stable yields (Ramsey et al., 2021). This chapter focuses on land choices in the immediate aftermath of a temperature shock. These changes in land use could reflect either a short-term adjustment or a long-term adaptation.

In this chapter, we examine how land use patterns have changed in response to past temperature shocks, focusing on comparisons between periods of low and high government support. Specifically, we investigate whether land use has shifted away from agriculture to diversify income sources or whether agricultural land has been expanded to offset production losses. Additionally, we analyse whether districts have moved away from cultivating temperature-sensitive crops, particularly wheat, as part of their adaptive strategies. Throughout this analysis, we aim to understand how the Minimum Support Price (MSP) policy has shaped these decisions by comparing land use responses across the two periods.

To examine the effects of past temperature shocks on land allocation, we employ a log-linear regression approach. Our key variable, 'temperature shock (heat),' is derived from climate data. This variable is a binary indicator that equals one if the current season's temperature is more than 1.5 standard deviations above the long-term district-level average temperature, which is calculated over a 40-year period from 1940 to 1980. We integrate district-level data on three types of land use, total agricultural land, other cropland, and land under wheat with cliamte data that is geo-coded at the district level for the KP province, covering the years 1981 to 2019. To investigate how the support price interacts with adaptation strategies in terms of land allocation, we split the sample into two periods: low government support (pre-2006) and high government support (post-2006).

Our study presents several key findings. During the period of low government support, temperature shock reduces land allocated to heat-sensitive wheat in the following year, leading to an overall decline in agricultural land. This shift could indicate a broader transition away from agriculture, possibly reflecting a move toward other sectors. However, during the period characterised by a high support price, we observe no significant changes in the land allocated to either wheat or other crops. However, examining results by climatic region reveals distinct responses. In southern districts with higher extreme temperature exposure, wheat cultivation declines during low support (1981–2006), but total agricultural land expands as farmers shift to less temperature-sensitive crops. This diversification aligns with studies showing that farmers in hotter areas adapt by growing more resilient crops (Taraz, 2018; Kurukulasuriya and Mendelsohn, 2008). Conversely, resource-poor colder districts adopt a more conservative approach: both total agricultural land and wheat area decrease after temperature shocks, reflecting limited capacity to adjust cropping choices. These findings are align with evidence that resource-constrained regions favour minimising losses amid climate change (Gebrehiwot et al., 2016; Mumtaz et al., 2019).

During the highs upport period (2007–2019), our findings suggest that support prevented a decline in wheat land after temperature shocks. Across the province, wheat area remained stable, instead increased, particularly in the southern and northern regions, where land shifted from other crops to government-supported wheat. In particular, the northern region, which is poorer and more resource-constrained, shifted away from growing more heat-resistant crops and instead devoted more land to wheat cultivation. These results suggest that while government support provides a sense of security in the face of climatic risks, it may also inadvertently increase reliance on a vulnerable crop.

This study makes significant contributions to the literature, particularly in the context of Pakistan. It enhances the understanding of how government policies interact with adaptation strategies, with a focus on the dynamics of land-use choices over time. While existing research predominantly highlights short-term adjustments—such as changes in sowing dates, crop rotation, and irrigation practices (Ali et al., 2017; Mumtaz et al., 2019; Abid et al., 2016; Gorst et al., 2018), there is limited emphasis on long-term adaptations. Recognising that land-use decisions can function as both short-term and long-term strategies, this study investigates their evolution in response to climate variability and government interventions, with a particular focus on the role of support prices for wheat.

The rest of this study is organised as follows. Section 3.1 provides an overview of the study area, highlighting the background information relevant to the temperature conditions and the support price offered to wheat growers. Section 3.2 presents a comprehensive review of the existing literature concerning potential strategies to climate shocks, specifically focusing on the role of land use change within the agricultural sector. Section 3.3 discusses the conceptual framework, and Section 3.4 presents our empirical framework. Section 3.5 discusses our data. Section 3.6 presents the main results and discussion, while Section 3.7 concludes.

3.1 Background

In this section, we first explore the temperature profile, highlighting regional variations over time across the climatic zones. Following this, we discuss the role of the government-set support price for wheat and how it influences wheat cultivation in the province. With 80% of KP's population reliant on agriculture for their livelihood, the province is particularly vulnerable to extreme temperatures (Chaudhry et al., 2009). Despite this high reliance on agriculture, KP depends on wheat supplies from Punjab to meet its needs (BPS, 2018).

3.1.1 Historical temperature across climatic regions

As already discussed in the previous chapter, KP province is classified as northern, eastern, central, and southern climatic regions. Over the past 50 years, the annual mean temperature in the province has increased by approximately 0.52°C (Chaudhry, 2017). This warming, however, has not been uniform across the region. For example, the southern region, in particular, experiences significantly higher temperatures and more arid conditions compared to other regions.

Figure 3.1 shows plots regional average annual temperatures during the study period relative to their historical climate normals. The historical mean temperature is calculated using the reference period 1940–1980 across districts in the province, allowing us to assess how annual temperatures deviate from this long-term average. To account for spatial and temporal variability in these deviations and enhance comparability, we construct upper and lower bounds, shown as a grey band in Figure 3.1. These bounds are calculated at the climate region level by clustering districts into climatic regions in Stata. Specifically, the upper bound is defined as the historical mean temperature plus 1.5 times the historical standard deviation, while the lower bound is the historical mean minus 1.5 times the standard deviation. This band reflects the typical range of historical temperature variation ($\pm$1.5 standard deviations), helping to identify years in which temperatures fell outside the expected norm, indicating unusually warm or cool growing seasons.

We observe a gradual warming trend across the climatic regions, which is relatively consistent. However, the degree of temperature variation differs among the zones. Specifically, the northern and eastern regions experience the lowest mean temperatures, ranging from 20°C to 24°C over time, while the southern region exhibits the highest mean temperatures (30°C to 32°C).

In terms of deviations from the long-run average temperature, most data points before 2000 fall within the upper and lower bounds, indicating normal temperatures with a few exceptions in specific years. After 2000, we see a clear shift towards the upper bound, indicating relatively warmer years. While the overall pattern of temperature change remains similar across regions during the study period, the warming trend is more visible in the southern region.

In the province, the central and southern regions are key economic hubs, where the majority of farming activities take place (EPA, 2016). These regions support the rest of the province by producing cereal crops. However, rising temperatures pose a significant threat to crop production in these areas. For instance, temperatures have already risen to 30°C in the central region and 32°C in the southern region, while major crops like wheat require an optimal temperature of around 20°C during the critical phase of the wheat-growing season. Although the northern and eastern regions may become more suitable for wheat cultivation, they are constrained by significant technical and financial challenges. These limitations place them in an increasingly precarious position as temperatures continue to rise. We also examine how rainfall patterns deviate from long-term regional averages and find that overall rainfall has remained relatively stable over time (see Figure B.1 in the appendix).

Given the observed negative impact of rising temperatures on wheat yields in KP, as demonstrated in the previous chapter, this chapter examines how land use has changed at the district level, specifically, whether land has been reallocated or abandoned in response to past climate stress across different regions of the province.

3.1.2 Support price for wheat

Pakistan is widely recognised as one of the major breadbaskets, with almost 80% of farmers growing wheat on nine million hectares (22 million acres) of land—nearly the size of the country of Jordan. Every year, 25 million tonnes of grain are produced, contributing 72% of the nation's daily caloric intake, with a

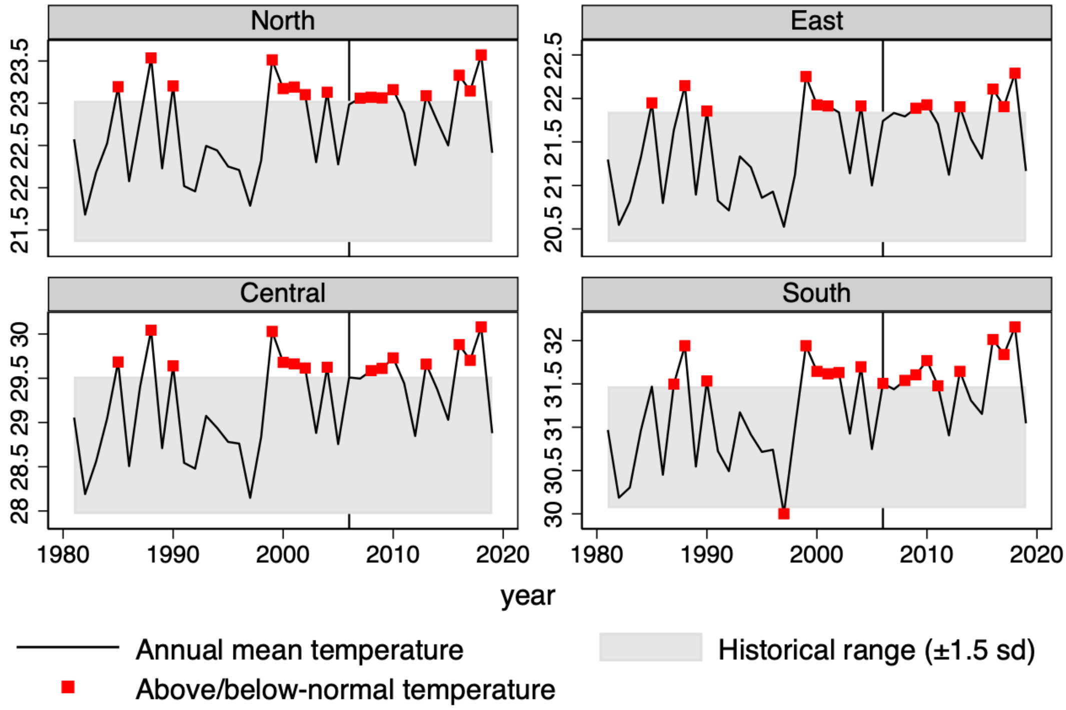


Figure 3.1: Average temperature against the historical mean temperature (1981-2019)

per capita consumption of around 124 kilograms (kg) per year—one of the highest in the region. To sustain self-sufficiency, the federal government guarantees a pre-announced price for wheat production. Through the provincial food ministries, the Government of Pakistan (GOP) procures wheat directly from farmers at a minimum support price before the wheat-growing season. This provides a strong incentive for farmers to continue producing wheat in the country. At the same time, it protects farmers from fluctuations in market prices, particularly when the market price falls. In other words, the support price functions as a form of crop insurance, offering farmers a safety net so they don't have to worry about market prices after the harvest. In a nutshell, support prices serve two key objectives: ensuring income security for farmers by encouraging more wheat cultivation, and providing food security for consumers—especially the poor—by offering wheat at prices lower than the market rate.

Wheat is one of the key strategic commodities in the country, so most of the decision-making regarding the crop is controlled and managed by the federal government. One of the major policies introduced to support wheat growers is the support price, which is determined based on the excess or shortage of its supply within the country.

In 1981, the government announced a support price of Rs. 58 (Pakistani rupees) per 40 kilograms (kg) of wheat output, along with a commitment to purchase wheat directly from farmers. Firstly, the establishment of a support price ensured that farmers would receive a fixed price for their crops, regardless of the actual production costs. Secondly, the support price consistently remained higher than the market price, as shown in Figure 3.2, although data for the initial years are unavailable.

However, this initiative remained relatively sluggish over time, as evidenced by Figure 3.2. It is observed that the increment in the support price from 1981 until 2006 was almost negligible, which we refer to as the low support period (Pre-2006) in our empirical estimation. After 2006, however, the support price increased to Rs. 625 per 40 kg of wheat, marking the start of a high support price period (Post-2006). This upward trend continued throughout the study period.

The support price is consistently higher than the market price of wheat, and the gap continues to widen over time (see Figure 3.2). This reflects the government's ongoing commitment to supporting wheat farmers. The price difference acts as a risk-reducing mechanism, providing farmers with a safety net against market fluctuations and uncertainties, thus ensuring a certain level of financial security in the agricultural sector.

The primary intention behind the support price is to sustain wheat production, a crop that is fundamental to the country's food security. However, wheat is particularly sensitive to high temperatures, more than many other crops. As a result, rising temperatures due to climate change pose a significant risk to wheat yields.

Given the underlying climatic conditions, the government may be placing farmers in a vulnerable position by providing price support for a crop highly sensitive to climate risks. While this support might offer short-term benefits, it may not be sustainable in the long run, particularly in Pakistan, where hybrid adoption is limited and financial resources for adapting farming technologies are

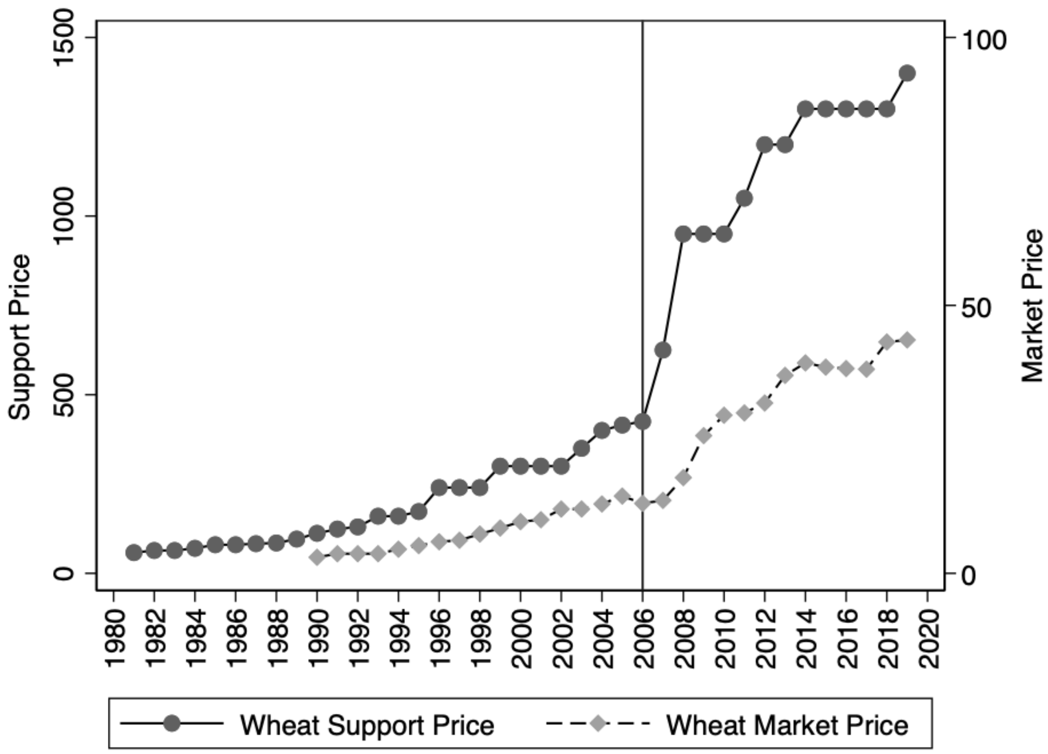


Figure 3.2: Minimum support price (MSP) and market price of wheat over time

scarce.

3.2 Connecting climate shocks to adaptation: Insights from the literature

In this section, we first present a conceptual map showing how climate change can potentially affect the agricultural sector and trigger various adaptation and coping responses. Second, provide an evidence from the literature on range of adaptation strategies in the agricultural sector in response to climate change. Next, we focus on how land allocation evolve as an adaptation strategy to climate change. Specifically, we examine studies from developing countries to understand the connection between weather shocks and land use in the context of our area of interest.

3.2.1 Possible adaptation strategies

Figure 3.3 presents a conceptual map showing how rising temperatures and anomalous rainfall can affect agricultural productivity, alongside some potential on-farm and off-farm strategies to mitigate these effects. For example, high temperatures can directly reduce crop yields, leading to negative productivity shocks that lower farm income and increase economic stress on agricultural households. In response to these perceived climate risks, households adapt by altering their practices based on available options—such as adjusting input use, investing in irrigation, or adopting heat-tolerant crop varieties, to sustain yields and reduce vulnerability. Beyond on-farm adaptations, households often diversify income by engaging in off-farm labour, seasonal migration, or, in some cases, permanently exiting agriculture.

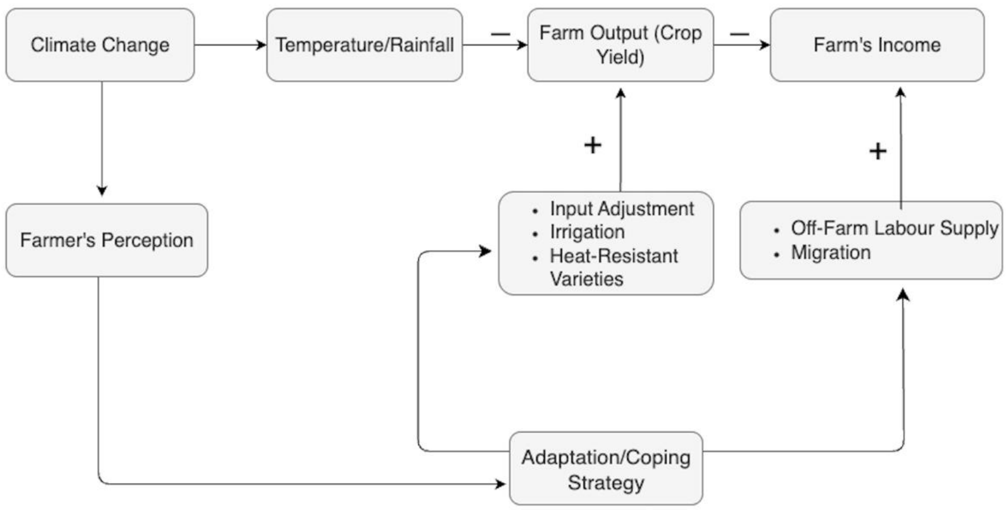


Figure 3.3: Conceptual map linking climate change to agricultural outcomes

A recent study by Islam et al. (2021) categorises climate change adaptation strategies into two main types: Stepping Up, which involves adjusting or improving farming practices, and Stepping Out, which refers to reducing or exiting farming altogether. They find a positive effect on agriculture among smallholders by adapting Stepping Up strategy in climatic hazard-prone areas of Bangladesh. Pakistani farmers particularly those residing in regions prone to excess rainfall often adapt by *altering planing dates* such as early and late sowing. For example, Abid et al. (2016) find that planting decisions among the farmers are made considering the rainfall situation in the region. They choose to grow those crops which require more water such as rice. In contrast, some regions may become too warm and dry for traditional crops like wheat and maize, leading farmers to switch to more *heat-resistant crops* such as sorghum, cassava and millet. These crops are better adapted to the extremely hot conditions and may offer the best possible alternative for farmers (Kurukulasuriya and Mendelsohn, 2008).

Other adaptive measures such as *crop diversification* (Bradshaw et al., 2004) and *livestock diversification* (Seo and Mendelsohn, 2008), are often called mix farming which involves livestock rearing and crop cultivation. Mix farming is considered to be a more effective form of adaptation, as associating livestock with crops reduces the vulnerability of the production system to a greater extent (Gautier et al., 2016). Since they are not equally sensitive to climate variations, and this kind of adaptation is often considered an advanced risk-coping strategy that can help secure crop production and income. It is, however, less common in poor farming communities given the limited access to financial and technological resources to invest in diversified production systems. Developing countries respond to climate vulnerabilities by diversifying their income sources, a buffer against income loss from weather-related risks and enhances the resilience of the rural sector to economic and environmental shocks (Girard et al., 2021).

Income diversification, often comes under the Stepping Out adaptation strategy. This can be achieved through participation in off-farm and non-farm activities to cope with the consequences of extreme weather events. Studies have shown that this approach involves reallocating labour from agricultural to non-agricultural activities (Dercon, 2002) and out-migration of some agricultural household members for better earning opportunities (Noack et al., 2019), we will consider this in the next chapter. Households that have diversified income sources generate higher off-farm or non-farm income and are less dependent on farm activities, and thus less vulnerable to climate shocks.

Nevertheless, transitioning from agricultural activities to non-agricultural income-generating activities as an adaptation strategy may affect the availability of labour in the agricultural sector (Aragón et al., 2021), which could potentially lead to reduced agricultural production (Abid et al., 2016). This implies that farmers reduce the land in response to an expectation of reduced agricultural production (Chen and Khanna, 2021). This concludes that if labour resources are reallocated or there is out-migration to mitigate climate variability and climate shocks, it could affect farmers' behaviour in terms of input utilisation, particularly land allocation.

In the following section , we are particularly focusing on studies reflecting on land allocation as an adaptation strategies to climate change.

3.2.2 Land use change: An adaptation strategy

Farmers use various strategies to manage risks during and after shocks to protect their crops, livelihoods, and subsistence. However, some of these practices can harm natural ecosystems, potentially leading to long-term land-use changes (Gautier et al., 2016). For example, extreme events like heatwaves, droughts, and floods, especially early in the growing season, may force farmers to adjust by expanding or reducing their farmland. These adjustments can cause temporary land-use shifts, which might become permanent if climate variability worsens. Despite this, few studies have identified climate variability, especially climate shocks, as a key driver of land-use change in agriculture.

Regarding land-use change, the literature can be broadly categorised into two strands focusing on how farmers adjust land-use decisions in response to climatic or climate shocks. When farmers notice an increase in the severity or frequency of these shocks, they may modify their land use to reduce negative impacts. Modification can be done by either expanding cropland (Salazar-Espinoza et al., 2015; Damania et al., 2017; Huang et al., 2015; Sesmero et al., 2018; Aragón et al., 2021; He and Chen, 2022) or abandoning and reducing the land under crops (Rei et al., 2000; Gebrehiwot et al., 2016; Ali et al., 2017; Shrestha and Shrestha, 2019; Mumtaz et al., 2019; Kabir et al., 2021; Wang et al., 2022).

The first strand of literature suggests that farmers expand their land in response to climate shocks such as heatwaves, extreme heat, drought, and floods.

According to Salazar-Espinoza et al. (2015), farmers in Mozambique tend to move away from cash and permanent crops (such as fruit trees) and shift towards growing more food crops in the aftermath of climate shocks. Farmers are more likely to allocate additional land to food crops after abnormal weather conditions like droughts and floods. For example, during droughts, they shift towards staple crops such as groundnut, beans, sorghum, and millet, while in floods, they turn to crops like maize and cassava. This shift allows farmers to devote more land to staple crops, buffering their cereal stocks for consumption after a bad year. Similarly, Damania et al. (2017) conducted a study examining the connection between land-use decisions and climate shocks among agricultural households in 56 developing countries. The study found that climate shocks directly influence land allocation, especially among subsistence farmers. In developing nations, where farmers lack financial and technological support and face poor infrastructure, they primarily rely on adjusting land use as an effective adaptation strategy to sustain production and income. The findings show that in the year following dry spells (defined as rainfall at least one standard deviation below normal), cropland area increased significantly. However, wet spells (rainfall at least one standard deviation above normal) had less of an impact on land-use change.

In some regions, extreme temperatures are the primary factor influencing farmers' land-use decisions. Aragón et al. (2021) found that extreme heat impacts agricultural productivity and land-use in rural Peru and India, leading farmers to adapt by shifting to drought-tolerant crops and reducing crop cultivation frequency. For instance, in India, rice cultivation decreases due to its high water needs, prompting a switch to drought-resistant crops like millet. In Peru, farmers favor maize and beans for their heat resistance. Additionally, farmers often expand their cropland to counteract the effects of high temperatures. He and Chen (2022) support this finding, showing that high temperatures lead to both cropland expansion and deforestation. Specifically, each additional harmful growing degree day (temperatures above 32°C) can increase land allocated to cereal production by 20%. These studies highlight that expanding cropland is a common adaptive strategy for farmers facing extreme climate shocks.

This strand of literature concludes that following a climate shock farmers tend to allocate more land to food crops. Damania et al. (2017) offer a framework to explain why farmers expand their cropland following adverse weather conditions. This behavior, termed "safety-first," involves farmers prioritizing the protection of their income and production levels to guard against future losses. Facing repeated challenging weather and reduced yields, farmers anticipate that future yields may also be low, leading them to expand their farmed areas as a strategy to sustain their production and income. The "safety-first" response is thus an adaptive strategy to manage risk, aiming to ensure a more stable income and food security in the future. This perspective underscores the importance of understanding farmers' decision-making processes in response to environmental shocks and their implications for the long-term sustainability of agriculture.

The second strand of literature suggests that adverse weather conditions can discourage farmers from expanding their crop cultivation by reducing the amount of arable land. Agricultural households, especially those vulnerable to heatwaves and droughts, may opt to decrease the land dedicated to crops sensitive to these conditions to protect against their negative impacts.

Rei et al. (2000) studied land-use changes among Ethiopian farmers from 1986 to 1996 and found a significant decrease in agricultural land, especially during the later years (1991-1996). This decline was attributed to frequent changes in rainfall patterns, which made it difficult for farmers to maintain land productivity and led to reduced cultivated areas. These findings are supported by Gebrehiwot et al. (2016), who investigated the effects of drought on agricultural land use in Ethiopia and found that farmers reduced cropland as an adaptation strategy during drought periods. This indicates that climate shocks can significantly impact land-use decisions, often leading to a shift away from agricultural land allocation. Similarly, temperature extremes can significantly affect crop yields, soil fertility, and water availability, all of which influence agricultural land-use decisions. Shrestha and Shrestha (2019), conducted a study examining the impacts of temperature extremes on agricultural land-use change in Nepal from 1995 to 2015. During this period, Nepal experienced significant changes in temperature patterns. The study found that temperature extremes led farmers to switch to more resilient crops, such as maize and mustard, which are better suited to handle extreme temperatures.

Similar to other developing countries, climate shocks pose a significant challenge to crop yields in Pakistan. As a result, farmers in Pakistan often reduce the cultivated land as an adaptation strategy to mitigate the adverse impacts of these shocks, leading to decreased cropland. For example, Ali et al. (2017) examined the effect of extreme weather events on crop choices and land-use patterns in Pakistan between 1992 and 2010. Their findings indicate that extreme weather events are pushing farmers away from traditional crops such as wheat and maize towards horticultural crops, which are more resilient to climate variability. A similar study by Gorst et al. (2018) explored how farmers in Pakistan adapt to climate shocks. They found that farmers are more likely to switch to crops with shorter growing periods and lower water requirements in response to drought conditions. Mumtaz et al. (2019) conclude that both rainfall and temperature shocks adversely affect agricultural output. In response to climate shocks, farmers adjust their land-use patterns by shifting towards less water-intensive crops in drought-affected regions and more water-intensive crops in flood-prone areas. These findings provide insights into the productive adjustments made by farmers in response to adverse weather conditions. However, it is important to note that while these studies offer valuable perspectives on the adaptation strategies adopted by farmers in Pakistan, they did not directly measure changes in land use or identify specific crops planted in response to climate shocks.

This suggests that by reducing land in the agricultural sector, farmers demonstrate risk aversion in response to climate shocks. Studies by Wik* et al. (2004) and Yesuf and Bluffstone (2009) have shown that farmers' land-use decisions are strongly influenced by their risk preferences. When farmers perceive an increase in weather-related risks, they are likely to adopt strategies to minimise their exposure. For instance, some farmers may reduce their exposure by limiting farm activities vulnerable to weather risks or by decreasing the total land under cultivation.

This concludes that land use change is a key pathway through which climate variability and extreme climate conditions can affect agricultural activities, particularly by affecting land allocation decisions. Therefore, understanding the dynamics of land use change and its relationship to climatic conditions is crucial for effective agricultural planning and adaptation strategies in Pakistan's agricultural sector in general, and in KP in particular.

3.3 Conceptual framework

In this section, we present a stylised framework to illustrate how farmers adjust their land use decisions in response to climate shocks. Our approach is based on agricultural producer-consumer household models in literature, as discussed by Benjamin (1992), Taylor and Adelman (2003), Cui (2020) and Aragón et al. (2021).

Suppose a representative farmer (or household) in a district seeks to maximize profit from their land by allocating it between two major crops and an outside option, such as non-agricultural land use. Crop production (denoted as c_1 and c_2) increases as more land (L_1, L_2) is allocated to each crop, though at a diminishing marginal rate (i.e., the rate of production increases more slowly as additional land is used). Crop production is also influenced by climate conditions (W) during the growing season (Aragón et al., 2021; Cui, 2020). For simplicity, the total amount of land available is assumed to be fixed at one unit.

Given the assumption that the farmer is a price taker, crop prices p_1 and p_2 are determined by market conditions. The return from non-agricultural land use is r. We also assume that the cost of producing each additional unit of crop is constant and denoted by s. The farmer's optimization problem can then be expressed as:

$$\max_{L_1,L_2,L_3} [p_1c_1(L_1,W) + p_2c_2(L_2,W) + rL_3 - s(L_1 + L_2)]$$

subject to the constraint:

$$L_1 + L_2 + L_3 = 1, \quad L_1, L_2, L_3 \geq 0$$

According to studies such as Cui (2020) and Aragón et al. (2021), when farmers can adjust non-agricultural land (L_3), then optimal land allocation is determined by equating the marginal value of land (MVL):

$$p_1 \frac{\partial c_1(L_1, W)}{\partial L_1} = p_2 \frac{\partial c_2(L_1, W)}{\partial L_2} = s + r$$

This means that the farmer will keep adjusting the land between crops and non-agricultural uses until the extra profit from each of them is the same. In other words, the farmer maximizes the profit when the marginal cost equals the marginal revenue of allocating an additional unit of land (see in the appendix, in Section B.1 for details).

While the model assumes that farmers are rational, profit-maximising agents, we acknowledge that this assumption may not fully reflect the reality of small-holder farmers in Khyber Pakhtunkhwa (KP), who often face credit constraints and subsistence needs. These challenges can limit their ability to make fully optimised decisions. Nevertheless, empirical studies have shown that, even under financial and technical constraints, farmers do adjust their productive inputs, particularly land use, in response to past climate shocks (Gorst et al., 2018; Mumtaz et al., 2019). Therefore, we adopt this framework as a simplified representation and interpret our findings with these practical limitations in mind.

3.3.1 Climate change effect

Now let us consider how the representative farmer chooses to allocate land in response to climate change. Climate change affects crop yields, and farmers adjust their land use accordingly. If the weather increases the yield of crop 1, (say, c_1), the farmer allocates more land to it to maximize profit. If crop 2, (c_2) benefits more, the land is shifted toward crop 2 and vice versa. The farmer continuously reallocates land to whichever crop has higher yields. The impact of climate shocks on the optimal level of land allocation (L) can be derived by differentiating both sides of the above equation with respect to weather(W). The relationship between climate change and crop land is captured as follows:

$$\frac{\partial^2 c_1(L_1, W)}{\partial L_1 \partial W} = \frac{\partial^2 c_2(L_2, W)}{\partial L_2 \partial W}, \text{For } n = 1, 2$$

$$\frac{\partial L_n^*}{\partial W} = \frac{\partial^2 c_n}{\partial L_n \partial W} \Big/ \frac{\partial^2 c_n}{\partial L_n^2}$$

By definition, $\frac{\partial^2 c_n}{\partial L_n^2} < 0$, meaning that climate change affects land allocation for crop depending on the marginal productivity of land (MPL) for producing that crop. For example, if climate change benefits the MPL of crop 1, it will increase the land under crop 1, potentially taking land from non-agricultural uses (given that farmers can make adjustments on non-agricultural land, see in the appendix, Section B.2).

When the adjustments cannot be made on non-agricultural land (i.e.,L_3 is fixed), the optimal land allocation for a crop is determined by equating the marginal value of land (MVL) for the two crops. For instance, the marginal effect of climate change on the optimal acres of crop 1 is presented by the following equation:

$$\frac{\partial L_1^*}{\partial W} = p_1 \frac{\partial^2 c_1}{\partial L_1 \partial W} - p_2 \frac{\partial^2 c_2}{\partial L_2 \partial W} \Big/ p_1 \frac{\partial^2 c_1}{\partial L_1^2} + p_2 \frac{\partial^2 c_2}{\partial L_2^2}$$

The denominator is negative due to the concavity of the production function. The effect of climate change on land allocation is driven by the relative change in the marginal value of land (MVL), which, in turn, is influenced by the climate-induced changes in the marginal productivity of land (MPL), assuming farmers are price takers.

This model captures the impact of climate change on land allocation decisions, building on the foundational work of Benjamin (1992), Taylor and Adelman (2003), Cui (2020), and Aragón et al. (2021). These studies typically assume that farmers adjust their land allocation throughout the year in response to prevailing climatic conditions. This approach is particularly relevant in regions with multi-cropping systems, where land adjustments serve as a coping mechanism, as discussed by Chen and Khanna (2021). However, our model adopts a different perspective by assuming that farmers make land allocation decisions once, based on their expectations of weather conditions prior to start of the crop season. This approach aligns with previous research, which suggests that farmers commit to their planting decisions based on anticipated returns and generally do not modify land use allocations once the growing season has already started (Huang et al., 2015; Gautier et al., 2016; Chen and Khanna, 2021).

3.3.2 Limitations and expectations

Our conceptual framework is based on capturing land use decisions at the household level. However, due to the unavailability of longitudinal household-level land use data for Khyber Pakhtunkhwa, our empirical analysis is conducted at the district level. While this aggregation limits direct observation of individual behaviors, district-level data provide consistent coverage across time and regions, providing a basis for analysis.

Importantly, government support for wheat, a central factor in our study, is implemented uniformly across districts, meaning that all households within a district face the same policy incentives. Therefore, district-level land use patterns can be viewed as an aggregate outcome of numerous household decisions made under similar environmental and institutional conditions.

While the conceptual framework cannot be directly tested at the household level in this analysis, it remains essential for interpreting district-level results. Changes in district-level land allocation serve as representative outcomes of farmer responses to climate shocks and government policies, shaped by their expectations and constraints. We acknowledge, however, that this approach does not fully capture the heterogeneity and specific limitations experienced at the household scale.

Drawing on the conceptual framework and existing literature from developing country contexts, we expect that agricultural households in hotter districts—those experiencing higher temperatures—are likely to adapt their land use in response to past climatic conditions. Specifically, farmers in these areas may reallocate land toward crops that are less sensitive to heat stress as a strategy to manage climate risks. At the aggregate (district) level, this adaptive behavior could result in an overall increase in agricultural land over time, as households attempt to maintain or boost production. Conversely, in resource-constrained districts, poorer households may reduce their cultivated area to minimize potential losses under adverse climatic conditions. Since our analysis focuses on adaptive responses in the context of government support for wheat—the only crop receiving a guaranteed minimum support price—we anticipate that land allocated to wheat may increase across districts. This would reflect farmers' response to the stable price incentive, even in the face of climatic risks. Therefore, changes in district-level land use patterns are interpreted as capturing the combined effects of farmers' climate adaptation strategies and the influence of government policy on cropping decisions.

3.4 Empirical framework

Our objective is to estimate the effect of past temperature shocks on farmers' land allocation decisions. We model this relationship using panel fixed effects framework as follow:

$$\mathrm{lnY}_{dt} = \beta \mathrm{Heat}_{dt-1} + \gamma \mathrm{Rain}_{dt-1} + \alpha \mathrm{Price}_{dt} + \lambda X_{dt} + \theta_t + \upsilon_d + \Omega_r t + \epsilon_{dt}, \quad (3.1)$$

Where (lnY_{dt}) is the natural log of land use type in a district, d at the time, t. (Heat_{dt-1}) is binary indicator taking value 1 if temperature is 1.5 standard deviation above the long-run temperature at district level. ($\mathrm{Rainfall}_{dt-1}$) is the total district level rainfall. We use one-year lagged climate variables ($t-1$), to estimate the previous year's climate change effect on current land allocation. In our estimation, (Price_{it}) is the pre-announced support price for the wheat growers in the region. (X_{dt}) shows district level controls such as irrigation and land holding. (θ_t) is year-fixed effects to account for shocks that would impact land use decisions. (υ_d) represents the set of district fixed effects which controls for district-specific factors, for instance, soil quality, climate, proximity to markets. For example, technological progress and policy changes within each year. Since districts experience shocks and other time-varying factors differently (for example, policy changes, economic and market conditions), we include district-specific time trends ($\Omega_r t$), to account for these variations is district. The last term (ϵ_{dt}) is stochastic error term.

Given the different types of land use under consideration, our key variable of interest, "Heat" is defined specifically for each land use type. For total agricultural land, we use the annual average temperature to examine its effects on land use over the entire year. For land allocated to summer crops during the Kharif season, we focus on the average temperature from May to October. Similarly, for wheat land cultivated during the Rabi season, we use the average temperature from November to April. To analyse the relationship between heat and land use, we conducted three sets of regressions focusing on total agricultural land, other cropland, and wheat land across both time and space.

Our goal is to estimate the effect of past temperature shocks on land use decisions in Khyber Pakhtunkhwa (KP), Pakistan, with a particular focus on the role of government policy, especially wheat support prices. In the first set of regressions, we consider the full sample period from 1981 to 2019 for each land use type. We then divide the analysis into two sub-periods: pre-2006 and post-2006, corresponding to periods of low and high government support prices for wheat. The low support period (1981–2006) precedes a sharp upward shift in support prices after 2006 (see Figure 3.2). By examining these different timeframes, we aim to capture any shifts in the relationship between extreme temperatures and land use decisions that may be driven by changes in wheat support prices.

Furthermore, we expanded our analysis to incorporate agroecological regions (or climatic regions) within the province. We aimed to gain a more comprehensive understanding of how different climatic regions within the province adapt and respond to past temperature shocks in their land allocation decisions.

3.5 Data

We compile a range of datasets from various sources: land use data from the Bureau of Statistics of Khyber Pakhtunkhwa Province in Pakistan, price data from the Agriculture Marketing Information Service (AMIS), Pakistan, and climate data from the Climate Research Unit (CRU) at the University of East Anglia, United Kingdom.

3.5.1 Land use data

Our study utilises panel data on three types of land use, measured in hectares, at the district level in Khyber Pakhtunkhwa (KP) Province, Pakistan, from 1981 to 2019. The first category is total agricultural land, encompassing all cultivated land within a district. The second type, labeled "other cropland", represents areas used for major crops excluding wheat. The third category focuses on harvested land for wheat by district.

3.5.2 Wheat prices data

Our study examines the impact of past temperature shocks on land allocation in the province, with particular focus on the role of government policy. For our analysis, we collected data on both support and market prices of wheat during the sample period from the Agriculture Marketing Information Service (AMIS), Pakistan.

3.5.3 Climate data

In this chapter, we use the same Climate data as in the previous chapter but the focus is on how past temperature shocks influence land allocations at district level over time.

The temperature shock, referred to as "Heat" is a binary indicator constructed using a method similar to that described in Section 2.6.2.1 of the previous chapter. However, in this chapter, we use lagged temperature shocks (from the previous year) instead of contemporaneous shocks used in the earlier chapter. Additionally, the base period for calculating long-term averages is set to 1940–1980. We constructed three types of "Heat" variables, each specific to different land uses. For total agricultural land, the "Heat" variable is constructed using annual temperature data. For other cropland, we use summer season temperature, as the cropping calendar for these crops begins with sowing in May and harvesting in October. For wheat, which is a winter crop, we consider temperature during the wheat-growing season, with sowing starting in November and harvesting in May.

Similarly, our rainfall variable, measured in millimeters, is customised for each land use category: annual rainfall for total agricultural land, average growing season rainfall for summer crops, and rainfall during the wheat-growing season.

Similar to the previous chapter, we constructed our final dataset by geo-coding our climate variables with district-level land use type data.

3.6 Results

Our regression analysis examines changes in land use following temperature shocks (heat) at both the district and climatic region levels in Khyber Pakhtunkhwa (KP) province, Pakistan. We analyse this within the context of government support policy in the form of a minimum price for wheat. We estimate three separate regression models for each land category: total agricultural land, other cropland, and wheat land. To examine how the support price interacts with adaptation strategies, we analyze land changes in response to climate change across three periods. The first regression model covers the entire period (1981–2019). The Pre−2006 period (1981–2006) is characterised by a very low support price, while the post-2006 period (2007–2019) is marked by a higher support price.

3.6.1 Overall estimates

The analysis of the effects of one-year-lagged temperature shocks on district-level land use types is presented in Table 3.1. Columns (1), (4), and (7) illustrate the impacts on total agricultural land, other cropland, and wheat land, respectively, for the entire study period (1981–2019). Similarly, columns (2), (5), and (8) focus on period of relatively low government support, while columns (3), (6), and (9) correspond to period of higher government support across the land use categories.

The results indicate a significant decline in land allocated to wheat following temperature shocks, with reductions of 7% during the overall period (column (7)) and 12% during the low support period (column (3)). These reductions are accompanied by a decrease in total cultivated land, which declined by 10% during the overall period (column (1)) and 15% during the low-support period (column (2)). However, no significant changes in land use for other crops were observed during either period (columns (4) and (5)). The results suggest the possibility of shifting away from agricultural activities, with districts potentially transitioning to non-agricultural uses of land in response to climatic and economic pressures. This shift is consistent with the findings of Parveen (2020) and Saqib et al. (2024), who document similar findings among marginalised farmers in the province. When experienced with rising climate-related vulnerabilities and insufficient financial support, farmers appear to be abandoning agriculture for alternative land uses. Consequently, agricultural production in the province has declined substantially, with the share of cultivated land falling from 65% to just 25% over time.

During the high support period (post-2006), we observe no significant reduction in the land allocated to wheat following a bad year. Despite 41% of districts experiencing temperature shocks—an increase from 30% in the pre−2006 period—and the average temperature exceeding the optimal threshold for wheat growth (30.02°C), the share of land devoted to wheat increased by one percentage point to 57% (see column (9) at the bottom of Table 3.1). Moreover, at the district level, no decline in total land use or in the area allocated to other crops was observed in the aftermath of temperature shocks during this period of high government support. These finding are suggestive that the support price played in preventing a decline in wheat cultivation, even under conditions where the crop is highly sensitive to high temperatures. On one hand, this highlights the effectiveness of the support price in providing with a buffer against price volatility. On the other hand, it raises concerns about the potential overreliance on wheat, which may increase districts' vulnerability to future climate shocks and limit the diversification of agricultural production.

3.6.2 Regional estimates

In this section, we extend our analysis to the climatic regions such as southern, central, eastern and northern. Given the varying climates and farming practices, farmers' land allocation may differ significantly across the regions. For example, in hotter regions, farmers are likely aware of past climate shocks and may anticipate these by allocating land to heat-resistant crops to minimize potential losses and ensure stable yields. On the other hand, in colder regions with limited

Table 3.1: Overall estimates: Effects of past heat on land-use (1981-2019)

	ln(Total Agri-Land)			ln(Other cropland)			ln(Wheat land)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Overall	Pre−2006	Post−2006	Overall	Pre−2006	Post−2006	Overall	Pre−2006	Post−2006
Heat $(t-1)$	-0.101*	-0.152**	-0.032	0.063	-0.223	0.045	-0.074*	-0.124***	-0.020
	(0.079)	(0.019)	(0.389)	(0.244)	(0.241)	(0.457)	(0.062)	(0.009)	(0.592)
Rainfall $(t-1)$	-0.167	0.032	0.036	-0.036	0.165	-0.289**	0.018	0.029	0.009
	(0.345)	(0.659)	(0.572)	(0.561)	(0.311)	(0.019)	(0.514)	(0.308)	(0.720)
Support price	-0.127**			-0.020			-0.055*		
	(0.010)			(0.805)			(0.053)		
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	801	489	312	792	480	312	781	469	312
Agriland (%)	60.05	65.90	51.95						
Share				0.57	0.57	0.57	0.56	0.56	0.57
Shocks	0.41	0.35	0.51	0.25	0.38	0.10	0.35	0.30	0.41
Temperature (°C)	25.97	25.85	26.13	32.35	32.25	32.49	29.50	29.15	30.02

Note: The dependent variables represent the natural log of land use types. Weather variables are season-specific, with columns (1) to (3) reflecting annual weather, (4) to (6) focusing on the summer season, and (7) to (9) on the wheat season. 'Heat' is a binary variable taking the value of 1 when the temperature from the previous year exceeds 1.5 standard deviations above the long-run average temperature for a given district. 'Rainfall' (in millimeters) is the one-year lagged average district-level rainfall. Our district-level controls include irrigation, total agricultural land, and one-year lagged yields in columns (4) to (9). The pre−2006 and post−2006 periods represent low and high agricultural support to wheat, respectively. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

resources, farmers may face greater constraints in adapting to climatic shocks. Their reliance on a narrower range of input adjustments—such as fertiliser, irrigation, or crop rotation—and limited access to advanced technologies or financial support may restrict their capacity to respond effectively, leaving them more vulnerable to temperature variations and other climatic risks.

Before estimating the region-specific results, we first formally test for regional heterogeneity in adaptation responses in terms of land use to past temperature shocks. We extend the baseline model (equation 3.1) by interacting the lagged heat variable with regional dummies for the East, Centre, and South climate zones, using the North as the reference category. The interaction terms reveal statistically significant differences in how districts across regions adjust land allocation following temperature shocks. Specifically, compared to the North, districts in the Centre and South experience a significantly larger reduction in land under wheat. These effects are accompanied by an increase in other cropland, indicating a substitution away from wheat. Total cultivated land in all the regions also expands as compared to northern regions. The results are reported in appendix Table B.1. These findings strengthen the empirical basis for understanding regional variation and provide evidence on how land use changes across regions in response to past temperature shocks as an adaptation strategy.

The regional results presented in Tables 3.2, 3.3, 3.4 and 3.5 show the average effect of the previous year's temperature shock on three categories of land use by region: total agricultural land in columns (1)−(3), other cropland in columns (4)−(6), and wheat land in columns (7)−(9). In columns (1), (4), and (7), we are controlling for support price over the entire study period (1981−2019). The subsequent columns differentiate between sub-periods of low support (pre−2006) and high support (post−2006), specifically for wheat—the only crop subsidised by the government of Pakistan through a minimum support price. In columns (4)−(9), we control for total agricultural land across the regions. Additionally, irrigation is controlled for in all specifications. Each specification also includes region-specific time trends, region fixed effects, year fixed effects (columns (1)−(3)), and growing season fixed effects (columns (4)−(9)) to capture temporal and annual/seasonal variations.

3.6.2.1 Southern region

Table 3.2 presents the land use estimates for the southern region. The results display interesting findings, particularly regarding land allocated to wheat. Over the entire study period, shown in column (7), the share of land under wheat increased by 15% in response to the previous year's temperature shock. The support price is negatively related to land use allocation for wheat, partly due to the constant minimum support price until 2006. While market prices show a positive effect on land allocation, particularly in the southern regions. Results are reported appendix Table B.2. The expansion in land under wheat results in an overall increase of 23% in total cultivated land in the southern region, as shown in column (1).

During periods of low support prices for wheat, as shown in column (8), the share of land allocated to wheat declines following a temperature shock. Specifically, when past temperatures exceed the long-term seasonal average by more than 1.5 standard deviations, land devoted to wheat decreases by approximately 21%. Meanwhile, total cultivated land expands by around 33% (column (2)), likely driven by a 48% increase in other cropland (column (5)). This suggests that, in response to lower support prices, districts may choose to reduce wheat cultivation, a temperature-sensitive crop, to manage the risks associated with higher temperature. This shift likely enables a reallocation of land to more heat-tolerant crops, such as maize or rice.

The findings show that the southern region adapts to past temperature shocks by reallocating land to other crops during periods of low government support. Rather than moving away from agriculture in the wake of climatic risks, the region mitigates risks by diversifying its crop portfolio. In particular, when extreme temperatures reduce the viability of traditional crops, the region reallocates land to more heat-resilient options. For example, maize, which can tolerate heat stress up to 35°C (Waqas et al., 2021), becomes a more viable alternative to wheat. This shift reflects the southern region's ability to adapt to climatic challenges while maintaining agricultural production.

These findings are consistent with other studies from Khyber Pakhtunkhwa (KP) province. For instance, Saqib et al. (2024) show that crop diversification is an effective adaptation strategy in hotter regions under changing climatic conditions. Similarly, Taraz (2018) and Aragón et al. (2021) show that multi-cropping serves as a practical adaptation strategy in developing countries, enabling regions facing high temperatures to remain engaged in agriculture by diversifying their crop choices rather than abandoning the sector altogether.

During the high support period (post-2006), when government-set support prices for wheat were increased, the share of land allocated to wheat increased by approximately 10% following temperature shocks (see column (9)). This was accompanied by a 33% expansion in overall cultivated land (see column (3)). At the same time, there was no effect of a previous-year temperature shock on the allocation of land to other crops during this period (see column (6)). These results indicate that higher support prices encouraged greater wheat cultivation, even as the frequency of temperature shocks increased from 36% in the pre−2006 period to 61% in the post−2006 period, as shown in the descriptive summary at the bottom of the table.

These results indicate that higher support prices help shape land-use decisions in the face of climate change, offering financial protection that enables greater land allocation to wheat despite challenging climatic conditions. By reducing income variability, support prices serve as an effective substitute for formal crop insurance, which is often unavailable in these regions. This aligns with findings from previous studies that emphasise the importance of price support mechanisms in stabilising income and production decisions when formal insurance is lacking (Gautier et al., 2016; Dercon, 2002).

However, while these measures address immediate risks, they may promote dependence on wheat, a crop highly vulnerable to high temperatures. This reliance limits opportunities for diversifying agricultural production, leaving regions more exposed to future climate risks. In developing countries, where farmers tend to be risk-averse, government-supported crops like wheat often take precedence over exploring heat-resilient or alternative cropping options, sustaining this approach (Damania et al., 2017). While price supports mitigate short-term risks, they may also delay the transition to diversified and adaptive farming strategies that are critical for building long-term climate resilience.

Table 3.2: Effects of past heat on land-use in the south region (1981-2019)

Southern Region	ln(Total Agri-Land)			ln(Other cropland)			ln(Wheat land)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Overall	Pre−2006	Post−2006	Overall	Pre−2006	Post−2006	Overall	Pre−2006	Post−2006
Heat $(t-1)$	0.234*	0.330*	0.334***	0.698	0.478**	0.133	0.150**	-0.205*	0.097*
	(0.084)	(0.051)	(0.001)	(0.148)	(0.042)	(0.133)	(0.037)	(0.080)	(0.088)
Rainfall $(t-1)$	-0.361	0.012	-0.007	-0.461	0.883**	-0.147	0.064	-0.002	-0.005
	(0.667)	(0.729)	(0.312)	(0.184)	(0.037)	(0.261)	(0.295)	(0.378)	(0.258)
Support Price	-0.014			-0.224			-0.080***		
	(0.469)			(0.325)			(0.009)		
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	170	105	65	170	105	65	157	92	65
Share (%)				0.12	0.12	0.11	0.83	0.87	0.82
Shocks (%)	0.44	0.35	0.48	0.48	0.50	0.47	0.57	0.36	0.61
Temperature (°C)	31.09	30.94	31.33	35.12	34.91	35.26	31.19	31.00	31.33

Note: The dependent variables represent the natural log of land use types. Weather variables are season-specific, with columns (1) to (3) reflecting annual weather, (4) to (6) focusing on the summer season, and (7) to (9) on the wheat season. 'Heat' is a binary variable taking the value of 1 when the temperature from the previous year exceeds 1.5 standard deviation above the long-run average temperature for a given district. 'Rainfall' (in millimeters) is the one-year lagged average district-level rainfall. Our district-level controls include irrigation, total agricultural land, and one-year lagged yields in columns (4) to (9). The pre−2006 and post−2006 periods represent low and high agricultural support to wheat, respectively. Standard errors, in parentheses, are clustered at the district level. *** p-value $< 1\%$, ** p-value $< 5\%$, * p-value $< 10\%$.

3.6.2.2 Central region

In the central region, we observe a negative effect on wheat land use decisions following a temperature shock, particularly in the overall and low-support (pre−2006) periods. As shown in columns (7) and (8) of Table 3.3, when the previous year's temperature exceeds the long-term average, the share of land allocated to wheat decreases by 12% and 17%, respectively. However, for total agricultural land and other cropland, we observe no effect in the overall period (columns (1) and (4)). During the low-support period (pre−2006), both types of land use experience substantial declines, with total agricultural land shrinking by 73% (column (2)) and other cropland by 24% (column (5)).

These results indicate a potential shift away from agricultural use in the central region, particularly when financial support is limited in the wake of climate change. Also, as the economic hub of the province, the central region appears more inclined to reduce or even abandon agricultural land amid climate change. Land may be left uncultivated, repurposed for commercial activities, or sold for non-agricultural uses. Our findings are consistent with prior studies, which document a gradual transition of fertile agricultural land in the central region to built-up areas. For instance, Rehman and Khan (2022) highlight that the conversion of agricultural land into urban infrastructure has diminished food production capacity and reduced livelihood opportunities tied to agriculture.

During the post-2006 period, the introduction of higher support prices for wheat helped mitigate the negative impact of temperature shocks on land allocated to wheat. As shown in column (9) of Table 3.3, wheat land use remained stable despite extreme temperature events, with the share of wheat land increasing from 54% in the pre-2006 period to 59% post-2006, even as 47% of districts experienced temperature shocks, as indicated in the descriptive summary at the bottom of the table. However, despite this stability in wheat land, total agricultural land shrinks by 8% in response to temperature shocks during this period, as shown in column (3).

These results suggest that while government support for wheat helps sustain its cultivation, the central region continues to reduce its overall agricultural land as part of an adaptation strategy to climatic risks. This reduction likely reflects a shift away from agriculture, particularly from climate-sensitive sectors, toward more resilient, non-agricultural sectors. The move away from agriculture may be driven by the availability of alternative economic opportunities that are more accessible and less vulnerable to climate risks. While wheat cultivation remains a stable component of land use due to financial incentives, the overall decline in agricultural land indicates that farmers might increasingly turn to sectors where climate risks are lower and income-generating opportunities are more secure. Although we do not explicitly measure this transition in this chapter, our analysis of uncultivated land at the district level captures potential shifts in land use. Our findings show an expansion of uncultivated land during both the pre−2006 and post−2006 periods, as detailed in Table B.3 in the appendix. This expansion showcases reduced agricultural land use in response to the past temperature shocks, further supporting the idea that the central region is gradually moving away from agriculture in favour of non-agricultural sector. This shift is consistent with findings in studies such as Parveen (2020) and Rehman and Khan (2022), which document a reduction in agricultural land in response to climate risks.

Table 3.3: Effects of past heat on land-use in the central region (1981-2019)

Central Region	ln(Total Agri-Land)			ln(Other cropland)			ln(Wheat land)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Overall	Pre−2006	Post−2006	Overall	Pre−2006	Post−2006	Overall	Pre−2006	Post−2006
Heat $(t-1)$	-0.054	-0.734***	-0.082**	-0.259	-0.242**	0.000	-0.124**	-0.166**	-0.039
	(0.199)	(0.002)	(0.030)	(0.406)	(0.038)	(0.000)	(0.017)	(0.014)	(0.330)
Rainfall $(t-1)$	-0.023	0.001	0.001	-0.043	0.083	0.023	0.060	0.001	0.002*
	(0.856)	(0.650)	(0.567)	(0.918)	(0.239)	(0.428)	(0.892)	(0.193)	(0.055)
Support Price	0.014			-0.190			-0.058		
	(0.469)			(0.240)			(0.362)		
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	234	143	91	231	140	91	227	136	91
Share (%)				0.28	0.30	0.27	0.56	0.54	0.59
Shocks (%)	0.17	0.10	0.27	0.44	0.50	0.41	0.49	0.36	0.47
Temperature (°C)	28.91	28.97	29.19	33.28	33.19	33.34	29.12	28.98	29.19

Note: The dependent variables represent the natural log of land use types. Weather variables are season-specific, with columns (1) to (3) reflecting annual weather, (4) to (6) focusing on the summer season, and (7) to (9) on the wheat season. 'Heat' is a binary variable taking the value of 1 when the temperature from the previous year exceeds 1.5 standard deviation above the long-run average temperature for a given district. 'Rainfall' (in millimeters) is the one-year lagged average district-level rainfall. Our district-level controls include irrigation, total agricultural land, and one-year lagged yields in columns (4) to (9). The pre−2006 and post−2006 periods represent low and high agricultural support to wheat, respectively. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

3.6.2.3 Eastern region

Table 3.4 presents the regression results, indicating the impact of past temperature shocks on land use in the eastern region across different types of land use and time periods. The results are similar to the central region particularly during the pre−2006 period. During this period, a previous year's temperature shock leads to a reduction in the share of land allocated to wheat by around 25% (column (8)) and to other cropland by 15% (column (6)). As a result, total agricultural land during this period declines by 26%. This reduction can be attributed to limited access to improved farming technologies in the region, which has left farmers with few adaptation strategies. Land adjustment is one of the primary means of adapting to climate risks in the absence of government support (Qureshi et al., 2021). Thus, decreasing the share of land use represents a major adaptation strategy to minimise potential losses from heat stress.

However, after 2006, particularly for wheat, the relationship between temperature shocks and land use appears to be positive, albeit not significant. This change is likely due to increased government support for wheat, as indicated by the descriptive analysis, which shows that the share of land allocated to wheat rose from 31% to 34%, despite a higher percentage (50%) of districts experiencing temperature shocks. In the case of total agricultural land and other cropland, we find no effect of past temperature shocks during the post-2006 period. These findings suggest that districts in the eastern region, which are predominantly resource-poor Ali et al. (2017), often exhibit risk-seeking behaviour when confronted with uncertainties in the wake of low/limited financial support. This aligns with existing studies indicating that in developing countries, where crop insurance is limited or unavailable, farmers' land use decisions are influenced by their risk preferences (Dercon, 2002; Mumtaz et al., 2019). Consequently, farmers tend to adopt risk-averse strategies, such as reducing the area allocated to vulnerable crops, in order to minimise their exposure to climate risks. On the other hand, high support prices shield farmers from price volatility, offering immediate relief against climate-related risks. However, they potentially encourage the allocation of land to a government-supported crop that is more vulnerable to heat stress, thereby limiting farmers' capacity to diversify their crop portfolio and adapt to changing climatic conditions.

Table 3.4: Effects of past heat on land-use in the eastern region (1981-2019)

Eastern Region	ln(Total Agri-Land)			ln(Other cropland)			ln(Wheat land)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Overall	Pre−2006	Post−2006	Overall	Pre−2006	Post−2006	Overall	Pre−2006	Post−2006
Heat $(t-1)$	-0.210	-0.263**	-0.019	0.014	-0.151*	0.003	0.039	-0.246**	0.014
	(0.128)	(0.043)	(0.306)	(0.631)	(0.089)	(0.883)	(0.163)	(0.036)	(0.660)
Rainfall $(t-1)$	-0.039	-0.110	0.019	-0.005	-0.034	-0.063	0.054	-0.026	0.131
	(0.400)	(0.168)	(0.338)	(0.917)	(0.776)	(0.322)	(0.217)	(0.863)	(0.533)
Support Price	-0.033			-0.013			-0.060		
	(0.351)			(0.410)			(0.361)		
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	169	104	65	168	103	65	169	104	65
Share (%)				0.67	0.68	0.66	0.33	0.31	0.34
Shocks (%)	0.37	0.34	0.46	0.41	0.50	0.34	0.49	0.32	0.50
Temperature (°C)	21.40	21.32	21.53	24.82	24.63	24.96	21.41	21.31	21.53

Note: The dependent variable is the natural log of land use types (total agricultural land, land under other crops and and land under wheat). Weather variables are specific to growing season. Column (1) t0 (3) is yearly, (4) to (6) is summer season and (7) to (9) is wheat season. Heat is a binary indicator taking value 1 when temperature exceeds 1.5 standard deviations from the growing season historical average for a given district. Rainfall (mm) is the average rainfall during each crop-growing season at district level. Pre and post indicate the low and high support periods respectively. Total agricultural land is used as a control in the last three columns. Standard errors, in parentheses, are clustered at the district level. *** p-value $< 1\%$, ** p-value $< 5\%$, * p-value $< 10\%$.

3.6.2.4 Northern region

The regression estimates for the northern region, presented in Table 3.5, show distinct land-use responses to temperature shocks compared to the southern region. During the low-support period, past temperature shocks led to a significant reduction in both total agricultural land and other cropland, while the land allocated to wheat showed no detectable impact. This suggests that the northern region may respond to limited financial resources and climatic risks by shifting away from agricultural production, opting instead to leave land barren or repurpose it for non-agricultural uses such as residential, commercial, or infrastructure development. Although our analysis does not account for these land-use conversions due to data limitations, we controlled for barren (uncultivated) land during the pre- and post-2006 periods. The results indicate that, during the low-support period, the share of wheat land shrinks following a temperature shock, accompanied by a significant expansion in barren land. These findings align with recent studies, such as Parveen (2020), which highlight that over the past few decades, more than half of the cropland in the northern region has been repurposed for non-agricultural uses, including residential housing, educational institutions, and healthcare facilities.

During the period of high support for wheat, we observe a significant 12% expansion in land devoted to wheat following temperature shocks (column (8)). This shift likely came at the expense of diversification, with an 8% reduction in land allocated to other crops. Despite this, overall cultivated land in the northern region increased by 84% in response to the temperature shocks (column (3)). These findings are indicative of high government support influencing land-use decisions by providing a sense of security that encouraged continued reliance on wheat cultivation by allocating more land, despite its vulnerability to climate risks. However, the shift away from more heat-resilient crops highlights limitations in farmers' ability to diversify and adopt adaptive strategies that could better mitigate climatic risks. While such support may mitigate short-term impacts of climatic shocks, it also increases dependence on a climate-sensitive crop, which could increase farmers' vulnerability to future climate shocks, exposing them to higher risks associated with ongoing climate change.

Table 3.5: Effects of past heat on land use in the northern region (1981-2019)

Northern Region	ln(Total Agri-Land)			ln(Other cropland)			ln(Wheatland)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Overall	Pre−2006	Post−2006	Overall	Pre−2006	Post−2006	Overall	Pre−2006	Post−2006
Heat $(t-1)$	-0.064***	-0.778***	0.842**	0.016	-0.232**	-0.057**	0.031	0.020	0.123**
	(0.017)	(0.000)	(0.032)	(0.851)	(0.031)	(0.021)	(0.489)	(0.740)	(0.037)
Rainfall $(t-1)$	-0.127	-0.004**	0.003***	0.166	-0.241*	-0.129	0.002	0.002	0.000
	(0.237)	(0.046)	(0.012)	(0.399)	(0.085)	(0.194)	(0.228)	(0.229)	(0.655)
Support Price	-0.004			0.045			-0.015		
	(0.599)			(0.193)			(0.409)		
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	228	137	91	223	132	91	228	137	91
Share (%)				0.45	0.47	0.44	0.54	0.58	0.55
Shocks (%)	0.39	0.36	0.48	0.46	0.51	0.43	0.48	0.35	0.48
Temperature (°C)	22.36	22.17	22.65	25.67	25.50	25.77	22.57	22.14	22.65

Note: The dependent variable is the natural log of three land use types (total agricultural land, land under other crops and and land under wheat). Weather variables are specific to growing season. Column (1) t0 (3) is yearly, (4) to (6) is summer season and (7) to (9) is wheat season. Heat is a binary indicator taking value 1 when temperature exceeds one standard deviation from the growing season historical average for a given district. Rainfall (mm) is the average rainfall during each crop-growing season at district level. Pre and post indicate the low and high support periods respectively. Total agricultural land is used as a control in the last three columns. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

3.7 Conclusion

We estimate district-level land allocation as an adaptation strategy to past temperature shocks in Khyber Pakhtunkhwa (KP), Pakistan, from 1981 to 2019. We analyse in context of government policy, particularly in form of a minimum support price for wheat. To investigate how the support price interacts with adaptation strategies in terms of land allocation, we split the sample into two periods: low government support (1981-2006) and high government support (2007-2019).

The results indicate that during the first period (1981–2006), land allocated to wheat decreased in response to the previous year's temperature shock, leading to an overall reduction in cultivated land across the province. However, regional responses varied significantly. The southern region adapted by reallocating land to more heat-resistant crops, leading to an expansion in total cultivated land. In contrast, other regions experienced a decline in both wheat and other crops, resulting in a reduction in total agricultural land. These results suggest a potential shift away from agriculture toward non-agricultural activities, except in the southern region, which adapted by reallocating land to more climate-resilient crops following a temperature shock.

During the high support period (2007–2019), government support played a significant role in stabilising wheat cultivation across all regions following a temperature shock. As a result, the land devoted to wheat expanded, particularly in the southern and northern regions. However, in the resource-constrained northern region, this expansion occurred at the expense of heat-resistant crops, limiting opportunities for crop diversification in the aftermath of a temperature shock. In the other two regions, such as the eastern and central regions, while there was no shrinkage in land allocated to the government-supported crop, the overall reduction in cultivated land indicates the limited capacity for diversifying to other crops. Especially in the central region, which is resource-rich, this suggests a shift toward the non-agricultural sector, possibly driven by opportunities for income diversification as an adaptation strategy to climate change.

These findings suggest that high government support influenced land-use decisions by preventing a reduction in land allocated to wheat following a temperature shock. Across the province, there was no reduction in land allocated to wheat; instead, it expanded in the southern and northern regions. However, this expansion, particularly in the northern region, came at the expense of the capacity to shift to more heat-resistant crops. While such support mitigates the immediate impacts of climatic shocks, it also fosters dependence on a climate-sensitive crop, thereby restricting opportunities for crop diversification.

Chapter 4

Extreme temperature, labour supply, and subsistence farming: Evidence from Pakistan

4.1 Introduction

In chapters 2 and 3, we performed district-level analysis to investigate how inputs and land use are adjusted in response to adverse weather conditions within the agricultural sector, illustrating that climate change significantly impacts agricultural output at the district level. Building on these findings, in this chapter we explore whether climate change also drives agricultural households to diversify their livelihoods through off-farm employment. Specifically, we analyse how high temperatures impact households' decisions to seek supplementary income sources beyond agriculture. This chapter thus focuses on off-farm employment as a means of income diversification, serving as an adaptation strategy to mitigate the risks associated with climate change for agricultural households in Pakistan.

While the concept of off-farm labour holds promising avenues for rural development, its prevalence in rural Pakistan remains relatively low (Ahmad et al., 2024). Adaptation responses have largely focused on on-farm adaptive strategies, such as inputs and crop choices or sustainable land management practices (Siddiqui et al., 2012; Ali and Erenstein, 2017; Khan et al., 2020). However, our data show a clear shift towards off-farm labour in more recent years. This shift reflects a growing recognition of the limitations of relying solely on farm practices and the need to diversify income sources to withstand the challenges posed by climate variability.

In this chapter, we investigate this transition towards off-farm labour and identify factors that either promote or hinder households' ability to diversify income. Our primary objective is to analyse the effects of past temperature shocks on off-farm labour response among agricultural households over the past two decades (2001 to 2018). We develop a conceptual framework that links off-farm labour productivity choices to farmers' expectations about future climate shocks and labour market conditions. To test the main predictions of our conceptual framework, we exploit data on self-reported employment status for about 21200 rural households, across six survey years from 2001 to 2018. We combine these data with district-level high resolution gridded weather data for 107 districts to measure temperature and other climate shocks.

We employ a linear probability model to examine the impact of year-lagged temperature shocks, during the growing season, on off-farm labour choices across waves. We control for district fixed effects, district-time trends, and province-year fixed effects to mitigate the influence of potential local and regional confounders such as changes in local economic conditions, agricultural practices, and policy changes. We first validate our measure of temperature shocks by showing that contemporaneous temperature shocks have a negative effect on yields for five major crops. Additionally, we empirically test potential mechanisms that could explain the changes in off-farm labour supply responses over time. We explore three possible mechanisms, derived from our conceptual framework. First, we investigate whether households may have become more responsive in terms of off-farm labour response due to the increasing severity of temperature shocks over time. Second, we investigate whether local development conditions have improved over time, implying greater availability of off-farm opportunities. Third, we explore whether households have undertaken a learning process, by experiencing multiple past temperature shocks, which would influence their off-farm labour choices.

We find that while past temperature shocks had a null effect on off-farm labour supply choices in the first four survey years (2001-2011), the effects have become positive and significant in the most recent waves (2015 and 2018). We consider these latter results as evidence that households, in most recent years, are diversifying income sources as an adaptation strategy. Our findings are robust to the use of alternative measures of income diversification and to the inclusion of contemporaneous shocks. We find that these changes in off-farm labour responses over time are not driven by an increase in the severity of temperature shocks, nor by households learning from accumulated past shocks. On the other hand, we find that local development conditions have substantially improved and this partly explains the pattern of labour supply responses over the last two waves.

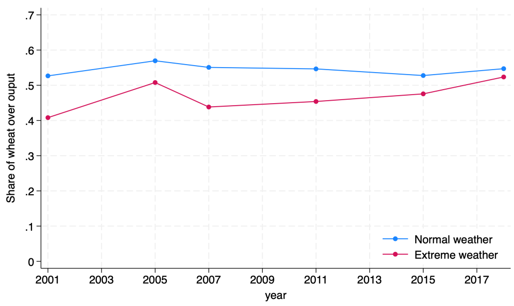
This paper contributes to the literature by investigating the dynamics of rural adaptation strategies, over two decades, amidst changes in local weather and economic conditions. Many adaptation studies have been constrained by limited temporal coverage and have overlooked fluctuations in local market conditions (Hussain et al., 2020; Shahid et al., 2021). We embrace the notion that adaptation to climate change is a dynamic, long-term process. We provide a conceptual framework that embeds changes in local market conditions and farmers' expectation over time and test our hypotheses comparing off-farm responses over six waves of household-level data. In addition, to the best of our knowledge, this is the first study to examine off-farm labour supply as an adaptation strategy in Pakistan.

The remainder of this study is organised as follows. Section 4.2 provides background and motivational evidence on weather conditions and off-farm labour supply in rural Pakistan. Section 4.3 presents a conceptual framework linking past climate shocks to off-farm labour supply. Section 4.4 discusses the empirical strategy, while Section 4.5 describes the data and summary statistics. Section 4.6 presents baseline results and explore potential mechanisms which could explain the changes if off labour supply decisions over time. Section 4.8 concludes.

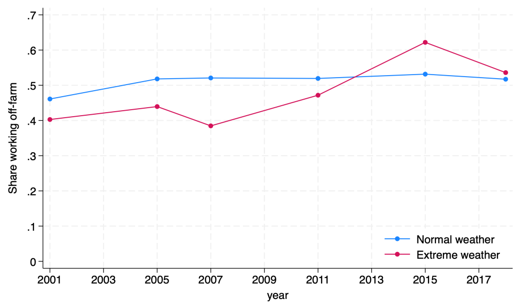
4.2 Background and motivational evidence

Based on the findings from previous chapters, we show that Pakistan's agricultural sector is significantly affected by climate shocks, with wheat yields particularly vulnerable. However, these adverse effects are mitigated through adaptive strategies. One key approach is input adjustment, such as improved irrigation during periods of extreme heat (see chapter 2). Additionally, land-use changes following temperature shocks serve as an adaptive strategy to safeguard against yield losses and maintain agricultural productivity (see chapter 3).

Despite the critical role of agriculture among rural economies, there has been a notable, albeit gradual, shift towards off-farm employment opportunities over the last decade. According to the Labour Force Survey (LFS), the agricultural labour force in Pakistan has declined by an average of approximately 7% over the past decade (BPS, 2018). On the other hand, recent studies show that climate shocks are positively correlated with farm exits among Pakistani farmers (Ahmad et al., 2020, 2024). For instance, Ahmad et al. (2024) show that about 31% of farmers exit farming in face of climate change. This shift is seen as a rational response to the pressures exerted by climate change, offering a buffer against the uncertainties of agricultural production (Abid et al., 2015; Ali et al., 2017), and providing an avenue for diversifying income sources with the impacts of increasing temperatures on wheat cultivation (Ashfaq et al., 2011).



(a) Share of wheat over total output



(b) Share of working off-farm

Figure 4.1: Prevalence of wheat production and off-farm labour over time

Note: Extreme weather refers to those districts experiencing average temperature above 2 standard deviations from historical district-level mean temperature, in the previous year. Panel b, shows the share of households with at least one member working off-farm.

In Figure 4.1, we categorise districts depending on whether they have experienced extreme temperature in the previous year. Panel a) shows that while districts exposed to extreme temperatures had a lower share of wheat over total crop output in 2001 (40% compared to 53% in non-affected areas), the relative importance of wheat has increased over time, reaching about 53%. Similarly, in these districts, the percentage of households exclusively cultivating wheat increased from 40% in 2001 to 53% in 2018.[1] This indicates that households increased their reliance on wheat, even in the face of its susceptibility to heat stress and the rising occurrences of extreme temperatures. This could be partly explained by the fact that the government of Pakistan has implemented various policies and initiatives to support wheat production, including the provision of subsidies, and price supports.

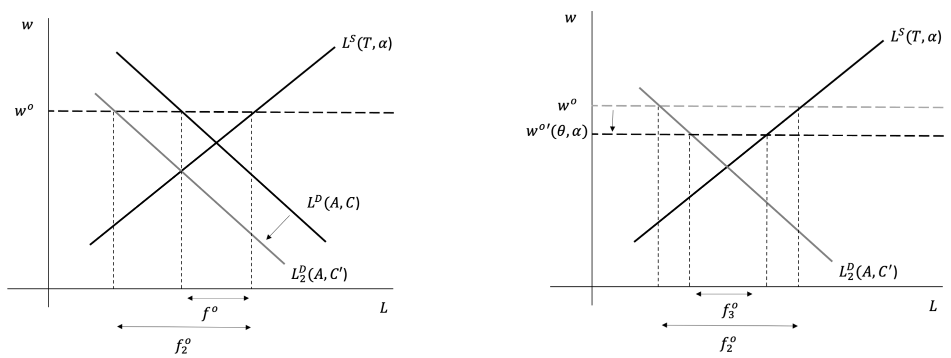
This pattern is particularly concerning as agricultural households often lack resources, and face challenges in accessing technical, financial, and institutional services to face and adapt to the consequences of extreme temperatures on agricultural yields. Adaptation options can usually take the form of improved on-farm practices or diversification towards off-farm opportunities. In Figure 4.1 panel b), we show the percentage of household members working off-farm. It shows that, in the first decade of 2000, off-farm participation in areas exposed to extreme temperatures (40%) was lower than in unaffected areas (50%). We instead observe a catch-up and even greater participation, in the second decade, up to 60% in 2015. This suggests that, although wheat-producing households may face greater exposure to climatic shocks, their sensitivity to these shocks could be reduced by diversifying their income through off-farm labour.

This transition from lower to higher off-farm participation in climate-change affected areas, can be possibly be explained by various mechanisms that we aim at exploring from both a conceptual and empirical perspective to understand the factors can promote or hinder off-farm labour as an adaptation strategy.

[1]Unfortunately, the survey does not provide information on the share of land devoted to wheat.

4.3 Conceptual framework

In this section, we provide a conceptual framework that considers off-farm labour supply as an adaptation strategy. To do so, we adopt a simple farm household model with imperfect labour market conditions, following Lovo (2012) and Sadoulet et al. (1998). Labour market participation is explained by the relationship between the on-farm marginal productivity of labour and its opportunity cost, i.e. off-farm labour. The original model assumes that household members have differentiated skills and only those with a higher opportunity cost, i.e. skilled workers, work off-farm for a higher salary of w^o.



(a) Off-farm labour as adaptation strategy (b) Transaction costs in the labour market

Figure 4.2: Off-farm labour decisions under market imperfections

Panel a) of Figure 4.2 provides a stylised depiction of the baseline scenario. Household decisions are based on off-farm market wages, w^o, and farm technology, which determines the on-farm demand for labour. The graph depicts the labour supply curve (L^S), which is a function of time endowment T and household characteristics α, and labour demand L^D, which is function of assets, A and climate C. The intersection between the two curves determines the on-farm labour productivity in the case of autarky. In the baseline case depicted in Panel a) of Figure 4.2, the on-farm labour productivity is below market wages, hence the household supplies labour off-farm for an amount corresponding to f^o.

Adaptation can be modelled as a household's response to a change in expectations regarding future climate shocks, i.e. future climate C'. This is also in line with the theoretical approach in Wimmer et al. (2024) who assume that farmers decide on planned output and input levels depending on their weather expectations. Because the worsening of climate conditions is likely to reduce future on-farm labour productivity, a household can adapt by taking this future reduction into consideration when making decisions about labour supply. Panel a) of Figure 4.2 shows this adjustment in expectations as a downward shift in the labour demand curve, L_2^D. Adaptation is, therefore, depicted as the off-farm labour supply based on a household 'expected' on-farm labour productivity, rather than actual on-farm productivity. The shift in expectations reduces the expected on-farm labour productivity and induces the household to work more off-farm, f_2^o. This is consistent with a number of studies such as Grabrucker and Grimm (2018), Grabrucker and Grimm (2021), and Branco and Féres (2021), which focus on the labour supply as an adaptive strategy. They show that past climate shocks lead households to engage in non-agricultural activities, which are less affected by weather conditions, to achieve diversified income and mitigate future weather-induced farm losses. These findings align with our theoretical framework, which shows an increase in off-farm labour in response to a decrease in expected on farm productivity.

Further, we can argue that a negative climate shock in the past period can cause such changes in expectations. This is broadly in line with Wimmer et al. (2024) who assume that the magnitude of weather events in past growing seasons affect farmers' expectations for the current growing season. Below, we discuss potential factors that could hinder this adaptation process and prevent households from expanding their off-farm labour supply, after experiencing a negative shock in past growing seasons.

First, we consider the possibility that a past shock fails to bring a shift in expectations concerning future climate, i.e a shift in the expected on-farm productivity. Whether a past shock is likely to trigger a shift in expectations can depend on its magnitude, as suggested in Wimmer et al. (2024). The role of the intensity of past shocks is also investigated in Di Falco et al. (2022) for a number of sub-Saharan African countries. The authors find that only when climate shocks become severe and persistent, households respond by diversifying their income sources through rural-to-urban migration.

In addition, irrespective of shock severity, the influence of past shocks on expected on-farm productivity can be weakened by several other factors, such as the adoption of resilient agricultural technologies or government policies supporting the agricultural sector. For instance, our findings in chapter 3 show that government support for wheat plays a key role in shaping land-use decisions amid the challenges posed by climate change. When temperature shocks occur, farmers in regions receiving high levels of government support for wheat are more likely to increase the share of land allocated to wheat, rather than reducing it. This suggests that financial assistance, such as price support or subsidies, helps farmers continue wheat cultivation despite adverse climatic conditions, providing an important adaptation strategy and enabling them to remain in farming rather than exiting agriculture. Similarly, Burke and Emerick (2016) show that government agricultural support measures, such as subsidised crop insurance, are key factors limiting adaptation through off-farm labour supply in U.S. agriculture. Providing insurance coverage for farmers experiencing productivity losses due to extreme heat weakens farmers' motivation to transition to off-farm opportunities.

Finally, even when past climate shocks have had a negative effect on farm income, households might not consider these to be indicative of a changing climate. Recent qualitative research by Wheeler and Lobley (2021), reveals that a signifiant number of farmers in the UK perceive extreme weather as a regular phenomenon and dismiss scientific claims about climate change. Besides potential scepticism, in developing countries, many farmers lack necessary information. According to a recent study by Ahmad et al. (2024), in Pakistan, one-third of farmers are not aware that temperature and rainfall patterns have changed in the last 20 years. To summarise, the magnitude of shocks, government farming support and the lack of awareness are among the factors that could explain why farmers might not adjust their expectation about future on-farm productivity.

Another important factor affecting the ability of households to work off farm is the presence of labour market imperfections. These can take a variety of forms, from cultural norms to rationing and high transaction costs, such as search and transportation costs. Panel b) of Figure 4.2 shows the effect of transaction costs, which reduces the *effective* off-farm wage to w_o'. Transaction costs largely depend on local market characteristics, θ, but can also be household specific, depending on α. Hence, when farmers adjust their expectations about future on-farm productivity (L_2^D), labour market imperfections, effectively limit the increase in off-farm labour supply to f_3^o. This is consistent with Aragón et al. (2021) who find that in rural Peru, where several market imperfections exist, subsistence farmers prefer utilizing input adjustments, such as altering land use and crop choices as adaptive responses instead of adjusting their labour supply. For Pakistan, Ahmad et al. (2024) show that only richer farm households are able to migrate to nearby cities following a bad year, suggesting that they are better positioned to overcome transaction and search costs, which characterise Pakistan's labour market. To summarise, following a negative climate shock, households can adjust their expectations about future on-farm labour productivity downwards. Transaction costs in the labour market, however, can make off-farm opportunities less desirable or accessible, leading to a weaker response in terms of off-farm labour supply.

Based on the conceptual framework and Pakistan's rural context, we expect to observe an increasing trend in off-farm labour supply among agricultural households over time, particularly in response to past temperature shocks. Theoretically, such shocks reduce expected on-farm productivity, prompting households to reallocate labour toward non-agricultural activities. This response is likely to be facilitated by improvements in local development conditions that might help lower the barriers to off-farm employment.

In addition, as climate extremes become more frequent and severe, households may be learning from past experiences and adjusting their livelihood strategies accordingly. This process of climate learning is likely to enhance their responsiveness to future risks, with increased participation in off-farm labour serving as an adaptive strategy to diversify income sources and mitigate climate-induced losses.

Overall, we expect these factors to contribute to a shift toward off-farm labour as an adaptive response among agricultural households facing increasing climate risks.

4.4 Empirical framework

Before investigating the relationship between labour choices and temperatures, we validate our measure of excessive temperature by estimating its impact on yields. Although yields may mediate the relationship between climate shocks and labour choices, we did not include them in the regression because the household survey data do not provide yield and labour data for the same time periods. Given this difference, including yields as regressors could bias the results

The existing literature has established a negative relationship between excessive temperatures and agricultural output. While we previously developed the relationship between yield and climate variables at the district level for wheat yields using equation (2.1) in chapter 2, there are several key differences in this analysis. In the earlier panel data model, district-level output was measured in tons per hectare. In contrast, this analysis shifts focus to pooled yields of major crops cultivated by households, is measured at household level and in kilograms per acre. Moreover, in this chapter, The household data is drawn from six cross-sectional waves covering different survey years (between 2000/01 and 2018/19) with different households sampled in each wave, meaning the dataset forms a repeated cross-section rather than a panel. Additionally, while rainfall shocks were considered in the previous model, we control for rainfall (in millimeters) in this specification. Our results in the previous chapter demonstrate that our measure of climate shocks negatively impacts wheat yields, and we expect a similar negative effect on crop yields at the household level. More specifically, in this chapter, we employ the following empirical specification:

$$y_{cidt} = \beta \text{Heat}_{dct} + \gamma R_{dct} + \lambda_c + \theta_t + \Omega_{cd} t + \mu_{pt} + \epsilon_{cidt} \tag{4.1}$$

Where y_{cidt} represents the log of yields for crop c produced by household i, in district d at time t. Heat_{dct} is a binary indicator taking value one if temperatures are 1.5 standard deviations above the historical mean for a given district and crop-specific growing season. R_{dct} indicates rainfall (in mm) at the district level, also determined over each crop-specific growing season. We include crop (λ_c) and year (θ_t) fixed effects to account for unobserved crop and year-specific shocks that are common across households. $\Omega_{dc}t$ are district and crop-specific time trends that control for pre-existing patterns at the crop-by-district level. We also include a full set of province-by-time fixed effects (μ_{pt}) to control for shocks affecting a province in a given year as, for example, province-specific agricultural policies, which could also be correlated with temperature. The last term is the stochastic error term, ϵ_{cidt}.

To investigate whether households adapt to temperature shocks by diversifying their labour supply, we investigate the effect of past temperatures (lagged one year) on participation in off-farm labour activities, by estimating the following equation:

$$\text{Off}_{idt} = \beta_w \text{Heat}_{dt-1} + \gamma R_{dt-1} + NL_{dt} + \lambda X_{idt} + \theta_t + \Omega_{dt} + \mu_{pt} + \epsilon_{idt}, \qquad (4.2)$$

where Off is a binary indicator taking value 1 if household i in district d had at least one family member working off-farm in year t, and 0 if all members work in agriculture. This choice is primarily driven by data limitations, as the survey does not provide information on individual-level hours worked. Heat_{dt-1} indicates the one year-lagged temperature shock. The estimated coefficient is interpreted as the effect of past temperature shocks on probability of households engage in off-farm work, controlling for other variables. This specification allows us to estimate whether exposure to past temperature shocks is associated with a greater likelihood of diversifying into off-farm employment. R_{dct-1} represents rainfall (in mm), also lagged one year. Since more than 80% of households in our study sample cultivate wheat, we consider temperature shocks and rainfall during the wheat season for this specifcation. In all specifications, we include average annual luminosity (NL_{dt}), a measure of the level of economic activity at district level, to control for conditions that might affect off-farm opportunities. X_{idt} is a vector of control variables at the household level, which include household size, age and gender of the household head. Similarly to the specification above, we also include year-fixed effects, province-by-year fixed effects, and district-specific time trends.

In order, to investigate whether off-farm labour supply responses have changed over time, we estimate the following equation:

$$\text{Off}_{idt} = \beta_w \text{Heat}_{dt-1} \times \text{Wave}_t + \gamma R_{dt-1} + NL_{dt} + \lambda X_{idt} + \theta_t + \Omega_{dt} + \mu_{pt} + \epsilon_{idt}, \quad (4.3)$$

where temperature shocks are interacted with a set of dummy variables for each of the 6 waves (Wave). We estimate both specifications 4.2 and 4.3 by using a linear probability estimator. Although the dependent variable is binary in nature, we prefer using a linear probability model because it allows the inclusion a full set of fixed-effects. Linear probability models provide good estimates of the partial effects for average values of the explanatory variables and the coefficients allow for a straightforward interpretation of the effects (Wooldridge, 2005). Measurement errors also cause a smaller bias in linear models than in discrete choice models. Because the residuals of a linear probability model are heteroskedastic by definition, all estimations report standard errors clustered at the district level. For robustness we also estimate our specifications using a logit model. Results are presented in the appendix (see Table C.1).

4.5 Data

Our empirical analysis uses data from three different sources; household-level data for six cross-sectional waves (2000/01-2018/19), weather data on temperature and rainfall at grid level from the Climatic Research Unit Time Series version 4.07 (CRU TS v. 4.07), and nightlight data at the district level from National Oceanic and Atmospheric Administration (NOAA). Below we describe each source separately.

4.5.1 Household-level data

We use the Household Integrated Economic Survey (HIES) conducted by the Pakistan Bureau of Statistics (BPS), drawn from six cross sectional waves covering the survey years 2000/2001, 2005/2006, 2007/2008, 2011/2012, 2015/2016 and 2018/2019 (waves 1-6). The survey is representative and covers 107 out of the

170 districts of Pakistan. The survey gathers information on socio-economic characteristics, land ownership, cultivated land, yields of major crops (wheat, rice, maize, cotton and sugarcane), household income and employment conditions.

The overall sample consists of a total of 21,679 farm households, about 3500 households per wave. As mentioned above, the large majority of households grow wheat, and the share has been increasing over time (Panel a of Table 4.1). Overall, of those households engaged in wheat production, about 21% (4872 households) do not engage in the cultivation of any other crop.

Table 4.1: Descriptive statistics

	All years	Survey year					
	Mean	2001	2005	2007	2011	2015	2018
Panel (a): Share of households growing:							
Wheat	0.857	0.800	0.881	0.851	0.846	0.891	0.877
Maize	0.160	0.187	0.165	0.158	0.137	0.154	0.154
Rice	0.281	0.269	0.276	0.285	0.308	0.290	0.271
Cotton	0.262	0.260	0.260	0.221	0.291	0.290	0.261
Sugarcane	0.121	0.124	0.109	0.141	0.137	0.115	0.106
Panel (b): Household characteristics							
Working off-farm	0.497	0.443	0.487	0.480	0.492	0.553	0.537
Household size	7.750	8.169	8.067	7.800	7.490	7.573	7.379
Age of household head	47.804	46.759	47.810	47.905	47.723	47.820	48.608
Land size (acres)	7.286	7.997	7.925	9.132	7.465	6.105	5.360
Panel (c): Weather variables							
Heat (t)	0.852	0.813	0	0.824	0.830	0.869	0.875
Heat (t-1)	0.845	0.833	0.827	0.803	0.831	0.873	0.877
Wheat season rainfall (mm)	37.392	32.770	39.729	40.669	39.700	51.694	27.628
Wheat season rainfall (mm) (t-1)	38.315	29.700	33.067	49.548	53.160	32.053	35.712
Panel (d): Development variables							
Annual luminosity	5.403	4.857	3.972	5.297	4.825	5.681	7.324
Observations	21,679	3925	3946	3467	2980	2602	4759

Note: Authors' calculations using data from the Household Integrated Economic Survey (HIES), the Climate Research Unit (CRU), and the National Oceanic and Atmospheric Administration (NOAA). Heat is a binary indicator, taking value 1 if temperatures are above 1.5 standard deviations from historical district-level averages.

The survey collects information on whether the household head, spouse, and children (of working age) are involved in agricultural or non-agricultural jobs, but the amount of hours devoted to each activity is not recorded. Our measure of off-farm labour participation takes value one if at least one family member is engaged in off-farm activity, either as employee or self-employed. Panel b) of

Table 4.1 shows that only 44% of agricultural households were engaged in off-farm activities in the 2001 survey, the percentage increasing to 53% in the 2018 survey, suggesting a move towards greater income diversification. Another notable trend is the decrease in land size from about 8 acre in the 2001 survey to 5.39 acre in the 2018 survey. This trend is more apparent in last two waves as compared to the first four waves (2001 to 2011). This, also, aligns with households relying less on agricultural activities as their sole income source and diversifying into other sectors.

4.5.2 Climate data

The climate data used in this chapter and the process of aggregating the grid level climate data is the same as that in the previous chapters. In this chapter, we consider all districts of Pakistan, so we overlaid the climate data with administrative district boundaries using shapefile of Pakistan. This allowed us to obtain average district-level climate measures for the entire country using GIS techniques.

To merge the district-level climate data with household level data, we used the information on household's district of residence. We were able to match each household's reported district with the corresponding climate data by using this district identifier.

To capture temperature anomalies, we follow a similar method to that used in chapter 2. Specifically, we first calculated the long-term averages and standard deviations of temperature over the period 1960-2000 for each district and crop-specific growing seasons. We then computed the difference between season-specific average temperature in each year and the corresponding historical averages. Consistent with the previous definition of temperature shocks, values exceeding 1.5 standard deviations from the long-run average are classified as high temperatures and are assigned a value of one in the binary indicator variable, "Heat". To validate this binary specification, we also estimated models using the lagged temperature shock as a continuous variable. The results, reported in appendix Table C.2, show no significant effect on off-farm labour supply, supporting the selection of the binary approach. For studying the impact of temperature shocks on crop yields, we use contemporaneous temperature indicators specific to each crop's growing season.

To examine labour supply responses, particularly during the wheat-growing season, we focus on a lagged indicator, similar to the approach in Chapter 3. Focusing on labour responses during the wheat season is particularly relevant, as 80% of the households in our sample cultivate wheat. We also calculate the number of shocks experienced over the last five years, to capture the degree of exposure to repeated shocks. Descriptive statistic for our main explanatory variables are shown in panel c) of Table 4.1. The share of households living in districts affected by extreme temperatures varies over time, from no extreme events (contemporaneous) experienced by households in the 2005 survey to almost country-wide extreme temperatures (lagged) experienced by households in the 2019 survey.

We constructed measures of average rainfall (in mm) by year and growing season, which we use to control for possible correlations between excessive temperatures and rainfall. We also constructed rainfall shocks (both deficit and excess rainfall), in the same way as we computed our temperature shocks, which we use for robustness checks (Table C.3 of the appendix).

4.5.3 Nighttime lights data

Nighttime lights data from satellite imagery provided by the National Oceanic and Atmospheric Administration (NOAA). This data is sourced form two types of satellites, Defense Meteorological Satellite Program (DMSP)-Operational Linescan System (OLS) from 1992–2013 and the Visible Infrared Imaging Radiometer Suite (VIIRS) from 2012 to present. However, due to inherent dissimilarities in their characteristics, such as varying spatial resolutions and time periods, we use the harmonised version of the data calibrated and compiled by Li et al. (2020). The harmonised dataset, which is standardised on a global level, merges inter-calibrated observations of nighttime lights (NTL) from both the DMSP data and the VIIRS data. Li et al. (2020) confirmed that the resulting global DMSP NTL time series data (1992-2020) exhibits consistent temporal trends. Therefore, the data ensures reliability and consistency across space and time.

To analyse this dataset at the district level for Pakistan, we used shapefiles to extract district boundaries and processed GeoTIFF files using QGIS software, allowing spatially consistent estimates to be matched with administrative units. Specifically, we used GeoTIFF files to extract nightlight intensity data and align it with administrative units, enabling us to generate district-level measures of night-time luminosity. The unit of observation is a pixel, which we aggregate to obtain average annual luminosity at the district level. The average annual luminosity at district level across waves is presented in Table 4.1, panel d) and has been increasing over time. As we could not match data for 11 out of 107 districts in the survey, we exclude these districts from our analysis. Nevertheless, our results are consistent when we include these districts and omit the nightlight variable.

4.6 Results

This section has three main parts. First we investigate the effect of contemporaneous climate shocks on crop yields to test whether our measure "Heat" is able to capture negative productivity shocks. Second, we present our main results on the effects of past temperature shocks on off-farm labour supply, and test whether impacts have changed over time. Finally, we investigate possible mechanisms underlying the observed labour supply responses.

4.6.1 Temperature shocks and yields

Table 4.2 presents the results of the impact of temperature shocks on yields, considering the five major crops grown in Pakistan: wheat, maize, rice, cotton and sugarcane. We consider yields separately for each of the five major crops and include crop fixed-effects to account for crop-specific time invariant factors. We also estimated separate specifications for each crop, and the results are largely consistent (see Table C.4). Results show that temperature shocks have a significant negative effect on crop yields. The effect persists after the inclusion of land size (column 2) and a range of fixed effects (columns 3 and 4). A temperature shock reduces crop yields by 17 to 29% on average. We also find that average rainfall (in mm) is negatively related to yields. However, the effect is, however, negligible. For example, 30 millimetres of additional rainfall (one standard deviation) reduces the yields by .15 to .25%, on average. This variable is not aimed at capturing any rainfall related shock, but simply to control for average conditions. Indeed, we do find a negative effect of a measure of rainfall shock (see Table C.3). However, we do not explore this further as this is beyond the scope of this paper. We obtain very similar results when excluding rainfall from our specifications (Table C.5).

Our results align with the international evidence. For instance, Burke and Emerick (2016) estimate a 0.56 % yield reduction for every one degree increase above 29°C in the US agriculture. While in India, Taraz (2018) reports a 0.99% reduction in aggregate yields when the average temperatures fall within the range of 27 to 30°C during the crop growing season. Similarly, Hussain and Mudasser (2007), Ashfaq et al. (2011) and Siddiqui et al. (2012) find that beyond a certain optimal temperature, further increases in temperature become harmful for the yields of major crops in Pakistan. For instance, in the case of wheat, a one-degree increase above the optimal window (12-20°C) leads to adverse effects on crop harvest.

In addition to the existing literature, our results are consistent with findings in Chapter 2, where we observe a negative effect of high temperature on wheat yields. For instance, the results show up to 28% yield reduction associated with high temperature. This result also serves to validate the shock variable used in this study. We also estimate separate specification for each crop. We find negative and significant effects of contemporaneous temperature shocks for all crops, except rice (Table C.4). This, however,is consistent with the fact that rice is typically grown in flooded paddies, which help moderate soil temperature (Siddiqui et al., 2012), and reduce the impact of extreme heat on yields (Taraz, 2018). Overall, results confirm that our measure of temperature shocks has a direct negative effect on crop yields. Below, we investigate whether after having experienced a negative shock, farmers alter their expectations about future yields and adapt their labour supply to accommodate more diversified sources of income.

Table 4.2: Contemporaneous effects of temperature shocks on crop yields

Dep var: Crop yields	(1)	(2)	(3)	(4)
Heat (t)	-0.176**	-0.215***	-0.264***	-0.295***
	(0.029)	(0.001)	(0.000)	(0.000)
Rainfall (t)	-0.008***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Landholding (acres)		0.677***	0.676***	0.679***
		(0.000)	(0.000)	(0.000)
Crop FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province-year FE	No	Yes	Yes	Yes
Crop time-trend	No	No	Yes	Yes
District time-trend	No	No	No	Yes
Observations	38933	38493	38493	38493
Households	21200	21200	21200	21200

The dependent variable is the natural log of yields from the 5 major crops (wheat, rice, maize, cotton and sugarcane). Weather variables are specific to each crop growing season. Heat is a binary indicator taking value 1 when temperature exceeds 1.5 standard deviation from the growing season historical average for a given district. Rainfall (mm) is the average rainfall during each crop-growing season at district level. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

4.6.2 Past temperature shocks on off-farm labour supply

Table 4.3 reports the results of the impact of temperature shocks on the probability of working off-farm. Column (1) includes year fixed effects, column (2) include district-time trends and, column (3) includes both district-time trends and province-year fixed effects. In column (4), we include contemporaneous shocks during wheat season.

Our results are consistent across all specifications, revealing two primary findings. First, we find no effect of temperature shocks on off-farm labour supply, in the first four waves (2000-2012), except for a negative effect for the third wave, which is, however, not robust across the different specifications. Second, we find a positive and significant effect of temperature shocks on off-farm labour supply in more recent waves (2015 and 2018). These estimates are consistent with our motivational evidence presented in Figure 4.1. The likelihood of engaging in off-farm labour supply in the aftermath of a negative temperature shock increases over time. This suggests that off-farm labour increasingly serves as an adaptation strategy.

However, households may choose to participate in off-farm activities even when they anticipate unfavourable conditions in the current season. In such instances, opting for off-farm work serves as a coping strategy adopted by the household to alleviate the adverse impacts of temperature shocks on their income. If contemporaneous and past shocks are correlated, our estimates could be capturing a mixture of adaptation and coping strategies. To disentangle these effects, in column 4, we control for contemporaneous temperature shocks, also interacted with year dummies. Our results remain largely unchanged and confirm that our estimates reflect households' adaptation responses to past temperature shocks.

Table 4.3: Effect of Previous year's extreme temperature on off-farm labour supply

Dep var: Labour Supply	(1)	(2)	(3)	(4)
Heat (t-1) × Wave-1 (2001)	-0.020	-0.032	-0.062	-0.041
	(0.612)	(0.636)	(0.509)	(0.657)
Heat (t-1) × Wave-2 (2005)	-0.039	0.021	0.133	0.139
	(0.569)	(0.772)	(0.229)	(0.195)
Heat (t-1) × Wave-3 (2007)	-0.109**	-0.014	-0.062	-0.075
	(0.036)	(0.724)	(0.144)	(0.222)
Heat (t-1) × Wave-4 (2011)	-0.023	0.022	0.046	0.049
	(0.683)	(0.245)	(0.253)	(0.218)
Heat (t-1) × Wave-5 (2015)	0.142**	0.131*	0.058***	0.056***
	(0.026)	(0.058)	(0.000)	(0.001)
Heat (t-1) × Wave-6 (2018)	0.074**	0.019*	0.012*	0.012*
	(0.043)	(0.060)	(0.060)	(0.081)
Annual luminosity	Yes	Yes	Yes	Yes
Rainfall (mm)	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household-level controls	Yes	Yes	Yes	Yes
District-time trend	No	Yes	Yes	Yes
Contemporaneous shock	No	No	No	Yes
Province-year FE	No	No	Yes	Yes
Households	21200	21200	21200	21200

Note: The dependent variable is Off-farm labour supply which is an indicator variable taking value one for households that have at least one of the family members working off-farm. Heat indicates the one-year-lagged temperature shock for the wheat season. Household-level controls include household size, age and gender of household head. Column (4) controls for contemporaneous shocks. Standard errors, in parentheses, are clustered at the district level. *** p-value <1%, ** p-value <5%, * p-value <10%.

4.6.3 Mechanisms

In this section, we empirically explore a few mechanisms that could explain the changes over time in off-farm labour supply responses. More specifically, we investigate 3 main mechanisms. First we consider whether households might have become more responsive, in terms of off-farm labour responses, because temperature shocks have become more extreme over time. Second, we explore whether labour market conditions have instead improved over time. Finally, we investigate whether households have become increasingly aware of the consequences of climate change on yields, prompting them to engage in adaptation strategies.

4.6.3.1 Shock Intensity

In this section we investigate whether changes in labour supply responses are related to shocks, and their impact on yields, becoming more extreme over time. In Table 4.4 we show average and maximum standardised temperatures (z-scores) across waves. These data refer to the year preceding the survey years (lagged shocks), which is what we use in our labour supply specification. We notice that both average standardised temperature and temperature above 1.5 standard deviation (column 2) are similar across the two periods. Even, when considering maximum standardised temperature, it a bit higher in the first period. Indeed, while there was a large shift in average temperatures at the beginning of 2000, temperatures have remained high but stable during the last two decades (see Figure C.1 of the appendix, which plots average temperature over the period 1980-2020).

Second, we empirically test whether the effect of temperature shocks on crop yields has increased over time. In Table 4.5 we show the results of the impact of contemporaneous temperature shocks on yields across waves. We exclude the second wave (2005) from the analysis, since no districts experienced extreme temperatures in that year. Results show a negative effect of temperature shocks across all waves except for the last wave (2018), where the effect is negative but small and not statistically significant. In earlier survey years, the impact is stronger and statistically significant, such as a 59% reduction in 2001, though it weakens over

Table 4.4: Extreme temperature over time

	(1) Average z-score	(2) Average z-score above 1.5	(3) Maximum z-score
2001	1.71	2.20	2.43
2005	2.11	3.08	4.03
2007	1.56	2.76	3.13
2011	2.58	3.33	4.93
First period (2001-2011)	1.97	2.91	4.93
2015	1.04	2.31	2.70
2018	2.38	3.09	4.08
Second period (2015-2018)	1.90	2.94	4.08

Note: Z-score is calculated as deviation of current year's average temperature from historical average temperature during wheat season with the base year of 1960-2000

time, declining to a significant 23% in 2015. This trend suggests a diminishing effect of heat on crop yields over time. The p-values reported at the bottom of the table reflect a joint test for differences in coefficients across the two sub-periods (2001-2011 and 2015-2018). It shows no significant difference, suggesting that the negative impact of temperature has not worsened over time. In general, there is no noticeable worsening of the impact of extreme temperature on yields. This, however, does not exclude that households might have experienced accumulated shocks, which will be investigated below (in Section 4.6.5). Note that these are contemporaneous shocks on yields, hence they do not correspond to those used in our labour supply specifications, which instead use lagged temperature shocks. Nevertheless, these results exclude the possibility that the impact of temperature shocks has worsened over time, during the period of analysis.

4.6.4 Local development

Improvements in local economic development and/or urbanization could potentially facilitate the transition from agricultural to non-agricultural sectors by increasing demand for labour in the non-agricultural sector. In order to test whether changes in off-farm labour responses are influenced by changes in local development conditions, we conduct an empirical test to examine the impact of local development in the context of climate shocks.

We use nighttime lights to measure economic development at the district level. Night luminosity observed from satellites is found to be a good proxy for

Table 4.5: Effect of extreme temperatures on crop yields by survey year (wave)

Dep var: Crop yields	(1)	(2)
Heat(t) × Wave-1 (2001)	-0.589***	-0.589***
	(0.000)	(0.000)
Heat(t) × Wave-3 (2007)	-0.300***	-0.304***
	(0.000)	(0.000)
Heat(t) × Wave-4 (2011)	-0.190**	-0.181**
	(0.027)	(0.022)
Heat(t) × Wave-5 (2015)	-0.233***	-0.209***
	(0.003)	(0.007)
Heat(t) × Wave-6 (2018)	-0.046	-0.008
	(0.439)	(0.914)
Landholding (acres)	0.674***	0.673***
	(0.000)	(0.000)
Rainfall (mm)	Yes	Yes
Crop EF	Yes	Yes
Province-year FE	Yes	Yes
Crop-time trend	No	Yes
No. of obs.	38448	38448
Test of differences between first 4 waves and last 2 waves (p-value)	0.641	0.401

Note: The dependent variable is the natural logarithm of aggregate crop yields. Heat is temperature shocks, and calculated as 1.5sd above historical temperature over the growing season months. We use annual data from HIES spanning 2000/01 to 2018/18. All columns include year fixed effects. We control for rainfall (mm), average over growing season months. We present standard errors clustered by district in parentheses. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

measuring economic activity in developing countries, where the challenge of data availability is consistently prevalent. One of the latest reports on South Asian countries, WB (2017) uses nightlight intensity (annual brightness) to analyse economic activities to predict Gross Domestic Product (GDP) across space and over time. They find a strong correlation between the intensity of nightlights and levels of GDP in eight South Asian countries including Pakistan. The regions with higher nightlight intensity tend to exhibit stronger economic activity. While areas emitting lower levels of light appear to have lower economic development. Considering these findings, we use annual luminosity as a proxy to measure economic development at the district level for Pakistan.

By controlling for changes in local development (annual luminosity) in our specifications, we have dealt with the potential correlation between exposure to extreme heat and local development, e.g. the possibility that areas affected by temperature shocks are also less/more developed. In this section, instead, we are interested in understanding how the responses to extreme temperature varies across levels of development. Before doing so, we first test whether our measure of local development is indeed correlated with higher off-farm labour supply, and estimate the following equation:

$$\text{Off}_{idt} = \beta NL_{dt} + \lambda X_{idt} + \theta_t + \mu_{pt} + \epsilon_{idt} \tag{4.4}$$

The unit of observation is household i in district d at time t. Off_{idt}, as before, takes value one if at least one member of the household is working off-farm. X_{idt} is the same vector of controls used in previous specifications. θ_t and μ_{pt} indicate year and year-by-province fixed effects. Standard errors, ϵ_{idt}, are clustered at district level.

The results in Table C.6 of the appendix confirm the positive relationship between light intensity and off-farm labour. A one standard deviation increase in light intensity increases the probability of working off-farm by 3%. This indicates that nightlight predicts off-farm labour. This is consistent with districts with higher light intensity exhibiting greater economic activity, which in turn correlates with a higher proportion of households engaged in off-farm work.

We then test empirically, whether the positive response of off-farm labour supply in the last two waves (see Table 4.3) is driven by a district's level of local development (measured by nightlight intensity). We do so by augmenting previous specification as follows:

$$\text{Off}_{idt} = \beta_1 \text{Heat}_{dt-1} + \beta_2 Heat_{dt-1} \times NL_{dt} + \beta_3 NL_{dt} + \lambda X_{it} + \theta_t + \mu_{pt} + \epsilon_{idt} \tag{4.5}$$

where $(\text{Heat}_{dt-1} \times NL_{dt})$ is the interaction between lagged temperature shocks and luminosity. We estimate this specification separately for the first 4 waves (2001-2011) and the last 2 waves.

Figure 4.3 plots the conditional effects, while the point estimates are shown in Table C.7 of the appendix). The figure shows that impact of lagged temperature shocks on off-farm labour supply differs notably before and after 2011, as indicated by the green and orange lines. Before 2011 (green line), temperature shocks generally have a negative effect on off-farm labour, particularly in areas with lower levels of local development (lower nightlight values). However, as nightlight intensity increases, this negative effect diminishes and eventually crosses into positive region (crosses zero). This suggests that, in more developed districts, lagged temperature shocks may be associated with an increase in off-farm labour, as indicated by the interaction effect in column (3) of Table C.7 in the appendix. This pattern indicates that higher levels of local development may enable households—particularly in the most developed districts—to respond to temperature shocks by diversifying into off-farm employment. While households in the less developed districts tend to decrease their off-farm labour supply in response to lagged temperature shocks. After 2011 (orange line), the relationship between lagged temperature shocks and off-farm labour supply appears to weaken, but representing higher levels of local development, remains above zero and continues to increase. This suggests that the off-farm labor response to temperature shocks is particularly dependent on the level of local development. Districts with higher local development show a growing positive response to temperature shocks, indicating that these districts are better able to adapt by shifting labour to off-farm activities. This concludes that positive labour supply response we estimated above for the second period, can be partly explained by improvements in local development conditions.

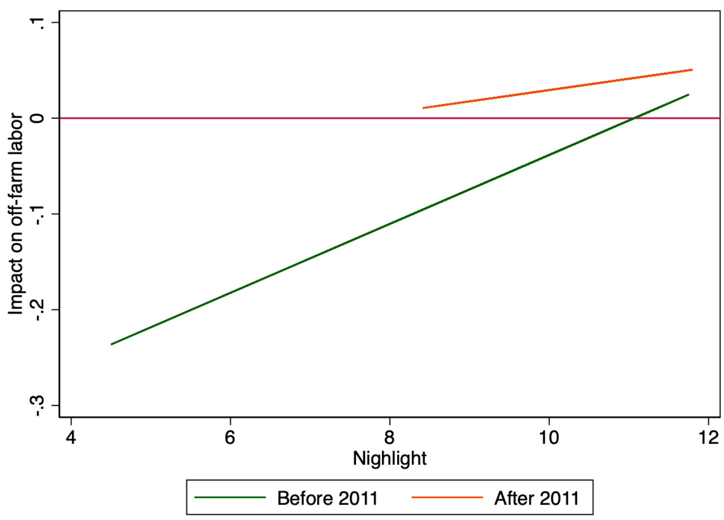


Figure 4.3: Off-farm labour responses by level of local development

Note: The values plotted are obtained by multiplying the coefficient of the interaction term multiplied by luminosity level. The regression results used to produce this graph are shown Table C.7 of the Appendix

4.6.5 Learning

People commonly base their assessment of risks on their past experiences, learn from them, and adapt their behaviour accordingly. The concept of adaptive expectation formation, introduced by Cohen et al. (2008), suggests that individuals adjust their expectations about the future based on what has happened in the past. In context of weather-related risks, this suggests that people evaluate the likelihood and the impact of adverse weather events by considering the past events. This means that individuals use their previous experiences with climate shocks, like high temperature or heat stress, to understand and anticipate the risks associated with weather in the present and future.

Table 4.6: Effects on off-farm labour supply conditional on past exposure to high temperature

	Before 2011		After 2011	
Dep var: Labour Supply	(1)	(2)	(3)	(4)
Heat (t-1)	0.010	0.021	0.080*	0.111**
	(0.767)	(0.626)	(0.094)	(0.045)
PastExp (t-2 to t-5)	-0.004		0.009	
	(0.920)		(0.801)	
PastExp × Heat (t-1)	-0.052		-0.060	
	(0.285)		(0.339)	
Years of Exposure		-0.010		0.018
		(0.631)		(0.498)
Years of Exposure × Heat (t-1)		-0.024		-0.041
		(0.336)		(0.125)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of obs.	13853	13853	7347	7347

Note: The dependent variable is Off-farm labour supply which is an indicator variable taking value one for households that have at least one of the family members working off-farm. Heat indicates the one-year-lagged temperature shock for the wheat season. PastExp is dummy equal to 1 if households experiences more than 1 shock in past 4 years. Years of Exposure indicate the number of years exposed to heat in the past 5 years. Household-level controls include household size, age and gender of household head.District-level controls include one-year-lagged rainfall (mm) in wheat season and annual luminosity. Standard errors, in parentheses, are clustered at the district level. *** p-value <1%, ** p-value <5%, * p-value <10%

Another possible explanation for the observed changes in off-farm labour responses, could be that in more recent years, households have formed a better understanding of the increasing likelihood of shocks due to repeated past exposure. For example, if households interviewed in the last two waves, are more likely to have experienced repeated heat shocks in the past, they may more likely to interpret subsequent shocks as indicative of a rising frequency of such events. This makes them more likely to adapt in the aftermath of a heat shock, and increase their labour supply. In this section, we empirically assess this mechanism by testing whether household responses to a previous year's heat shock (t-1) vary with their exposure to past shocks. To do so we estimate the following equation:

$$\text{Off}_{idt} = \beta_1 \text{Heat}_{dt-1} + \beta_2 \text{Heat}_{dt-1} \times \text{PastExp}_{dt} + \beta_3 \text{PastExp}_{dt} + \gamma R_{dt-1} + \lambda X_{it} + \theta_t + \epsilon_{idt}, \tag{4.6}$$

where PastExp is an indicator of exposure to heat shocks over the previous 5 years, excluding the last. We use both the number of years exposed to a shock in the past 5 years, and a binary indicator taking value one if a household experienced more than one shock over the period. As before, we run two separate regressions: one for the first four waves (2001 to 2011) and the second for the last two waves (2015 and 2018). Table 4.6 presents the findings. We find no detectable impact of past exposure on the off-farm labour responses for both periods. These results remain consistent even when considering the number of years exposed to past heat shocks (columns 2 and 4). This implies that the observed changes in off-farm labour responses over the waves, estimated above, are not driven by learning from past exposure. According to Tversky and Kahneman (1973), people tend to perceive something as more likely to occur if they can easily recall recent events, particularly if those events are more recent. Consequently, they adjust their expectations about the future. We interpret this finding as evidence that agricultural households are more likely to adapt their expectations based on shocks from the previous year, indicating a focus on learning primarily from recent past shocks. However, our analysis suggests a lack of significant learning from shocks occurring over the distant past. One of the reasons could be the low literacy rate across the rural areas, which prevent farmers from accessing information. This means that farmers might not perceive repeated shocks as an indication of climatic changes, which might limit their ability for long-term adaptation.

4.7 Heterogeneity test: Land size

In this section, we further investigate the influence on off-farm labour responses using land size. Table 4.7 shows the results pertaining to differences in land size. More specifically, we distinguish households with below and above median land size.

Table 4.7: Effects on labour supply by land size

	Before 2011	After 2011
Dep var: Labour Supply	(1)	(2)
Heat (t-1)	-0.052*	0.041**
	(0.020)	(0.011)
Small	0.042	-0.009
	(0.033)	(0.019)
Heat (t-1) × Small	0.119*	-0.002
	(0.045)	(0.044)
Rainfall	Yes	Yes
Controls	Yes	Yes
Year FE	Yes	Yes
No. of obs.	13853	7347

Note: The dependent variable is Off-farm labour supply which is an indicator variable taking value one for households that have at least one of the family members working off-farm. Heat indicates the one-year-lagged temperature shock for the wheat season. Small landholding is a dummy equal to 1 if the household is below median land size (4 acre). Household-level controls include household size, age and gender of household head. District-level controls include one-year-lagged rainfall (mm) in wheat season and annual luminosity. We present standard errors clustered by district in parentheses. *** p-value $<$ 1%, ** p-value $<$ 5%, * p-value $<$ 10%.

Our results show that the overall effects presented above, mask some interesting heterogeneity. Indeed, for the first four waves, households labour supply response is conditional on land size. More specifically, we find that while households with small land (below median) holding increase labour supply in the aftermath of a shock, larger farms show instead a decrease in off labour supply.

While we cannot directly test this hypothesis, these results could be indicative of larger farmers adapting by investing in labour-intensive adaptation strategies, such as conservation practices, which would lead to a transition from off-farm labour supply to on-farm labour supply. On the other hand, small farmers, having fewer resources and land available, respond by increasing their off-farm labour supply. These findings are aligned with other studies in Pakistan, such as Abid et al. (2015) and Ali et al. (2017), who show that households with larger landholdings are less inclined to shift to the non-farm sector and more likely to invest in agricultural practices. In the second period (column 2), instead, we find that the positive labour supply responses does not depend on the size of the farm.

4.8 Conclusion

In this study we use a comprehensive six-wave cross-sectional dataset (2000/01-2018/19) to investigate the effect of past temperature shocks on off-farm labour supply as an adaptation strategy among agricultural households in Pakistan. First, we examine the effects of contemporaneous climate shocks on major crops to validate our measure of temperature shock, ensuring its ability to capture the negative productivity shock. Second, we address our primary objective regarding how past temperature shocks influence the supply response decisions among agricultural households over time. Third, we explore the potential mechanisms underlying the transition in off-farm labour supply.

Our findings show a significant negative impact of temperature shocks on the yields of major crops among farmers. This confirms the validity of our measure of temperature shock, demonstrating its potency to bring about productivity shocks among agricultural households. However, in case of off-farm labour supply response, we find no effect of past temperature shock on off-farm labour supply in the first four waves of our analysis. But in the later two waves, we see a positive and significant effect, showing an increase in off-farm labour supply in the aftermath of temperature shocks. This indicate the role of off-farm labour participation as an adaptation strategy among agricultural households.

In our final set of estimations, we test the three potential mechanisms underlying the observed responses in labour supply. We find that off-farm labour responses are unlikely to be driven by the increase in severity of temperature shocks and households learning from repeated shocks. Instead, these responses are more likely driven by improvements in local development conditions.

Overall, this study sheds light on the adaptation strategies employed by agricultural households in Pakistan in response to recent climate change. It provides valuable insights for policymakers and stakeholders. These insights assist in formulating effective policies and interventions to enhance resilience and promote sustainable rural development.

Chapter 5

Conclusion

This thesis provides an analysis of the impact of climate change on Pakistan's agricultural sector, focusing on the adaptive responses that have emerged as a result. The three chapters are interlinked, as they focus on different yet interconnected dimensions of adaptation to climate change within Pakistan's agricultural sector.

5.1 Summary of results

The first chapter finds that warming during critical growth stages, such as the reproductive phase of wheat, significantly reduces yields, underscoring wheat's sensitivity to temperature variability in the KP province of Pakistan. The impact of temperature shocks is even more severe in hotter districts, potentially reducing yields by disrupting both the growing and maturity stages. Excess rainfall during the planting stage benefits wheat by supporting early growth. However, excess rainfall at later stages, particularly during the reproductive and maturation phases, adversely affects yields. Adaptive strategies, such as improved irrigation, are shown to be effective in mitigating heat stress during the wheat season in the province. Overall, these findings highlight wheat's vulnerability to weather shocks and their serious implications for food security in developing countries like Pakistan.

The second chapter examines land use changes as adaptive responses to past temperature shocks, with a focus on the role of government policy through wheat support prices. To analyse how support prices influence adaptation by shaping land use decisions, the study period is divided into two periods. The first period (1981–2006) is characterised by low support prices, while the second period (2007–2019) is characterised by higher support prices. During the first period (1981–2006), land allocated to wheat declined following a temperature shock, leading to an overall reduction in cultivated land across the province. However, the responses varied across climatic regions. In the southern region, there was a reallocation of land to heat-resistant crops, increasing total cultivated land. In contrast, other regions experienced declines in both wheat and other crops, resulting in reduced agricultural land and a potential shift toward non-agricultural activities. In the second period (2007–2019), higher support prices prevented a decline in the land allocated to wheat following temperature shocks, resulting in an overall expansion of cultivated land, particularly in the southern and northern regions. In the resource-constrained northern region, strong government support for wheat increased the land allocated to wheat, encouraging the cultivation of a heat-sensitive crop. However, this shift potentially limited opportunities for crop diversification. These findings indicate that while higher support prices provided a safety net against climate risks, they also encouraged dependence on a climate-sensitive crop, increasing vulnerability to future climate challenges. The third chapter examines labour responses among agricultural households over the past two decades. The findings indicate that, in recent years (2015–2018), off-farm labour has had a positive and significant effect, suggesting that income diversification has become a critical adaptation strategy for these households. The chapter explores three potential drivers behind this shift: the increasing severity of temperature shocks, improvements in local development, and households' learning from past shocks. The results show that off-farm labour responses are unlikely to be driven by the severity of temperature shocks or by households' learning from past weather shocks. Instead, improvements in local development conditions appear to have partly influenced these labour responses in recent years.

5.2 Policy implications

Wheat, a staple crop in Pakistan, is particularly vulnerable to rising temperatures, which adversely affect its yields. Government policy on the only agricultural commodity, wheat support prices, has been effective in shaping land allocation decisions in response to climate shocks, especially when set at higher levels. While high support prices provide immediate relief by stabilising wheat cultivation during adverse weather conditions, they also foster dependency on a climate-sensitive crop. This reliance amplifies the risk of future climate-related losses, leaving regions more vulnerable to the impacts of climate change. Reducing this vulnerability while maintaining agricultural stability requires promoting crop diversification through incentives for heat-resistant crops. Supporting more resilient and diversified farming systems not only mitigates immediate climate risks but also enhances long-term resilience, particularly in resource-constrained regions, ensuring sustainable agricultural livelihoods.

5.3 Theoretical implications

From a theoretical perspective, relying on district-level data limits our ability to test or contribute household-level models of farmer behaviour, particularly those involving decisions on yield and input use, such as land, under uncertainty. Household-level models focus on how individual farmers respond to risks and uncertainties, like those posed by climate change, based on their specific resources and constraints. Our findings at the district level broadly align with these models, demonstrating adaptive land use patterns consistent with risk management behaviour. However, the aggregation inherent in district-level data restricts observation of household decision-making processes.

5.4 Limitations and future research avenues

The analyses conducted in this thesis have some limitations, which, although discussed earlier in the text, are restated here to highlight potential ideas and suggestions for future research.

In the first chapter, while the analysis focuses on a single province with relatively high climate variability, the study could have benefited from a more granular, micro-level approach. However, data limitations across time and space restricted the analysis to the district level. Furthermore, although irrigation and fertilisation are examined as mitigating strategies during the wheat growing season, incorporating other potential measures—such as changes in planting dates and crop varieties—could offer valuable avenues for future research on adaptive measures in the face of climate change.

In the second chapter, although our primary focus was on land use as an adaptive response to climatic shocks in the context of government support price for wheat, this analysis did not explicitly examine transitions or switching between crops. However, this study could serve as a baseline for understanding broader shifts between crops such as wheat, maize, and other high-value crops at the household level. Future research could expand on this by investigating these sub-crop level transitions to gain more detailed insights into farmers' adaptive land allocation strategies under temperature stress (see, for example Cui (2020) and He and Chen (2022)).

Additionally, measuring the welfare impact of crop diversification could provide valuable insights for future research. This could involve examining how transitioning to diverse cropping systems affects household income stability, food security, and resilience to climatic shocks. For instance, analysing whether diversification into heat-resistant or high-value crops leads to higher returns or mitigates risks during extreme weather events would highlight its role as a sustainable adaptation strategy. Such research could offer a more comprehensive understanding of the economic and social benefits of diversification in the context of climate change.

The final chapter utilises labour supply as an indicator due to data limitations, particularly the lack of information on hours worked and gender-disaggregated labour participation. This creates opportunities for future research to strengthen the analysis by including hours worked in off-farm employment and examining gender differences in labour responses. Such detailed data would enable a more comprehensive understanding of labour responses and adaptation strategies to climate change, capturing both the intensity of labour effort and the potentially distinct roles and constraints faced by men and women.

Finally, the essays in this thesis employ a static agricultural household model, which treats households as single decision-making units and does not account for the internal allocation of resources among members. While this approach is appropriate for analysing the impacts of climate change, it simplifies the complexities of household responses to environmental risks (Dercon, 2004; Aragón et al., 2021). To better understand how current decisions influence future outcomes, particularly in the context of household behaviour and adaptation to climate risks, incorporating dynamic models could be highly beneficial. Such models would enable researchers to evaluate how present decisions, such as labour supply choices or investments in irrigation, shape future outcomes, including crop yields and household income. This highlights an avenue for future research to explore these dynamics in greater depth, offering a clearer perspective on how expectations of future climate impacts can be analysed and how households adjust their behaviour accordingly.

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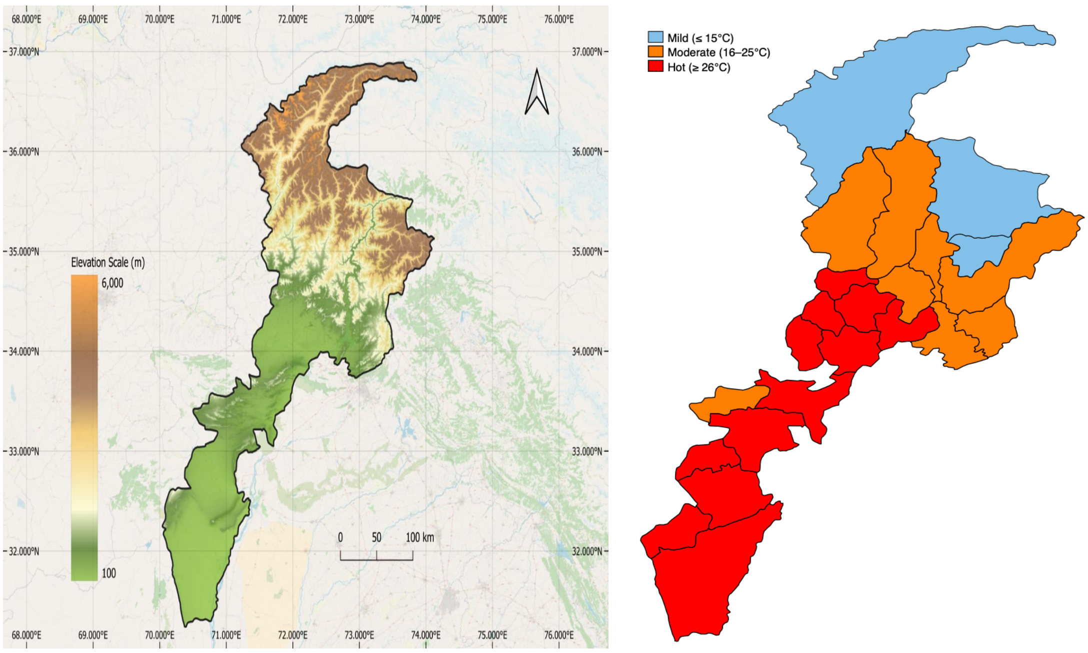
Appendix A

Wheat yield response to climate change: A district-level analysis in Pakistan



(a) Digital Elevation Model (DEM) for KP Province (b) District Categories by Temperature

Figure A.1: Geographical and climatic characteristics of districts in Khyber Pakhtunkhwa (KP) province

Note: Panel (a) shows the district-level Digital Elevation Model (DEM) of KP Province, obtained using the Copernicus Data Space Ecosystem browser, a web-based GIS platform that provides access to satellite imagery and digital elevation data. Panel (b) displays districts categorised as Mild (≤ 15°C), Moderate (16–25°C), and Hot (≥ 25°C), based on average temperatures during the wheat season. Temperature data were visualised using colour-coded categories in Stata with the `spmap` command.

Table A.1: Agroecological zones and their key characteristics

Zone	Description	Districts	District No.	Population (per km^2)	Climate	Rainfall (mm/year)	Temperature (°C)	Main Crops
North	Higher northern and northern highlands	Chitral, Upper Dir, Lower Dir, Swat, Buner, Shangla, Kohistan	7	15-150	Dry and cold	350-700	5-15	Wheat, Maize
East	Sub-humid eastern highlands and wet mountains	Abbottabad, Haripur, Mansehra, Battagram, Torghar, Kohistan	6	180-380	Humid and cold	700-1000$^+$	10-20	Wheat, Maize
Center	Central plain regions	Peshawar, Mardan, Charsadda, Nowshera, Swabi, Kohat, Hangu	7	500-700	Humid and warm	400-600	20-30	Wheat, Sugarcane
South	Piedmont plain, Suleiman piedmont	Bannu, Lakki Marwat, Dera Ismail Khan, Tank, Karak	5	90-100	Arid and hot	300-600	25-35	Wheat, Gram
		Total number of districts	25					

Source: Khyber Pakhtunkhwa Climate Change Policy, 2016 (POLICY (2016)). The classification into the four agroecological zones is based on geographical and climatic characteristics detailed in the policy. Temperature shows the wheat season temperature ranges, intended to offer a general overview of each zone. These values do not derive from the data used in our main analysis but provide a contextual background for understanding the agroecological zones.

Table A.2: Total number of temperature shocks experienced by districts in KP province from 2000 to 2019.

Zone	**District**	**Total Shocks**
North	Bunir	14
	Chitral	10
	Dir Lower	11
	Dir Upper	12
	Malakand	10
	Shangla	11
	Swat	10
East	Abbottabad	11
	Battagram	10
	Haripur	10
	Kohistan	10
	Mansehra	12
Central	Charsadda	13
	Hangu	14
	Kohat	17
	Mardan	12
	Nowshera	15
	Peshawar	14
	Swabi	12
South	Bannu	15
	D.I.Khan	17
	Karak	17
	Lakki Marwat	16
	Tank	17
Total	**Districts: 24**	**Shocks: 310**

Table A.3: climate variables exceed 1sd above long-run averages

Dep. var (wheat yield)	(1)	(2)	(3)	(4)
T_{max} at planting stage	-0.047	-0.048	-0.047	-0.046
	(0.273)	(0.249)	(0.261)	(0.294)
T_{max} at growing stage	0.003	0.002	0.007	0.007
	(0.936)	(0.947)	(0.845)	(0.843)
T_{max} at harvesting stage	-0.045	-0.045	-0.046	-0.046
	(0.406)	(0.401)	(0.368)	(0.370)
T_{min} at planting stage	0.004	0.004	0.002	0.004
	(0.933)	(0.933)	(0.960)	(0.930)
T_{min} at growing stage	0.007	0.007	0.011	0.010
	(0.876)	(0.878)	(0.817)	(0.824)
T_{min} at harvesting stage	-0.042	-0.043	-0.039	-0.040
	(0.375)	(0.380)	(0.424)	(0.403)
Excess rainfall at planting stage		0.100**	0.134***	0.134***
		(0.022)	(0.003)	(0.003)
Excess rainfall at growing stage		0.003	0.006	0.006
		(0.945)	(0.895)	(0.893)
Excess rainfall at harvesting stage		0.001	0.009	0.010
		(0.987)	(0.914)	(0.907)
Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
District-time trend	No	No	No	Yes
No. of obs.	480	480	480	480

Note: The dependent variable is the natural log of wheat yield. Climate variables are specific to three stages (planting, growing and harvesting) during wheat season. Weather variable at each stage is a binary indicator taking value 1 when the standardised weather variables exceed one standard deviations from their respective long-run district−level averages. District−level controls include total agricultural land, proportion of irrigated land for wheat, fertiliser application (in kg/ha) and share of population engaged in agriculture. Standard errors, in parentheses, are clustered at the district level. *** p-value $< 1\%$, ** p-value $< 5\%$, * p-value $< 10\%$.

Table A.4: Effects on wheat yields by using temperature as continuous variable (2000–2019)

Dep var: log(wheat yield)	(1)	(2)	(3)	(4)	(5)
T_{max} at planting stage	-0.058	-0.057	-0.046	-0.058	-0.059
	(0.464)	(0.535)	(0.597)	(0.500)	(0.496)
T_{max} at growing stage	-0.004	-0.001	0.036	0.055	0.058
	(0.893)	(0.991)	(0.603)	(0.451)	(0.432)
T_{max} at harvesting stage	-0.028	-0.004	0.010	0.003	-0.001
	(0.727)	(0.962)	(0.904)	(0.973)	(0.993)
T_{min} at planting stage		0.006	0.094	0.097	0.105
		(0.964)	(0.469)	(0.463)	(0.425)
T_{min} at growing stage		-0.004	0.011	-0.001	-0.005
		(0.953)	(0.868)	(0.986)	(0.944)
T_{min} at harvesting stage		-0.036	-0.063	-0.033	-0.027
		(0.705)	(0.620)	(0.745)	(0.790)
Rain at planting stage			-0.103	-0.108	-0.107
			(0.210)	(0.201)	(0.203)
Rain at growing stage			0.037	0.047	0.048
			(0.207)	(0.108)	(0.101)
Rain at harvesting stage			-0.033	-0.025	-0.024
			(0.293)	(0.281)	(0.292)
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	No	No	Yes	Yes	Yes
District-time trend	No	No	No	Yes	Yes
District Controls	No	No	No	No	Yes
Observations	480	480	480	480	480

Note: Dependent variable is the natural log of wheat yield. Climate variables correspond to climate anomalies—measured as continuous variables—during the planting, growing, and harvesting stages. District-level controls include the logarithms of irrigated area, total agricultural land, fertilizer usage, and the agricultural labor force. Standard errors, clustered at the district level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5: Effects on wheat yields by controlling for dry rainfall shocks at district level (2000-2019)

	(1)	(2)	(3)
T_{max} at planting stage	-0.057	-0.057	-0.054
	(0.465)	(0.465)	(0.529)
T_{max} at growing stage	-0.138*	-0.153*	-0.144*
	(0.077)	(0.079)	(0.084)
T_{max} at harvesting stage	0.031	0.037	0.036
	(0.425)	(0.394)	(0.434)
T_{min} at planting stage	0.004	0.002	0.014
	(0.942)	(0.968)	(0.795)
T_{min} at growing stage	0.013	0.014	0.004
	(0.782)	(0.783)	(0.925)
T_{min} at harvesting stage	-0.078	-0.076	-0.065
	(0.358)	(0.367)	(0.430)
Low rainfall at planting stage		0.039	0.050
		(0.521)	(0.430)
Low rainfall at growing stage		0.024	0.059
		(0.686)	(0.273)
Low rainfall at harvesting stage		-0.065	-0.062
		(0.477)	(0.492)
Year FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
District controls	No	No	Yes
District-time trend	No	Yes	Yes
No. of obs.	480	480	480

Note:The dependent variable is the natural log of wheat yield. Climate variables are specific to three stages (planting, growing and harvesting) during wheat season. Weather variable at each stage is a binary indicator taking value 1 when the standardised weather variables exceed 1.5 standard deviations from their respective long-run district−level averages. District−level controls include total agricultural land, proportion of irrigated land for wheat, fertiliser application (in kg/ha) and share of population engaged in agriculture. Standard errors, in parentheses, are clustered at the district level. *** p-value $<$ 1%, ** p-value $<$ 5%, * p-value $<$ 10%.

Table A.6: Ideal temperature and rainfall ranges for wheat

	wheat crop cycle		
Climate Variables	**Planting (Stage-I)**	**Growing (Stage-II)**	**Harvesting (Stage-III)**
Minimum Temperature (°C)	7-10	12-15	17-20
Maximum Temperature (°C)	20-26	16-20	30-35
Optimal Temperature (°C)	17-20	16-18	20-25
Rainfall (mm)	65-120	75-120	50-100
Sources	Rasul (1993); Musick et al. (1994); Porter and Gawith (1999); Kahlown et al. (2003); Prasad et al. (2008); Masters et al. (2010);Farooq et al. (2011); Siddiqui et al. (2012); Tack et al. (2015); Hussain and Bangash (2017); Harkness et al. (2020); Khan et al. (2020) Liu et al. (2023)		

Table A.7: Effects of fertiliser application on wheat yields under drought condition (2000-2019)

	Milder districts	Moderate districts	Hotter districts
	(1)	(2)	(3)
T_{max} at planting stage	0.000	0.139	-0.029
	(0.000)	(0.652)	(0.887)
T_{max} at growing stage	-0.238**	-0.180**	-0.028
	(0.035)	(0.021)	(0.900)
T_{max} at harvesting stage	-0.045	-0.021	-0.157**
	(0.598)	(0.690)	(0.020)
T_{min} at planting stage	-0.167	-0.059	-0.197
	(0.403)	(0.618)	(0.299)
T_{min} at growing stage	0.276	-0.024	-0.101
	(0.697)	(0.730)	(0.501)
T_{min} at harvesting stage	0.216***	0.113	0.255
	(0.006)	(0.227)	(0.129)
Deficit rainfall at planting stage	-0.112	-0.206	-0.242**
	(0.846)	(0.447)	(0.017)
Deficit rainfall at growing stage	0.170**	0.031	0.007
	(0.048)	(0.592)	(0.964)
Deficit rainfall at harvesting stage	-0.195	0.031	0.245**
Controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
District-time trend	Yes	Yes	Yes
Observations	115	277	115

Appendix B

Adaptation to extreme temperature: Evidence from land allocation decisions in agricultural sector of Pakistan

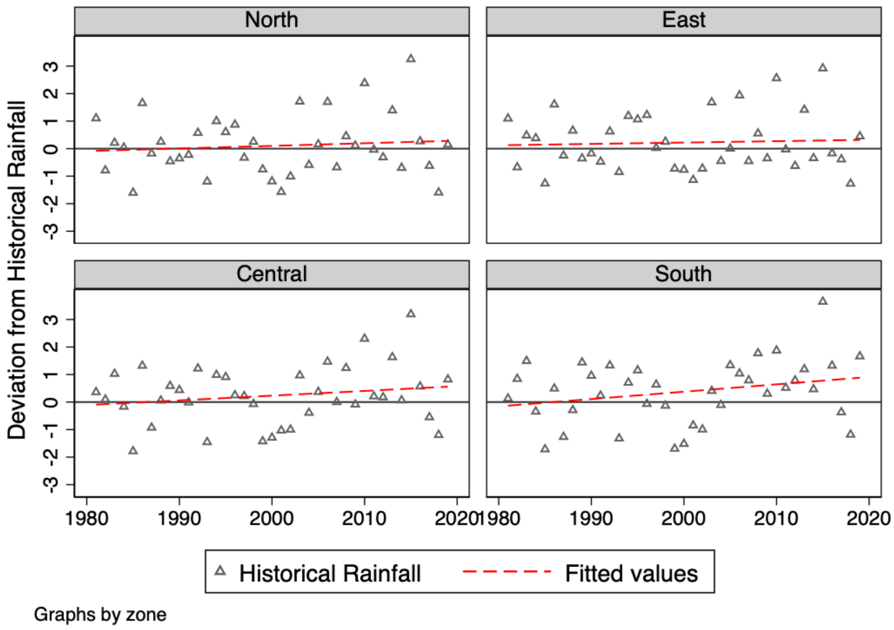


Figure B.1: Deviation of annual rainfall from the historical mean

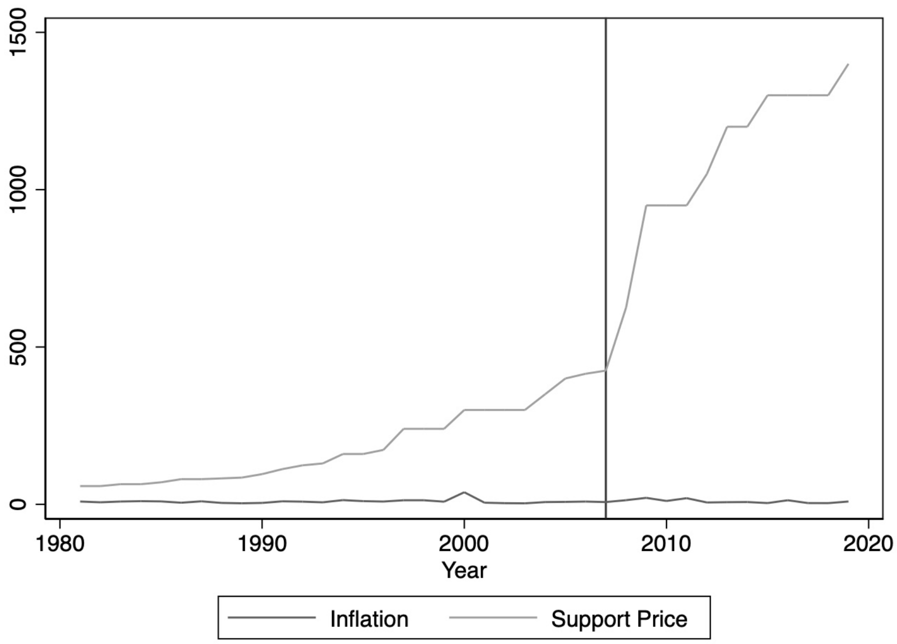


Figure B.2: Support price vs deflated GDP

Table B.1: Regional variation in land allocation in response to lagged heat

	Wheat land	Other Cropland	Total Agric. land
	(1)	(2)	(3)
Lagged Heat (L1)	-0.048*	0.037**	-0.006
	(0.028)	(0.015)	(0.004)
Base Catagory = North			
Heat (t-1) × East	-0.048	-0.033*	0.008*
	(0.069)	(0.017)	(0.004)
Heat (t-1) × Centre	-0.144**	0.052*	0.013***
	(0.057)	(0.029)	(0.003)
Heat (t-1) × South	-0.258**	0.072*	0.014**
	(0.115)	(0.041)	(0.006)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Obs.	801	801	801

Notes: The dependent variables represent the natural logarithm of land use type. 'Heat' is a binary variable set to 1 when the temperature from the previous year exceeds 1.5 standard deviations above the long-run annual average for a given district. 'Rainfall' (in millimeters) is the one-year lagged yearly average at the district level. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Table B.2: Effect of market price on wheat across the regions

	North (1)	East (2)	Centre (3)	South (4)
Heat $(t-1)$	-0.030	-0.015	0.208	-0.101
	(0.103)	(0.559)	(0.250)	(0.345)
Rainfall (mm)	0.046	0.179	0.092	0.143
	(0.716)	(0.440)	(0.694)	(0.306)
Market price $(t-1)$	-0.006	0.001	-0.002	0.015***
	(0.211)	(0.797)	(0.293)	(0.010)
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Region time trend	Yes	Yes	Yes	Yes
Obs.	189	140	194	138

Table B.3: Impact when controlling for uncultivated land in in pre− and post− periods

	North		East		Centre		South	
	Pre−2006 (1)	Post−2006 (2)	Pre−2006 (3)	Post−2006 (4)	Pre−2006 (5)	Post−2006 (6)	Pre−2006 (7)	Post−2006 (8)
Heat $(t-1)$	-0.263***	0.268**	-0.879***	0.095	-0.729***	-0.106	-0.753**	0.340***
	(0.001)	(0.036)	(0.001)	(0.336)	(0.000)	(0.132)	(0.017)	(0.002)
Rainfall (mm)	-0.177*	-0.105	-0.168*	0.041	-0.195	0.098	0.115	0.035
	(0.062)	(0.188)	(0.065)	(0.363)	(0.508)	(0.793)	(0.769)	(0.628)
Uncultivated land (ha)	0.270**	0.046	0.820	0.002*	0.109*	0.005*	0.083	-0.000
	(0.048)	(0.512)	(0.167)	(0.066)	(0.064)	(0.099)	(0.787)	(0.995)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	141	91	107	65	138	91	93	65

The dependent variables represent the natural logarithm of wheat land. 'Heat' is a binary variable set to 1 when the temperature from the previous year exceeds 1.5 standard deviations above the long-run annual average for a given district. 'Rainfall' (in millimeters) is the one-year lagged yearly average at the district level. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Appendix B.1 Differentiation of FOC with respect to weather (W)

Given the First-Order Conditions (FOC):

$$p_1 \frac{\partial c_1}{\partial L_1} = p_2 \frac{\partial c_2}{\partial L_2} = s + r$$

We differentiate this condition with respect to weather (W):

$$\frac{\partial}{\partial W} \left(p_1 \frac{\partial c_1}{\partial L_1} \right) = \frac{\partial}{\partial W} \left(p_2 \frac{\partial c_2}{\partial L_2} \right)$$

Since p_1 and p_2 are constants and optimal land allocation for both crops (say, $n = 1, 2$):

$$\frac{\partial L_n^*}{\partial W} = \frac{\partial^2 c_n}{\partial L_n \partial W} \bigg/ \frac{\partial^2 c_n}{\partial L_n^2}$$

This equation explains how changes in weather W affect the optimal land allocation L_n^* for a crop. Such as:

- L_n^*: This is the optimal amount of land allocated to crop n.
- W: Weather or climate conditions.
- c_n: The amount of crop yield produced with a certain amount of land.
- $\frac{\partial L_n^*}{\partial W}$: This shows how much the optimal land for the crop changes in response to a change in the weather.
- Here the numerator, $\frac{\partial^2 c_n}{\partial L_n \partial W}$, tells us how the yield of the crop changes with both land use and weather. It shows how responsive the crop's yield is to weather changes when more land is used.

  If the weather improves for the crop (e.g., ideal temperature), the yield per unit of land increases. This would increase the marginal productivity of land (MPL), which means more benefit from each additional unit of land.
- The denominator, $\frac{\partial^2 c_n}{\partial L_n^2}$, tells us about diminishing returns. This means that when more land is allocated to grow the crop, the extra yield you get from each additional unit of land decreases (after a certain point). This value is negative because more land does not always mean more yield.

The denominator is negative (because of diminishing returns), so the overall value of land depends on the numerator, which is how weather affects crop yield when more land is added.

If climate change brings better weather for Crop 1, the productivity of land used for Crop 1 improves. The farmer will then allocate more land to Crop 1 by shifting land away from non-agricultural uses (or from another crop like Crop 2). This happens because the weather makes it more profitable to grow Crop 1.

Appendix B.2 Land adjustment

When land cannot be shifted to non-agricultural uses, the farmer's optimization focuses on land allocation between crops 1 and 2. The objective is to maximize profit while L_3 is fixed.

The optimal land allocation is when the marginal values of land for both crops are equal:

$$p_1 \frac{\partial c_1}{\partial L_1} = p_2 \frac{\partial c_2}{\partial L_2}$$

This ensures that land is allocated where the additional value from land is the same for both crops.

Impact of Climate Change: To determine how climate change affects the land allocation of Crop 1, we analyze:

$$\frac{\partial L_1^*}{\partial W} = \frac{p_1 \frac{\partial^2 c_1}{\partial L_1 \partial W} - p_2 \frac{\partial^2 c_2}{\partial L_2 \partial W}}{p_1 \frac{\partial^2 c_1}{\partial L_1^2} + p_2 \frac{\partial^2 c_2}{\partial L_2^2}}$$

The numerator:

$$p_1 \frac{\partial^2 c_1}{\partial L_1 \partial W} - p_2 \frac{\partial^2 c_2}{\partial L_2 \partial W}$$

It represents the change in yield with both land and weather. It captures how weather affects the marginal productivity of land for each crop.

The denominator:

$$p_1 \frac{\partial^2 c_1}{\partial L_1^2} + p_2 \frac{\partial^2 c_2}{\partial L_2^2}$$

This is negative due to diminishing returns. It combines the effects of diminishing marginal productivity for both crops.

Interpretation:

- If $\frac{\partial L_1^*}{\partial W}$ is positive, the optimal land for Crop 1 increases as weather improves.
- If $\frac{\partial L_1^*}{\partial W}$ is negative, the optimal land for Crop 1 decreases as weather becomes less favorable.

Appendix C

Extreme temperature, labour supply, and subsistence farming: Evidence from Pakistan

Table C.1: Effect of lagged temperature shock on share of off-farm income

Dep var: Share of off-farm income	(1)	(2)
Heat(t) × Wave-1(2001)	-0.192*	-0.040
	(0.072)	(0.080)
Heat(t) × Wave-2 (2005)	0.000	0.000
	(0.000)	(0.000)
Heat(t) × Wave-3 (2007)	-0.240***	-0.167
	(0.008)	(0.058)
Heat(t) × Wave-4 (2011)	-0.205*	-0.064
	(0.082)	(0.656)
Heat(t) × Wave-5 (2015)	0.352***	0.240*
	(0.001)	(0.091)
Heat(t) × Wave-6 (2018)	0.235***	0.163**
	(0.000)	(0.011)
Landholding (acres)	-0.347***	-0.338***
	(0.000)	(0.000)
Rainfall (mm)	Yes	Yes
Individual Controls	Yes	Yes
Year FE	Yes	Yes
Province-year FE	No	Yes
Households	21200	21200

Note: The dependent variable is share of off-farm income. Heat is temperature shocks, and calculated as 1.5sd above historical temperature over the growing season months. All columns include year fixed effects. We control for rainfall (mm)-averaged over growing season months. We present standard errors clustered by district in parentheses. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Table C.2: Effects on off-farm labour: Lagged temperature as continuous variable

Dep var: Labour supply	(1)	(2)	(3)	(4)
Heat(t) × Wave-1 (2001)	-0.041	-0.094	-0.118	-0.092
	(0.177)	(0.579)	(0.478)	(0.620)
Heat(t) × Wave-2 (2005)	-0.042	-0.037	0.046	0.035
	(0.198)	(0.651)	(0.669)	(0.745)
Heat(t) × Wave-3 (2007)	-0.066**	-0.037	-0.041	-0.093
	(0.043)	(0.488)	(0.408)	(0.172)
Heat(t) × Wave-4 (2011)	-0.041	-0.038	-0.036	-0.040
	(0.102)	(0.335)	(0.500)	(0.477)
Heat(t) × Wave-5 (2015)	0.068**	0.061	-0.025	-0.084
	(0.013)	(0.182)	(0.655)	(0.310)
Heat(t) × Wave-6 (2018)	0.033*	0.038	-0.025	-0.043
	(0.071)	(0.278)	(0.288)	(0.366)
Household Size	0.033***	0.032***	0.032***	0.032***
	(0.003)	(0.004)	(0.004)	(0.004)
Age of Household Head	0.000	0.000	0.000	0.000
	(0.947)	(0.742)	(0.812)	(0.803)
Landholding (acres)	-0.120***	-0.122***	-0.122***	-0.122***
	(0.005)	(0.003)	(0.003)	(0.003)
Night Lights (mean)	0.001	0.003	-0.001	-0.001
	(0.465)	(0.380)	(0.455)	(0.432)
Rainfall (mm)	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District Trends	No	Yes	Yes	Yes
Province-Year FE	No	No	Yes	Yes
Households	21200	21200	21200	21200

Note: The dependent variable is off-farm labour supply, which is an indicator variable taking value one for households that have at least one of the family members working off-farm. Heat is a continuous variable representing average temperature over the growing season, expressed as standardised z-scores. All specifications include year fixed effects. We control for rainfall (mm)-averaged over growing season months. We present standard errors clustered by district in parentheses. *** p-value $< 1\%$, ** p-value $< 5\%$, * p-value $< 10\%$.

Table C.3: Effects on Off-farm labour supply by controlling for Rainfall shocks: A robust test

	(1)	(2)	(3)
Heat(t) × Wave-1(2000/01)	-0.021	-0.047	-0.056
	(0.649)	(0.540)	(0.461)
Heat(t) × Wave-2 (2005/06)	-0.023	0.121	0.116
	(0.577)	(0.194)	(0.181)
Heat(t) × Wave-3 (2007/08)	-0.100***	-0.066	-0.101
	(0.010)	(0.122)	(0.192)
Heat(t) × Wave-4 (2011/12)	0.002	0.040	0.039
	(0.963)	(0.244)	(0.248)
Heat(t) × Wave-5 (2015/16)	0.157**	0.066***	0.061***
	(0.011)	(0.000)	(0.001)
Heat(t) × Wave-6 (2018/19)	0.092**	0.032*	0.031*
	(0.013)	(0.099)	(0.099)
Rainfall Shock	-0.026**	0.002	0.003
	(0.047)	(0.846)	(0.709)
Landholding (acres)	-0.117***	-0.122***	-0.124***
	(0.006)	(0.003)	(0.003)
Individual Controls	Yes	Yes	Yes
Annual luminosity	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
District-time trend	No	Yes	Yes
Province-year FE	No	Yes	Yes
No. of obs.	21233	21233	20927

Note: The dependent variable is share of off-farm income. Heat is temperature shocks, and calculated as 1.5sd above historical temperature over the growing season months. Col (3) excluding districts where less that 50% of household cultivate wheat.All columns include year fixed effects. We control for rainfall shocks (-1.30=<SPI>=1.30) over growing season months. We present standard errors clustered by district in parentheses. *** p-value $< 1\%$, ** p-value $< 5\%$, * p-value $< 10\%$.

Table C.4: Contemporaneous effects of temperature on crop yields by crop

Dep var: Yield	Wheat (1)	Rice (2)	Cotton (3)	Maize (4)	Sugarcane (5)
Heat (t)	-0.152*	-0.139	-0.147**	-0.519***	-0.338*
	(0.094)	(0.482)	(0.021)	(0.001)	(0.065)
Rainfall (t)	-0.006***	0.009***	-0.011***	-0.009***	-0.023***
	(0.000)	(0.000)	(0.005)	(0.001)	(0.000)
Land size (acres)	0.707***	0.738***	0.735***	0.527***	0.574***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall (t)	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Growing season FE	Yes	Yes	Yes	Yes	Yes
District time-trend	Yes	Yes	Yes	Yes	Yes
Observations	19303	6446	5660	4234	2705

The dependent variable is the natural log of individual crop yield. Weather variables are specific to each crop growing season. Heat is a binary indicator taking value 1 when temperature exceeds 1.5 standard deviations from the growing season historical average for a given district. Rainfall (mm) is the average rainfall during each crop- growing season at district level. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Table C.5: Contemporaneous effects of temperature shocks on yields

Dep var: Crop yields	(1) With rainfall	(2) Without rainfall
Heat (t)	-0.295***	-0.300***
	(0.000)	(0.000)
Rainfall (t)	-0.005***	
	(0.003)	
Landholding (acres)	0.679***	0.679***
	(0.000)	(0.000)
Crop FE	Yes	Yes
Year FE	Yes	Yes
Province-year FE	Yes	Yes
Crop time-trend	Yes	Yes
District time-trend	Yes	Yes
Observations	38493	38493

The dependent variable is the natural log of yields from the 5 major crops (wheat, rice, maize, cotton and sugarcane). Weather variables are specific to each crop growing season. Heat is a binary indicator taking value 1 when temperature exceeds 1.5 standard deviations from the growing season historical average for a given district. Rainfall (mm) is the average rainfall during each crop-growing season at district level. Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Table C.6: Impact of local development

Dep. Var: Off-farm labour	(1)	(2)
Light intensity	0.025**	0.030**
	(0.013)	(0.047)
Controls	Yes	Yes
Year FE	Yes	Yes
Province-year FE	No	Yes
No. of obs.	21233	21233

Controls include household size, household head age and landholding (acres). Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

Table C.7: Regression results: heteorgenous effects by luminosity levels

Dep Var: Off-farm labour	(1) Before 2011	(2) After 2011	(3) Before 2011	(4) After 2011
Heat (t-1)	-0.027	0.069**	-0.411**	-0.131
	(0.508)	(0.032)	(0.034)	(0.785)
Heat (t-1) $\times$ Luminosity			0.037**	0.016
			(0.042)	(0.719)
Rainfall (t-1)	0.000	-0.002	0.000	-0.002***
	(0.726)	(0.120)	(0.782)	(0.002)
Annual luminosity	0.025	0.016	0.017*	0.012
	(0.145)	(0.38)	(0.081)	(0.528)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
No. of obs.	13853	7347	13853	7347

Controls include household size, household head age and landholding (acres). Standard errors, in parentheses, are clustered at the district level. *** p-value < 1%, ** p-value < 5%, * p-value < 10%.

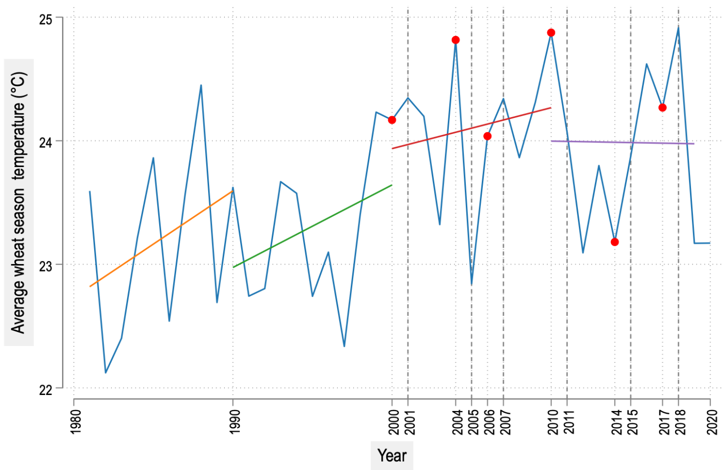


Figure C.1: Average temperature over time

Dots correspond to the years used for our lagged "Heat" variable.The Vertical lines present survey years