Essays on climate change, wheat production, and adaptation strategies in Pakistan.

by

Abdur Rub

B.A., University of Hertfordshire, 2009
M.Sc., University of Glasgow, 2013

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

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Abstract

Pakistan is one of the most vulnerable countries to climate change and sustainable growth in its wheat supply holds one key to food security. Therefore, the purpose of this research is to analyze the relationship between weather and wheat production in Pakistan and assess the adaptation possibility. The first paper, using district-level agricultural data spanning 37 years and covering more than 80% of wheat production in the country, provides estimates of the overall and intra-seasonal impacts of extreme temperature exposure. It finds that the impact of temperature extremes varies across different seasons such that the freezing temperatures in the fall season and warming of the winter season are found to be the biggest drivers of yield loss, with 16.7% and 8.8% yield reduction respectively. The future warming scenarios suggest overall mild gains in wheat yields. The second paper utilizes a richer farm-level dataset with 33,621 plot-year observations to estimate the warming impacts across irrigation status and explore heterogeneities across wheat varieties. It finds that warming temperatures are particularly harmful in rainfed conditions and irrigation provides significant protection against heat stress. estimating a 70% smaller yield reduction. Moreover, the paper examines the heterogeneity of temperature effects across wheat varieties and finds that newer varieties are associated with higher yields and more heat resistance. Further, variety selection is also found to have significant potential in mitigating the adverse impact of warming temperatures. The research aims to inform future research on the relationship between weather and wheat yields in Pakistan by providing evidence of the impact of temperature on wheat yields and measuring the effectiveness of possible adaptation measures.

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Table of Contents

List of Figures

List of Tables

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Chapter 1 - Introduction

Extreme weather events such as floods, droughts, and heat waves are becoming increasingly frequent in Pakistan, making it among the top ten countries most affected by climate change. The vulnerability to climate change along with heavy reliance on the agricultural sector makes the relationship between weather and agricultural production an important area of research.

Therefore, this research presents two papers on the relationship between climate change and wheat production in Pakistan. Chapter 2 presents the first paper that aims to estimate the nonlinear impact of temperature extremes on the wheat production of two of the largest wheat-producing provinces of Pakistan. It extends the analysis by estimating the intra-seasonal impact of the temperature changes. This research links 37 years of agricultural data with globally-gridded weather observations and employs the exposure variable treatment of the weather data. As the temperatures are expected to rise, it further provides evidence of future warming scenarios on wheat yield. The purpose of this paper is to inform future research in Pakistan in the context of climate impacts on wheat production.

Chapter 2 utilizes are richer dataset of farm-level agricultural variables to extend the research toward analyzing potential pathways to climate adaptation. It focuses on exploring the heterogeneity of the warming impacts across wheat varieties and providing a comparison of two widely used adaptation methods, irrigation and variety selection, in mitigating the impact of future warming on wheat yields.

Chapter 2 - Estimating the Nonlinear Effects and Intra-seasonal Variation of Temperature Extremes on Wheat Yields in Pakistan

Introduction

Climate change is a global phenomenon with countries across the world joining hands in understanding its impacts and proposing adaptation and mitigation solutions (Pachauri et al., 2014). Developing countries are considered the primary recipients of the damages due to greater vulnerability caused by geographic factors and limited structural, institutional, and financial abilities (Wijaya, 2014). These countries typically rely on their agricultural sector for a significant portion of individual income, which is directly affected by the changing climate, as the climate variables serve as key inputs to the agricultural production process. For countries like Pakistan, the relationship between climate and agriculture is of key relevance due to its extreme vulnerability to climate change and heavy reliance on the agricultural sector. It is the largest source of foreign exchange earnings and contributes 24% of the country's GDP and employs half of the labor force (PBS, 2019). Among the agricultural contribution to the economy, wheat is Pakistan's largest staple crop which accounts for 14% of value-added in agriculture and three percent of Pakistan's GDP. It is grown by 80% of farmers on 40% of the country's total cultivated land (Prikhodko & Zrilyi, 2013). Therefore, sustainable growth in wheat production is of key importance to the economy of Pakistan.

Moreover, Pakistan is among the world's top ten wheat producers and a traditionally net exporter of wheat, but wheat production is not growing at the rate of the increasing demand, and it is increasingly becoming a net importer of wheat in recent years (Raza, 2023). Therefore, as a significant contributor to global wheat production, the wheat yield changes in Pakistan may also have considerable implications for the global wheat supply.

Despite the importance, Pakistan is increasingly facing extreme climate events including floods, droughts, and heat waves. According to Eckstein et al., (2021), Pakistan is among the top ten most affected countries by climate change. In August 2022, Pakistan faced record-breaking levels of precipitation throughout the country causing severe flooding resulting in over 1,500 deaths and 30 million people displaced. It was estimated that over one-third of the country is underwater with an estimated loss of over $15 billion to the economy (World Bank, 2022). The aftermath looks even bleaker, with agricultural and livestock reserves depleted and supply chains destroyed,[1] Pakistan is on the brink of famine and waterborne diseases have already reached endemic levels.

Furthermore, sustainable wheat production is also at the forefront of the food security policy in Pakistan. It is the staple crop of Pakistan which contributes to 72 percent of daily caloric intake and a per-capita consumption of around 124 kilograms (kg) per year, one of the highest in the world (Raza, 2020). Considering this extreme vulnerability towards climate change and a heavy reliance on wheat production make the assessment of weather impacts on crop yields a research area of key relevance for Pakistan.

Therefore, the objective of this paper is to estimate the nonlinear impacts of temperature extremes on the production of wheat crops in Pakistan. It provides a deeper understanding of weather impacts on wheat yields by estimating the intra-seasonal impacts of temperature changes. The current literature exploring the intra-seasonal warming impacts is limited to a few studies (e.g. Ortiz-Bobea et al., 2019; Tack et al., 2015) focusing primarily on the US. The evidence from developing countries and more specifically Pakistan is even more rare. The statistical studies on

[1] According to International Rescue Committee (2022), 4 million acres of crops and 800,000 livestock were destroyed.

Pakistan are limited to using aggregated weather data (Ali et al., 2017; Janjua et al., 2010; Shakoor et al., 2011; Siddiqui et al., 2012), thus unable to exploit the wide range of variation available in daily level datasets and runs the risk of biased estimates of the nonlinear effects (Schlenker & Roberts, 2009). These studies also lack the utilization of fine-scale satellite weather datasets and are primarily reliant on the weather station data which is sparsely located and argued to be less reliable (Parkes et al., 2019).

Therefore, this study aims to contribute to the literature on climate impacts on wheat yields in Pakistan by using daily weather data covering over 80% of the country's wheat production. Following the approach proposed by (Schlenker & Roberts, 2009), this study estimates the nonlinear effects of temperature changes on wheat yield by preserving the variations in the daily data. The temperature distribution within a day was approximated using a synodal function (Snyder, 1985) to provide hourly exposure for each degree of Celsius. These exposure variables provide the time the wheat crop was exposed to each one-degree temperature interval. These variables were then summed across all days of the growing season. The study further divides the growing season into three three-month periods to disaggregate the effects on different stages of the crop cycle. In addition to the estimation of the effects based on the historical data, future warming impacts for a uniform increase in the daily temperature of one degree through five degrees Celsius were also calculated.

The results show that the wheat yield in Pakistan has a varied response to changes in temperature. The impacts vary significantly in the three periods within the growing season. Depending on the period, both the low and the high extremes of the temperature show detrimental effects.

The following sections of the paper include in chronological order; a brief review of relevant literature, an outline of research objectives, a discussion of the study area and data sources, and methods employed to carry out the research, the results of the study, and a conclusion.

Literature Review

Climate change is one of the most prominent issues in the world evidenced by the increasing efforts to coordinate a global response to tackle its adverse impacts (Pachauri et al., 2014). Although the change in climate is a constant process in the history of the earth, the rate at which it is exhibiting weather variation is alarming for human life. The observed changes in the climate only in the 21st century are comparable to the magnitudes of the largest global changes in observed history (Kemp et al., 2015; Pecl et al., 2017). It is estimated that since the 19th century, the average global temperature has increased by ~0.8°C along with rising sea levels, changes in seasonal patterns, and abrupt extreme events, and expected to further rise to 1.5°C by 2050 (Pachauri et al., 2014). The majority of this rapid change is credited to anthropogenic activities leading to an increase in greenhouse gas emissions (GHG) which is exacerbated by excessive deforestation (Arora, 2019). This is highlighted by the fact that, in the last 50 years, the rate of increase in land temperatures (surface air temperature) is twice as high as the temperatures over oceans (Solomon et al., 2007).

Based on this rate of change, it is highly plausible that the warming of temperature will continue. These changes have the potential to influence a wide range of outcomes, among which the impact on agriculture is considered to be one of the largest (Nordhaus, 1991). Climate change influences agriculture through increased events of heatwaves, droughts, floods, irregular patterns of precipitation, and extreme temperatures (Arora, 2019). Both temperature extremes are found to be harmful to crop production. High temperatures adversely impact crop yields (Asseng et al., 2013; Rosenzweig & Parry, 1994) typically through the impact on the floral stage of plant growth (Hatfield & Prueger, 2015) where grain filling period is reduced by exposure to temperature extremes (Zabel et al., 2021) and thus, leading to lower yields. Whereas low temperatures affect different stages of crop growth. The temperatures below the required thresholds can cause poor germination, seedling stunting, and reduced tillering (Kaneda, 1970). Moreover, in the reproductive stage, the adverse impact of low temperatures is found to inhibit the fertilization process (Thakur et al., 2010).

Due to the strong influence of weather on crop production, the understanding of the impact of temperature extremes on crop yields has gathered considerable attention in the literature. Vogel et al., (2019) using machine learning algorithms find that climate variables explain 20-49% of the variance in global crop yields. Moreover, they show that temperature extremes have a stronger association with yield anomalies as compared to precipitation extremes. The study further finds evidence of irrigation mitigating the harmful impacts of weather on crop yields. In another study, Lesk et al., (2021) investigate the interaction of temperature and moisture to explain heat sensitivity of global crops. They find that crop yield reductions are more pronounced, and an additional five percent yield loss, in regions with hotter growing seasons, accompanied by decreased precipitation and evapotranspiration. Therefore, they provide evidence that the changes are beneficial in countries in Asia, where there is a weak linkage between temperature and moisture.

On the other hand, there is evidence of a positive impact of temperature changes on wheat yields. Zhao et al., (2017) provides a compilation of published results on the impact of temperature on crop yields from four different analytical strands of literature; global grid-based, local point-based, statistical regressions, and field warming experiments. They find that the majority of the results suggest a negative impact of warming temperatures whereas, in some studies, positive impacts are reported (e.g. Tian et al., 2012). Using a five-year field warming experiment, Tian et al., (2012) find that in Yangtze Delta Plain, China, warming increased winter wheat grain yield by 16.3%. They suggest that warming increased the numbers of productive spikes and filled grains and stimulated the filling rate, particularly for the inferior grains. Moreover, a study using the dataset for the Northwestern semi-arid region of China from 1981 to 2005, find similar results where the changes in the temperature were found to increase winter wheat yields at both high and low altitude sites by 3.1% to 4% respectively (Xiao et al., 2008).

A more recent branch of statistical studies includes degree days/exposure bin models with a focus on estimating the nonlinear impact of temperature extremes on agricultural production. These studies incorporate the whole distribution of temperature variables and thus, preserve the variation which is lost in the aggregation of weather observations. Schlenker & Roberts (2009) in their seminal study on the nonlinear effect of climate change on US crop yields provide thresholds of yield changes for corn, soybean, and cotton. They find that temperatures above 29°C are extremely detrimental to crop yield. Tack et al., (2015) estimated the effects of warming temperatures on US wheat yields utilizing a variety of field trial data. They disaggregated the growing season into three seasons to decompose the temperature impacts. They found that the largest drivers of yield reduction are freezing temperatures in the Fall season and extreme heat in the Spring season. Other studies that explore the seasonal variation of temperature impacts include Ortiz-Bobea et al., (2019) which explore the intra-seasonal sensitivity of crop yields in the US to temperature and moisture variables. They find that exposure to high temperatures in the warmer parts of the growing season and relatively low moisture in the middle portion of the growing season are the biggest drivers of yield loss.

Despite the considerable uptake of this approach in the last decade, the evidence from Pakistan is still limited to the use of monthly averages of weather variables (Ali et al., 2017; Siddiqui et al., 2012), the annual averages (Shakoor et al., 2011), or the growing season averages (Hanif et al., 2010; Janjua et al., 2010). As argued by Schlenker & Roberts (2009), the average weather variables can cause biased nonlinear estimates. Moreover, our literature review suggests that the use of global gridded datasets is not utilized to extract daily data for Pakistan which can be particularly useful given the geographic sparsity of weather stations. Parkes et al. (2019) provide a useful review of the availability and sensitivity of the gridded datasets available for South Asia.

Research Objective

Focusing on this research gap, the purpose of this paper is to provide a deeper understanding of the nonlinear impact of temperature extremes on wheat yields in Pakistan. We utilize the globally gridded satellite weather data that provides daily observations and link it with the wheat yield data reported at the district level to estimate the role of temperature changes on wheat production. Therefore, the research objective is to estimate the nonlinear impact of increased exposure to extreme temperatures. We extend the analysis considering the long growing season typically from September through May, by dividing the growing season into three seasons to estimate a season-wise disaggregated impact. Moreover, based on these estimates, we aim to forecast the future warming impacts of a uniform increase in temperatures for the growing season, as well as for each of the specific seasons, for a range of warming scenarios. The aim, therefore, is to generate evidence to inform future research on potential adaptation.

Study Area

The study area includes the provinces of Punjab and Sindh which collectively contributes to 84% of the wheat production in Pakistan, with Punjab accounting for 82% of the output and Sindh the remaining 18%.

Punjab is the largest province in Pakistan and has a significant contribution to the agricultural sector, with wheat being the major crop produced in the region. The province has a vast irrigated agricultural land supporting crop production. The irrigation system comprises a network of canals, distributaries, and watercourses, which supply water to the fields. Apart from wheat, other crops grown in Punjab include cotton, sugarcane, rice, and maize. In recent years, Punjab has seen a significant increase in the use of modern technology in agriculture, including precision agriculture, drip irrigation, and high-efficiency irrigation systems. This has led to higher crop yields, reduced water usage, and improved water management practices.

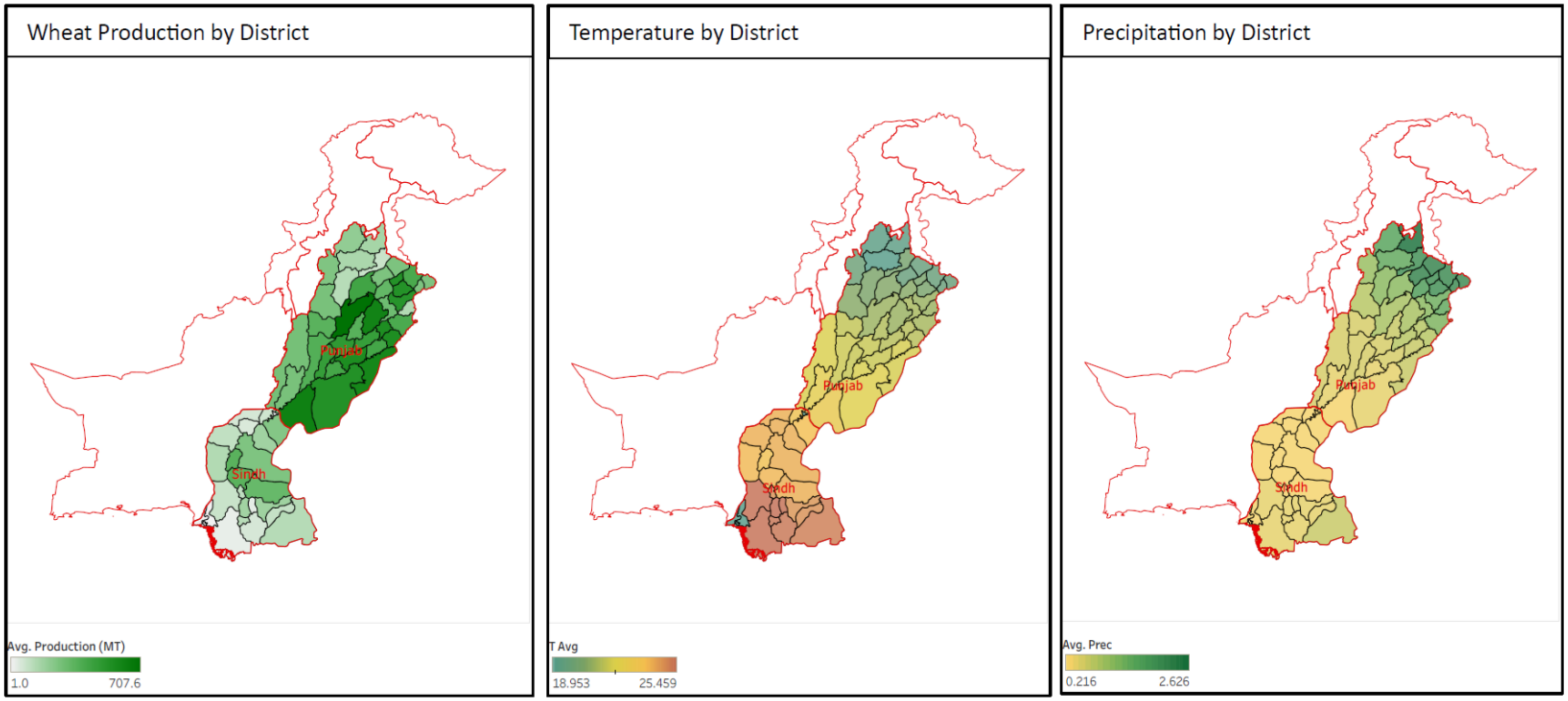
Sindh, on the other hand, is the second-largest province in Pakistan and also contributes significantly to the agricultural output of the country, especially in terms of rice and cotton production. However, wheat is also an important crop in the province, with the majority of production concentrated in the northern and central parts of the region.

Figure 1 provides an overview of the study area, displaying the average wheat production, average temperature, and average precipitation in each district of Pakistan from 1981 to 2017. Among the two provinces, most of the production is concentrated in Punjab, which includes the mountainous northern region and the plains of central and southern Punjab. The northern region of Punjab is characterized by lower wheat production, lower average temperature, and higher rainfall. These regions include the mountainous Murree Kahuta up-lands, the Potowar plateau, and the hilly Salt Range. Based on the topographical characteristics of this region, irrigation is extremely limited, and crop production relies heavily on rainfall. The central and southern regions of Punjab contribute the highest proportion of wheat production in Pakistan, despite having lower rainfall and higher temperatures, as compared to the northern region.

Whereas the climate in the Sindh region is hot and dry, with temperatures ranging up to 49°C. The annual rainfall in Sindh is relatively low, ranging between 100-300 mm, making irrigation a critical factor in crop production. The topography of Sindh is characterized by plains and desert areas, which support crop cultivation. Despite the challenging weather conditions, Sindh has been able to produce significant quantities of wheat due to the access to irrigation. The major irrigation systems in Sindh include the Indus Basin Irrigation System, the Left Bank Outfall Drainage (LBOD) System, and the Right Bank Outfall Drainage (RBOD) System, which provides water to the fields for crop production.

Administratively, the province of Punjab is divided into 36 districts and Sindh into 30 districts. Since 1981, the first year of the dataset, the district boundaries have changed for multiple districts. Therefore, to allow comparability over time, the district boundaries of 1981 were used. This reduces the total number of districts in both provinces to 34.

Figure 1: Study Area Characteristics



Data Sources and Description

The weather data were obtained from CPC Global Unified Temperature data provided by the NOAA PSL, Boulder, Colorado, USA, from their website at https://psl.noaa.gov. The dataset is created using the optimal interpolation of quality-controlled gauge records of the Global Telecommunication System (GTS) network (Fan & Dool, 2008). It provides daily observations of minimum and maximum temperature and precipitation variables on a spatial resolution of global 0.50 x 0.50-degree latitude/longitude grids. The subset for Pakistan was extracted through the latitude and longitude information of each district obtained from the weather station data by the Pakistan Meteorological Department.

The agricultural data includes yearly wheat production and crop area observations for 34 districts of Punjab and Sindh provinces, as per the 1981 boundaries. This covers all 66 present-day districts of the two provinces. The temporal range of the dataset is from the year 1981 through 2017. The data were obtained from the Pakistan Bureau of Statistics (PBS, 2010) through its yearly Agricultural Statistics of Pakistan publications. The yield variable equals total district-level production divided by the area harvested. Moreover, the irrigation data reflecting the percentage of irrigated area for each district was obtained from the Agricultural Statistics publication for each province. The data is reported only for the years 2003 through 2017. We used linear interpolation to fill in the remaining irrigation data.

Thus, the dataset includes wheat production, wheat area, and irrigation observations for each district in Punjab and Sindh from the years 1981 through 2017. Table 1 shows the descriptive statistics of each of these variables. The agricultural and weather data are the yearly observations for each district. The yield variable was calculated by dividing the production variable by the area variable. The area variable includes the area cultivated by the wheat crop for each district, and the production variable shows the wheat production accordingly. The irrigation variable shows the percentage of area irrigated in each district. Similarly, the Min Temp and Max Temp variables are the yearly averages of minimum and maximum temperature for each day for each district, whereas precipitation is the yearly average of rainfall recorded each day in each district.

Table 1: Descriptive Statistics of Source Data

Variable	Obs.	Mean	Std. dev.	Min	Max
Agricultural Data					
Production (‘000 tonnes)	1,171	365.5	260.3	0.3	1218.4
Area (‘000 hectares)	1,171	155.4	96.2	0.2	469.4
Yield (kg/hectare)	1,171	2305.4	702.2	598.9	4052.9
Irrigation	1,171	0.8	0.3	0	1
Weather Data					
Min Temp (°C)	1,171	16.4	1.9	11.6	21.8
Max Temp (°C)	1,171	30.1	2.2	24.4	34.9
Precipitation (mm)	1,171	127.5	124.0	0.56	983.5

For the calculation of the exposure variables, daily-level observations of weather data were used. Following Schlenker & Roberts (2009), the within-day distribution of temperature was approximated using a sinusoidal curve between the predicted minimum and maximum temperature. This hourly exposure for each degree Celsius was then aggregated for each day in each district to achieve annual district-level observations for the wheat-growing season of September through May. These variables were then summed to create eight exposure bins, and a freeze variable capturing exposures below 0°C. A similar exercise was conducted to create the exposure bin variables for each of the three seasons. This provides a total of 1,171 observations. The descriptive statistics of these variables for the growing season are in Table 2. The units are the exposure, in days (24 hours), the crop is exposed to the respective temperature bin during the growing seasons, September through May.

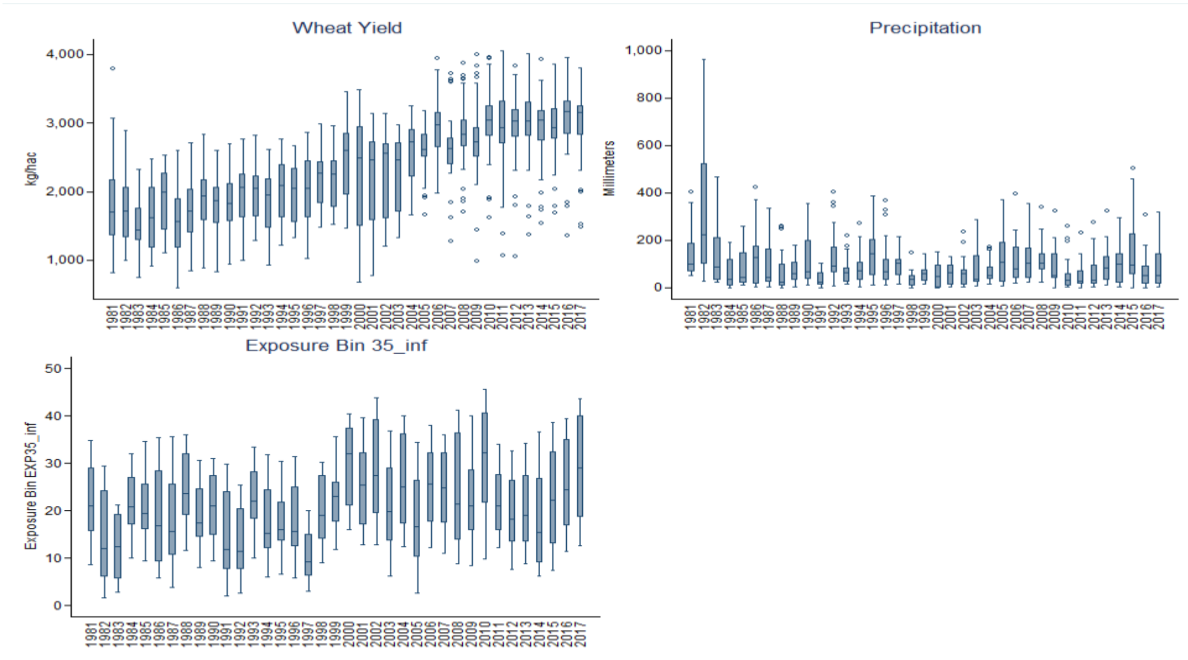
Table 2: Descriptive Statistics of Exposure Variables

Variable	Obs.	Mean	Std. dev.	Min	Max
Freeze	1,171	0.03	0.11	0.0	1.1
Exposure 0-4°C	1,171	2.5	2.7	0.0	15.5
Exposure 5-9°C	1,171	16.8	7.8	0.0	35.4
Exposures 10-14°C	1,171	34.1	8.3	7.8	59.0
Exposures 15-19°C	1,171	46.6	7.2	27.1	65.6
Exposures 20-24°C	1,171	54.0	4.2	42.2	72.6
Exposures 25-29°C	1,171	53.9	8.8	36.0	93.0
Exposures 30-34°C	1,171	38.4	8.2	19.2	73.1
Exposures > 35°C	1,171	26.2	11.3	2.2	54.8

Figure 2 shows the variation over the years in the wheat yields, precipitation, and Exposure > 35°C bin. Wheat yields exhibit an increasing trend over the years possibly due to advancements in technology and farmer practices. In the last ten years, the outliers increase showing higher sensitivity of wheat yields. Moreover, the Exposure >35°C graph shows variations over the years which tend to increase in frequency and intensity in the latter half of the graph.

It is important to note that in Pakistan, wheat is typically planted in the Fall and harvested in the Spring of the following year. Although the growing season follows the winter wheat cycle, the wheat genotype grown in Pakistan is spring wheat. Therefore, the wheat seed does not go through the vernalization dormancy period. For the intra-seasonal estimation of weather impacts, the growing season was decomposed into three seasons: Fall, Winter, and Spring. Wheat is typically planted in late September to October and harvested in late April to May. Therefore, the Fall season variables include data from September, October, and November; Winter from December, January, and February; and Spring includes data from March, April, and May.

Figure 2: Boxplots of Key Variables



Methods

The study dataset provides sufficient in-sample variation to support a robust estimation of wheat yield response to different weather conditions. It varies spatially across districts, and temporally across the growing season. Equation 1 shows the study regression model where y_{it} is the log wheat yield in kgs per hectare for district i and year t, $trend_t$ and $trend_t^2$ are the linear and quadratic trend variables, $precip_{it}$ is the precipitation in millimeters along with its quadratic approximation, Irr is the percentage area irrigated for each district, and d_i are district-fixed effects. The $\sum_{s=1}^{3} \sum_{k=1}^{8} \delta_{sk}\ bin_{skit}$ are the eight exposure bin variables with 5°C intervals, for each of the three seasons. $\sum_{s=1}^{3} \beta_{s1} Freeze_{sit}$ is the freeze variable capturing exposures below 0°C for each of the three seasons.

Equation 1: Regression Model

$$y_{it} = \sum_{s=1}^{3}\sum_{k=1}^{8}\delta_{sk}\, bin_{skit} + \sum_{s=1}^{3}\beta_{1s}Freeze_{sit} + \sum_{s=1}^{3}\beta_{2s}precip_{sit} + \sum_{s=1}^{3}\beta_{3s}\, precip_{sit}^{2} + \beta_4\, Irr_{it}$$
$$+ \beta_5 trend_t + \beta_6\, trend_t^2 + d_i + \varepsilon_{it}$$

The quadratic time trend was included to control for technological change and the district-specific fixed effects ensure controls for time-invariant heterogeneity such as soil type and quality.

Moreover, following Tack et al. (2015), the warming impacts were calculated for a uniform increase of 1°C to 5°C in the daily temperature. For this, exposure bins were recalculated with an increase of 1°C, and yield change was simulated based on the initial regression parameters and yield estimates. Similarly, the same steps were repeated for each of the four remaining warming scenarios. Equation 2 shows the formula for the calculation of the warming impacts where the *bin* is the vector of temperature exposure bins for increased (1) and initial (0) models.

Equation 2: Warming Impacts Formula

$$Warming\ Impact = 100\,\{e^{\widehat{\beta}(bin^1 - bin^0)} - 1\}$$

Results

Intra-seasonal Variation of the Impact of Temperature Exposures

The results show that the impact of temperature on wheat yields varies considerably across seasons where the freezing temperatures in the Fall and extreme heat in the Winter seasons are found to be detrimental to the wheat yields. However, the impact of extreme heat in the spring season was found to be marginally beneficial.

Table 3 summarizes the results of the regression model showing variation in the impact of temperature on wheat yields across three seasons: Fall, Winter, and Spring. The trend variables show that wheat yields are increasing in Pakistan over time with a positive estimate for the quadratic approximation. This increase can be credited to the improvements in the wheat variety breeding programs and other technical advancements in crop management. Moreover, the precipitation variable was found to have a statistically significant positive impact on the yield in the Fall season whereas, it impacts the yields adversely in the Spring season. Our understanding is that the rainfall closer to the harvest season can be damaging to the crops and thus resulting in a negative coefficient. Moreover, higher moisture near harvest creates a conducive environment for crop diseases such as rust and thus, can be responsible for a negative association with wheat yields. As expected, irrigation was found to have a considerable positive impact on the wheat yields, where a one percent increase in irrigation showing a yield increase of 8.1 percentage points. The coefficient is also statistically significant at a five percent confidence interval.

During the Fall season, the most striking finding is the impact of freezing temperatures. We find that an additional day (24h) of exposure to the freezing temperatures in the Fall season is associated with a 16.6% decrease in wheat yields, the estimate is statistically significant at a 95% confidence level. This result is supported by the agronomic literature, which suggests that cold stress, which is reported to be below 4°C, reduces wheat yields by delayed emergence and poor stand establishment at the initial seedling stage (Hassan et al., 2021). The exposure to lower temperatures causes leave chlorosis and wilting which leads to stunted growth and lower crop productivity (Janowiak et al., 2002). Moreover, it also conforms with the evidence from the US where the freezing exposure in the Fall season was identified as one of the biggest drivers of wheat yield loss (Tack et al., 2015). The results do not suggest any negative impact of high temperatures in the Fall seasons.

However, in the Winter season, the high temperatures (Exposure > 35°C) are associated with a considerable yield reduction where an additional day of exposure at these temperatures is associated with a yield loss of 8.8%. Of the 37 years in the dataset, 17 years have positive exposure to temperatures 35°C and above in the winter season. This suggests that the warming of the winter is the likely source of wheat yield reductions in Pakistan. Moreover, in the winter months, exposures above 35°C have had an increasing frequency in the last 20 years. If this trend continues, the warming of the winter will pose a serious threat to wheat production in Pakistan. The coefficient of freezing temperatures in the Winter seasons was found to be statistically insignificant and the low temperatures have a mild negative impact on wheat yields.

In the Spring season, the freezing temperatures have a high positive coefficient suggesting a 26% yield increase, but the estimate is not statistically significant possibly due to a very small number of observations below 0°C in the Spring season. Only 5 years exhibit positive exposure to freezing temperatures in the Spring season and all these years are before 1985. With the colder exposure decreasing, we can expect the yield gains to drop over time. Moreover, high temperatures are also found to have a small positive impact on wheat yields.

Table 3: Regression Output

Variables	Estimates			
Trend	0.01222***			
	(0.003)			
Trend^2	0.00015**			
	(0.00007)			
Irrigation	0.08121**			
	(0.038)			
		Fall	**Winter**	**Spring**
Precipitation		0.00057**	0.00010	-0.00045*
		(0.0003)	(0.0003)	(0.0002)
Precipitation^2		-1.10e-06	-1.57e-07	6.43e-07
		(9.88e-07)	(9.01e-07)	(6.51e-07)
Freeze		-0.16602**	0.05142	0.26825
		(0.071)	(0.059)	(0.269)
Exposure 0-4°C		-0.03228	-0.00750**	0.08630
		(0.040)	(0.003)	(0.083)
Exposure 5-9°C		0.00325	0.00167	0.01549
		(0.008)	(0.002)	(0.015)
Exposure 10-14°C		0.00751*	0.00735***	-0.00467
		(0.004)	(0.002)	(0.005)
Exposure 15-19°C		0.00491	-0.00039	0.01462***
		(0.004)	(0.003)	(0.005)
Exposure 25-29°C		0.00399	-0.00467	0.00389
		(0.003)	(0.004)	(0.004)
Exposure 30-34°C		0.00617**	0.00601	0.01013**
		(0.003)	(0.011)	(0.004)
Exposure > 35°C		0.00580*	-0.08806*	0.00832***
		(0.003)	(0.079)	(0.003)
Constant	5.77958***			
	(0.390)			
Observations	1,171			
R-squared	0.797			

Standard errors clustered by location-year in parentheses. Output includes district fixed effects.
**** p<0.01, ** p<0.05, * p<0.1*

Warming Impacts – Intra-seasonal Variation

The regression estimates from Table 3 show a mix of positive and negative effects of different temperature exposure variables. The offsetting nature shows that a reduction in exposure to freezing temperatures simultaneously increases the exposure to higher temperatures. To evaluate which effect dominates, we estimate the net effect by calculating the yield impact for a range of warming scenarios for each of the three seasons.

Figure 4 below shows the disaggregation of the warming impacts across the three seasons. The results are found to be statistically significant for the Winter and the Spring season, except for the +1°C scenario in Winter, and insignificant for the Fall season. As expected from the regression estimates, the winter season shows an expected negative impact of warming temperatures on wheat yields. The negative impact reaches a 14.30% yield loss for the most aggressive warming scenario of a +5°C increase in the temperatures. Similarly, based on the regression output, the Spring results show yield improvements. However, as the warming scenarios progress, the rate of yield improvement is slower in the Spring season as compared to the rate of yield loss in the Winter season, as shown in Table 5. Moreover, the table shows the high p-values associated with the warming impacts of the Fall seasons, and hence, the estimates for Fall cannot be considered different from zero.

Figure 3: Warming Impacts by Season

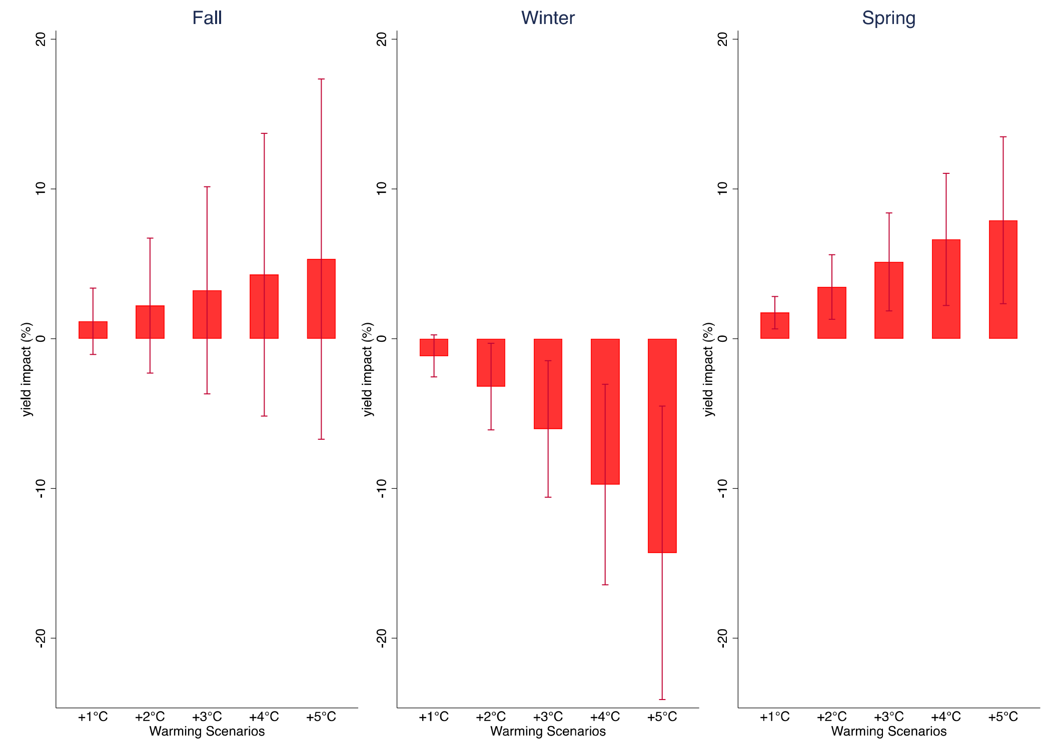


Table 4: Warming Impacts Estimates by Season

Scenarios	**Fall**		**Winter**		**Spring**	
	Impact	p-value	Impact	p-value	Impact	p-value
+1°C	1.15%	0.31	-1.16%	0.11	1.73%	0.00
+2°C	2.20%	0.34	-3.20%	0.03	3.45%	0.00
+3°C	3.23%	0.36	-6.03%	0.01	5.12%	0.00
+4°C	4.27%	0.38	-9.74%	0.00	6.62%	0.00
+5°C	5.31%	0.39	-14.30%	0.00	7.90%	0.01

Warming Impacts – Growing Season

The same regression model was used to estimate the warming impacts of the entire growing season. The results are shown in Fig. 3. The results show that warming temperatures are associated with a marginally positive effect such that the benefit of reduced exposure to low temperatures outweighs the adverse impact of high temperatures. However, the estimates were not found to be statistically significant for any of the warming scenarios.

Figure 4: Warming Impacts Growing Season

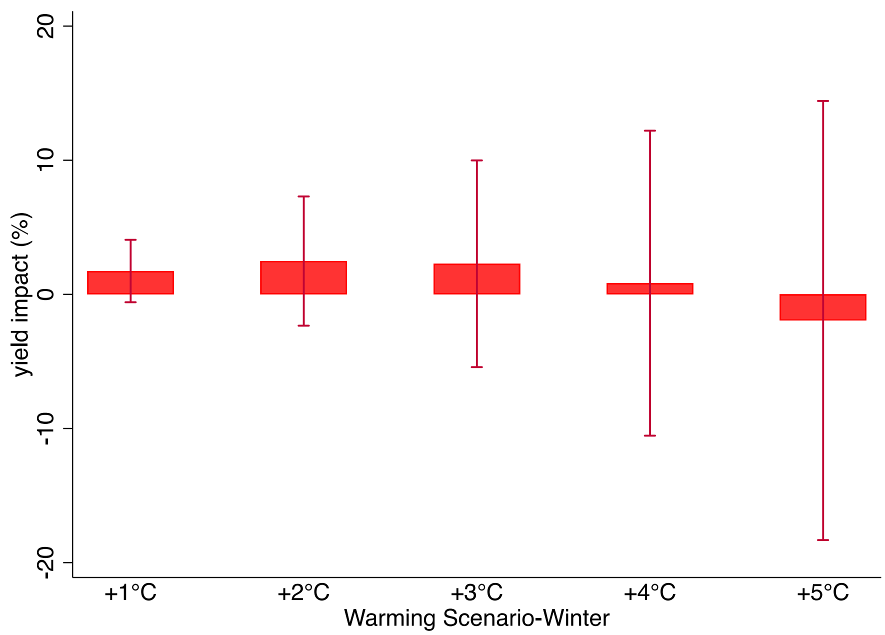


Table 5: Warming Impacts Estimates Growing Season

Scenarios	Impact (%)	p-value
+1°C	1.7%	0.14
+2°C	2.5%	0.31
+3°C	2.3%	0.56
+4°C	0.8%	0.89
+5°C	-2.0%	0.82

The horizontal identifies the five warming scenarios, and the vertical axis shows the yield impact expressed as a percentage change relative to historical weather. The whisker on each bar shows 95% confidence intervals.

The results show marginal improvements for scenarios +1°C through +4°C and a yield reduction for the scenario of +5°C. Pakistan being a semi-arid country, these results conform with the findings of the field warming experiment from the Northwestern semi-arid region of China which suggest that the warming of the temperature increases winter wheat yields by four percent (Xiao et al., 2008). The temporal range of the data for this study also begins in 1981 but ends in 2005.

Out-of-Sample Predictions

Following Schlenker & Roberts (2009), the study model with exposure bins as the explanatory set of variables was compared with two other specifications: (i) a base model with no weather variables, (ii) a model with the annual average temperature for the nine-month growing season. The comparison was made using the root-mean-squared error (RMSE) of out-of-sample predictions. The three models were estimated 1000 times for 80% of the observations. The estimates are then used to predict the remaining 20% of observations for each sample.

The results show that the model with exposure bins has the highest improvement in making out-of-sample predictions followed by the model with average temperature. This shows that the study model performs 18.8% better than the base model.

Conclusion

Climate change is one of the most pressing issues of our time, and its effects are being felt worldwide. Pakistan, like many other countries, is not immune to the impacts of climate change, and in fact, it is particularly vulnerable to extreme weather events, such as droughts, heat waves, and floods. These weather events have already caused severe impacts on the country's wheat production, which is its staple food. The consequences of these impacts are significant, given that millions of people rely on wheat as their primary source of food.

To develop a better understanding of the weather impacts on wheat yields in Pakistan, this study aimed to estimate the nonlinear impact of temperature on wheat yields in Pakistan. It exploits the immense variation available in the daily level weather data and employs the exposure bin treatment of weather variables to allow for unbiased nonlinear estimates of temperature impacts. Moreover, the study also contributes to a limited literature base that explores the intra-seasonal variations of the temperature impacts on wheat yields.

The results indicate that the freezing temperatures in the Fall season and hot temperatures in the winter season have the most significant negative impacts on wheat yields. However, future warming scenarios suggest a positive impact on yields, indicating that the benefits of reduced exposure to freezing temperatures outweigh the harmful effects of warmer winter temperatures. Disaggregating the findings by season reveals that warming temperatures may lead to yield reductions in Winter and yield gains in the Spring season.

Overall, the study underscores the urgency of developing effective adaptation strategies to mitigate the adverse effects of climate change on wheat production in Pakistan. A lot of effort is being made in developing heat-tolerant wheat varieties. The findings suggest a need to focus on developing frost-tolerant varieties to safeguard against the negative impact of freezing temperatures.

Given that Pakistan is one of the top ten wheat producers globally, the implications of disruptions in its production go beyond its borders, highlighting the need for international cooperation and collective action to address the challenges posed by climate change. The findings of this study may inform policy decisions aimed at promoting sustainable agriculture and ensuring food security for millions of people in Pakistan and beyond.

Chapter 3 - Exploring the Heterogeneity of Warming Impacts on Wheat Production in Pakistan – A Comparative Analysis of Adaptation Measures.

Introduction

There is a growing body of research that provides evidence of the future impacts of climate change on various aspects of human life, with a particular focus on food (Change, 2014). Among food crops, wheat is widely considered to be one of the most vulnerable to the impacts of climate change (Mall, 2014). This invites an opportunity to generate evidence on the factors at the interplay of weather outcomes and wheat yields for an informed response in terms of adaptation measures.

The adoption of improved varieties and irrigation are two of the most used adaptation measures by farmers in low or middle-income countries (Acevedo et al., 2020). The adoption of heat or drought-tolerant crop varieties and the use of irrigation to mitigate the adverse impact of climate change have been studied extensively by recent research (Shew et al., 2020; Tack et al., 2017). However, these adaptation measures are often studied in isolation from one another, and the interaction between them remains an open area of research. Therefore, this study aims to contribute to the literature by exploring the interaction of variety selection and irrigation as adaptation practices against the negative effect of warming temperatures on wheat yields.

This research is particularly relevant for Pakistan because its food security relies heavily on the performance of wheat production. Wheat is the staple crop of Pakistan which contributes to 72 percent of daily caloric intake and a per-capita consumption of around 124 kilograms (kg) per year, one of the highest in the world. It is also one of the largest crops in Pakistan, grown by over 80% of the farmers on 9 million hectares, making up 40% of the cultivated land in the country

(Raza, 2020). Despite its importance, the wheat yields in Pakistan are almost at half of their potential as compared to other countries with similar agroecological conditions (Prikhodko & Zrilyi, 2013). This is reflected in Pakistan's struggle to meet the growing local demand as evidenced by the recent and growing more frequent wheat flour crisis[2], despite being one of the world's top ten producers and a traditional net exporter.

Moreover, climate change poses serious concerns to wheat production in Pakistan, which is ranked among the top ten countries most affected by climate change (Eckstein et al., 2021). The warming temperatures and changing precipitation patterns along with the increasing frequency and intensity of extreme weather events such as droughts, floods, and heat waves are posing major threats to crop production (Rasul et al., 2012). Thus, to meet the growing demand for wheat, there is a dire need to explore possible adaptation measures to safeguard and enhance wheat production in Pakistan in the likely event of future warming of temperatures.

Therefore, the specific objective of this paper is to estimate the impact of warming temperatures on wheat yields in Pakistan and explore the heterogeneity of these impacts across wheat varieties and irrigation status. It intends to make a specific contribution to the literature by addressing the interaction of variety selection and irrigation as measures for adaptation to future warming of temperature. The paper also attempts to contribute to an even more limited evidence base from developing countries that are argued to be most affected by climate change (Wijaya, 2014).

To do this, we have created a unique dataset by combining the daily weather observations with agricultural data of 12,409 unique plots across all 37 districts of the province of Punjab from

[2] Multiple newspaper reports show acute wheat flour shortages, unprecedented inflation, stampedes during food distributions in the first quarter of the year 2023. Previously, Pakistan also faced wheat flour crisis in 2019-2020.

the year 2013 through 2018 yielding a total number of 33,621 plot-year observations. The dataset includes the irrigation status of each plot and the release year of each wheat variety.

To preserve the variation in the daily weather data, exposure "bin" variables are calculated by fitting a sinusoidal distribution between the daily minimum and maximum temperatures as in (Schlenker & Roberts, 2009). Exposures in days (24 h) for each 1°C interval are aggregated into nine temperature exposure bins with 5°C intervals with all exposures above 35°C allocated to the highest bin and all temperatures below 0°C allocated to the lowest. The warming impacts were obtained by uniformly shifting the entire distribution of observed historic temperatures for three scenarios, +1°C, +2°C, and +3°C, and expressed as the percentage change in yield relative to baseline climate.

The following sections of the paper include in chronological order; a brief review of relevant literature on the study of climate change adaptation measures and methodological approaches, an outline of research objectives and hypotheses, a discussion of the dataset and methods employed to carry out the research, the results of the study, and a conclusion.

Literature Review

The focus of this study is motivated by the research gap in estimating the comparative potential of two adaptation measures: adopting improved wheat varieties and irrigation. Both adaptation practices, irrigation (Tack et al., 2017; Zaveri & B. Lobell, 2019; Zhang et al., 2015) and adoption of wheat varieties (Shew et al., 2020; Tack et al., 2015, 2016; Zhao et al., 2022), have been studied extensively in recent statistical studies but usually independent of each other. Other strands of research do evaluate multiple adaptation measures but are specific to either agronomic approaches that employ biophysical models to simulate the yield response to changing weather conditions (Zeleke, 2021) or limited to measuring the adoption rate and dynamics rather than the performance of adaptation measures (Marie et al., 2020).

Irrigation plays a significant role in cereal production, it contributes to 40% of grain production despite being only 17% of the global cropped land (Cai & Rosegrant, 1999; Rosegrant et al., 2002). In regions that do not receive sufficient precipitation, irrigation contributes to the water requirement for crop production and protection against abiotic stress (Luan & Vico, 2021). It has the potential to mitigate the adverse impacts of warming temperatures in different ways; by cooling the canopy temperature (Siebert et al., 2014) and by reducing the evapotranspiration requirement caused by high temperatures (Lobell et al., 2013). Several statistical studies have provided evidence of the performance of irrigation as an adaptative practice. Tack et al. (2017) find that irrigation significantly reduces the negative impact of warming temperatures in the dryland winter wheat yields in the US. They find that a 1°C increase in temperature leads to a decrease of eight percent in yield for dryland wheat; whereas, irrigation completely offsets this negative effect. Troy et al. (2015) studies the impact of climate extremes on US crop yields and find that irrigation has a beneficial impact in increasing yields and providing a buffer against both precipitation and temperature-derived climate indices. Moreover, evidence from the developing world also shows the positive impact of irrigation where Zaveri & B. Lobell (2019) find that irrigated wheat yields in India were 13% higher in 2000 than they would have been without irrigation trends since 1970. Whereas, in their study on the central US for maize, soybean, and wheat crops, Zhang et al. (2015) did not find significant differences in heat resilience between irrigated and dryland locations for the wheat crop.

On the other hand, heat stress caused by high temperatures adversely impacts crop yields (Asseng et al., 2013; Rosenzweig & Parry, 1994) typically through the impact on the floral stage of plant growth (Hatfield & Prueger, 2015) where grain filling period is reduced by exposure to temperature extremes (Zabel et al., 2021) and thus, leading to lower yields. Wheat breeders develop new and improved varieties which are claimed as heat and/or drought-tolerant, intending to protect against this heat-stress (Driedonks et al., 2016). This provides a platform for the ongoing debate on the adaptative potential of adopting improved, heat or drought-tolerant, wheat varieties to mitigate the adverse impact of warming temperatures. Tack et al., (2015) find that the newer wheat varieties in the US are less resistant to heat stress as compared to older varieties. However, Shew et al. (2020) find that optimal cultivar selection and selective breeding provide possibilities to offset heat stress which is not the case in Tack et al., (2015). Moreover, Zhang & Zhao (2017) finds that using heat-tolerant varieties increases the maize yield in North China Plains by 6-10%. Whereas, studies such as Zhang et al. (2022) find the mixed performance of climate-resilient varieties where the winter varieties show fewer yield reductions as compared to traditional varieties but in the case of spring wheat, the advanced varieties perform even worse than the traditional varieties.

Previous studies on the interaction of weather and crop yields can be broadly divided into agronomic and regression-based statistical studies. Statistical studies aim to establish an empirical relationship between weather and yield based on observed data gathered typically from surveys and census (Cai et al., 2014; Duncan et al., 2016; Lobell & Burke, 2010; Ortiz-Bobea et al., 2019). Whereas, the agronomic studies rely on process-based bio-physical models such as APSIM (Holzworth et al., 2014) or AquaCrop (Foster et al., 2017) to model the plant physiology mathematically and simulate yield response to changing weather conditions and other determinants of crop yield i.e. soil characteristics, application of fertilizers, and management practices (Parkes et al., 2019). These studies focus on the dynamic plant growth process which is difficult to estimate in a regression framework and allows incorporating the complete distribution of daily or sub-daily variables into rich theoretical models to simulate the yield response (Adams et al., 1990; Rosenzweig & Parry, 1994).

The disadvantage, however, is that the predictions are limited to the simulated crops only and the results are highly dependent on the crop models used (Schlenker & Roberts, 2009). Rötter et al. (2011) suggest an overhaul of these models in favor of a multi-model approach to potential control for this bias. Whereas statistical models are equipped to account for the unobserved farmer preferences as well as other determinants of yield loss that cannot be simulated in agronomic models (Roberts et al., 2017). Roberts et al. (2017) provide a useful assessment of both approaches and find that statistical models show more severe predictions of warming impacts under uniform climate change scenarios as compared to process-based models.

The recent focus of the literature on the impact of climate change on crop yields is on contributing to model specifications with particular regard to the treatment of weather variables. Earlier statistical approaches mainly used aggregated weather observations to estimate impacts on different agricultural variables e.g., agricultural profits (Deschênes & Greenstone, 2007), and total factor productivity (Zhang et al., 2018). The aggregation of weather data loses significant variations which are otherwise available in disaggregated datasets (daily level) and thus, makes it harder to generate evidence on weather extremes.

A recent strand of research creates degree days/exposure bins weather variables to estimate the impact of temperature extremes on agricultural production (Schlenker & Roberts, 2009; Tack et al., 2015). These studies incorporate the whole distribution of temperature variables and thus, preserve the variation which is lost in the aggregation of weather observations. These studies combine the benefits of agronomic studies and earlier statistical studies by calculating the time a crop is exposed to each one-degree temperature interval. By doing this, they incorporate the complete weather distribution along with making predictions on historically observed yields. Schlenker & Roberts (2009) estimate the nonlinear temperature effects on crop yields in the US and identify temperature thresholds above which the crop yields decline. They further predicted a decrease of 30-46% in crop yields by the end of this century. Tack et al. (2015) decompose the impact of temperature by season to identify key climatic drivers of yield changes. They find that the freezing temperatures in the Fall and extreme heat in the Spring seasons are the biggest drivers of wheat yield loss in the US. Ortiz-Bobea et al. (2019) estimate the role of water stress in explaining historical yields by using intra-seasonal yield sensitivities to high-frequency fluctuations of soil moisture and temperature. Concerning adaptation practices, Tack et al. (2017) find that irrigation completely offsets the negative effect of heat stress on Wheat yields in Kansas, and Shew et al. (2020) find evidence of heterogeneity of the heat effect across wheat cultivars in South Africa. Our study attempts to contribute to this branch of research that employs temperature exposure variables to estimate the impact of temperature extremes on agricultural production.

Research Objectives and Hypotheses

The purpose of this paper is to estimate the warming impact on wheat yields in Pakistan and to investigate the interaction of the adaptation measures of irrigation and variety selection. To achieve this, the study aims to achieve three research objectives. The first objective is to estimate the impact of warming temperatures on wheat yields disaggregated by irrigation status. This will enable us to provide estimates on the role of irrigation in mitigating heat stress.

- **Hypothesis 1**: Warming temperatures have a significant negative impact on wheat yields in Pakistan.
- **Hypothesis 1a:** Irrigation provides substantial protection from the adverse impact of heat stress on wheat yields.

In addition to estimating the warming impacts, understanding the heterogeneity of these impacts provides a possible direction for adaptation. Newer varieties are often associated with higher yields and claim increased heat resistance. We aim to test these claims in this study. Therefore, the second research objective is to estimate the variety-specific heat resistance and mean yields. Exploiting the commercial release year information of each wheat variety in the dataset, we aim to provide insights into the performance of newer varieties in terms of heat resistance and mean yields. These results will be further disaggregated into irrigated and dryland to provide estimates independent of the irrigation status.

- **Hypothesis 2:** Newer wheat varieties exhibit higher yields and increased heat resistance compared to older varieties and this effect is more pronounced for irrigated yields than dryland yields.

Finally, the third research objective is to explore the interaction of irrigation and variety selection as adaptation measures. For this, the warming impacts of wheat varieties with minimum and maximum heat resistance will be calculated for both the irrigated and the dryland samples. This will allow us to estimate the protection against heat stress provided by the selection of wheat variety and how this protection changes across irrigation status.

- **Hypothesis 3:** Selecting wheat varieties with the highest heat resistance protects against heat stress, and this protection is greater for rain-fed yields than irrigated yields.
- **Hypothesis 3a:** Variety selection and irrigation in combination are more effective in mitigating the adverse impact of warming temperatures on wheat yields.

Data and Study Area

To achieve the above research objectives, we have assembled a unique dataset by linking daily weather observations with agricultural data from 12,409 distinct plots representing all 37 districts of the Punjab province and covering the period between 2013 and 2018. The following subsections will provide a detailed description of the dataset and its sources, and an explanation of additional weather exposure bin variables constructed for the analysis.

Agricultural Data

The agricultural data come from the Crop Reporting Survey conducted by the Crop Reporting Service (CRS), an attached wing of the Agriculture Department, Government of Punjab. Punjab is the major wheat-producing province of Pakistan contributing to over 70% of the production. Administratively, the province is divided into nine divisions, which are further divided into a total of 37 districts. Each district is divided into Tehsils and each Tehsil has urban towns and rural villages.

The CRS survey employs a two-stage random sampling technique for sample selection where the crop area of the village segment is the sampling unit. The sample size is around 5,500 cropped plots of size 15’ x 20’ (sq. feet) with a small variation each year. These plots are randomly selected from 2,088 villages representing all districts (37) and 133 of the tehsils of Punjab. Within each village, three farms are randomly selected and within each farm, two plots are randomly selected using a lottery system. Not all villages have six plots, the selection of plots varies significantly for each village and year. This makes a total of 12,409 plots from a total of 2,088 villages covering 133 tehsils and all 37 districts of Punjab. The temporal range is six years (2013 to 2018) giving 33,621 observations. However, the dataset is unbalanced and some of the variables do not have observations for certain years. Table 6 below summarizes the variables used in the available dataset.

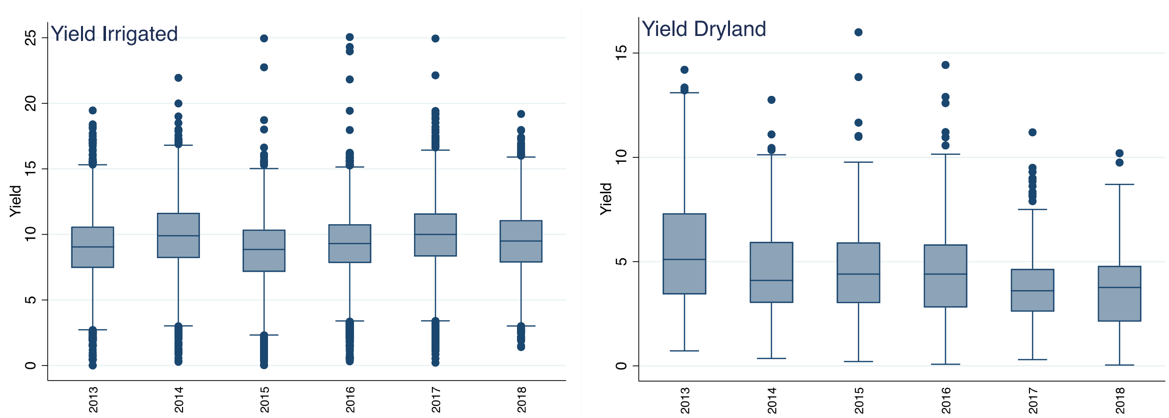
Table 6: Descriptive Statistics of Agricultural Data

Variable	Obs.	Mean	Std. Dev.	Min	Max
Wheat Yield (kg/acre)	33,621	9.014	2.823	0.009	25.05
Wheat Variety	33,621	11.943	7.594	1	25
Irrigation	33,621	0.931	0.254	0	1

The wheat yield variable provides the yearly observed yields in kg/acre for each plot, the wheat variety is a dummy variable that identifies the wheat variety used by the farmer for each plot in each year, and irrigation is a binary variable identifying the irrigation status of the plot.

Figure 5 below shows the temporal variation in wheat yields for irrigated and dryland subsamples respectively. The graph shows consistent interquartile ranges across the years with irrigated samples indicating higher mean yields. Whereas the dryland sample shows a larger spread as compared to irrigated, reflecting greater variability in yield over the years. The differences in the median of both groups indicate sufficient variation of wheat yield across irrigation status to make robust estimates.

Figure 5: Wheat Yield Boxplots by Irrigation Status



Weather Data

The weather data were obtained from the Climate Prediction Centre (CPC) dataset which is developed by the American National Oceanic and Atmospheric Administration (NOAA) using the optimal interpolation of quality-controlled gauge records of the Global Telecommunication System (GTS) network.

Globally gridded weather data is preferred over the in-situ monitoring stations data due to the sparse spread of weather stations in Pakistan. Moreover, the weather station data in developing countries is also argued to be less reliable (Parkes et al., 2019). Among other commonly used datasets, the CPC dataset has been evaluated to be the most efficient in the reconstruction of observed temperature (Salehie et al., 2022), and provides a high correlation with the observed precipitation (Gummadi et al., 2022). It provides daily observations of minimum and maximum temperature and precipitation on a spatial resolution of global 0.50 x 0.50-degree latitude/longitude grids. Table 7 below summarizes the three variables. Each weather variable provides daily observations for each of the 33,621 plots in the dataset ranging from the year 2013 through 2018.

Table 7: Descriptive Statistics of Weather Data

Variable	Obs.	Mean	Std. Dev.	Min	Max
Precipitation (mm)	27,253,849	1.089	4.748	0	162.586
Maximum Temp (°C)	27,253,849	31.398	7.824	2.602	47.791
Minimum Temp (°C)	27,253,849	18.389	8.536	-4.279	38.866

Creating Temperature Exposure Bin Variables

To enhance the measurement of temperature (Ortiz-Bobea et al., 2021; Schlenker & Roberts, 2009; Tack et al., 2015), exposure “bin” variables are calculated by fitting a sinusoidal distribution between the daily minimum and maximum temperatures as in (Schlenker & Roberts, 2009). Exposures in days (24 h) for each 1°C interval are aggregated into seven temperature exposure bins with 5°C intervals with all exposures above 35°C allocated to the highest bin and all temperatures below 0°C allocated to the lowest. Daily bins are then summed across all days in the growing season which is defined as the typical span of planting to harvest from September through May. This provides a total of nine exposure bin variables. Table 8 below shows the summary statistics of these variables. The units are the exposure, in days (24 hours), the crop is exposed to the respective temperature bin during the growing seasons, September through May.

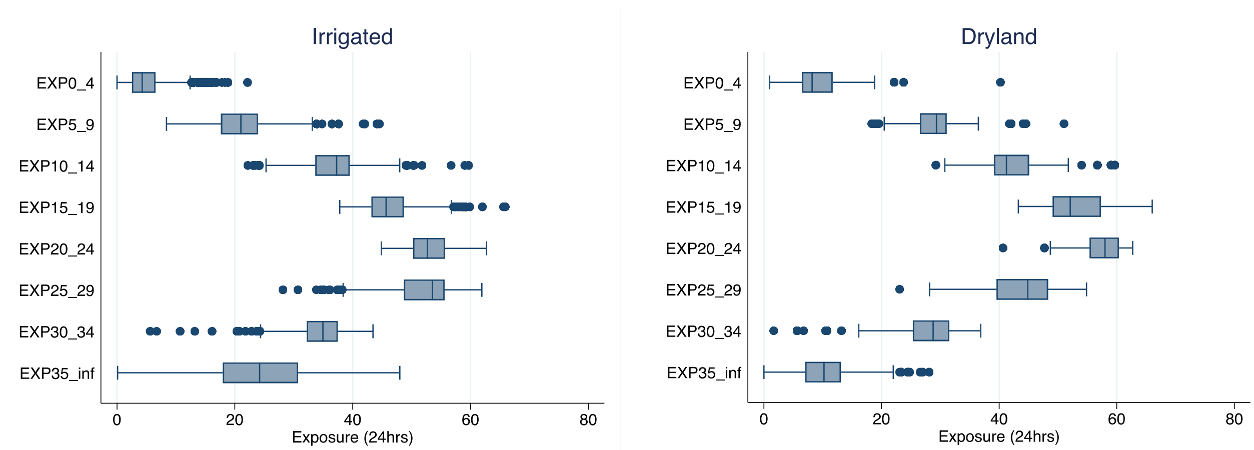
One exposure bin, Exposures 20-24°C, is omitted to avoid the dummy variable trap, and the remaining eight serve as covariates in the regression model. The Freeze bin includes exposure below 0°C, and the Exposure >35°C bin is the measure of exposure to extreme heat. The minimum values for the two lowest and the hottest bins are zero as there were instances when no exposures within these bins were recorded in the data.

Table 8: Descriptive Statistics of Exposure Bins

Exposure Bins	Obs.	Mean	Std. Dev.	Min	Max
Freeze	33,621	0.019	0.116	0	5.004
Exposure 0-4°C	33,621	5.12	3.6	0	40.227
Exposure 5-9°C	33,621	21.678	4.768	8.396	51.028
Exposure 10-14°C	33,621	37.063	4.607	22.202	59.669
Exposure 15-19°C	33,621	46.616	4.369	37.803	66.035
Exposure 20-24°C	33,621	53.521	3.72	40.66	62.713
Exposure 25-29°C	33,621	51.6	4.92	23.082	61.929
Exposure 30-34°C	33,621	34.086	4.307	1.679	43.449
Exposure >35°C	33,621	23.461	9.302	0	48.009

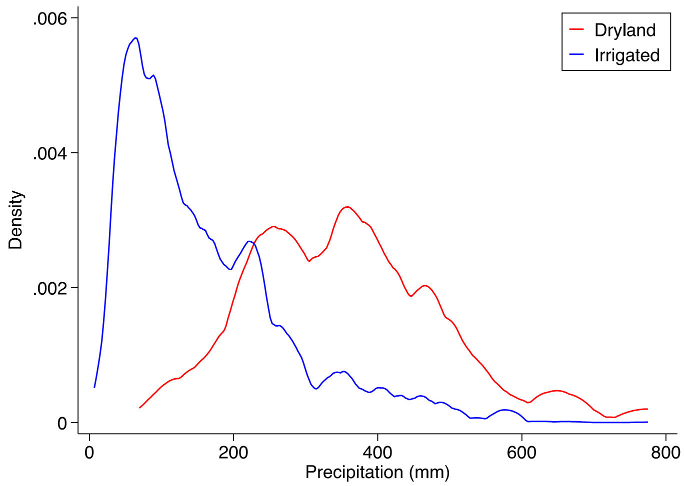
Figure 6 below demonstrates the variation available in the exposure bins for both the irrigated and dryland samples. The horizontal axis shows exposures in days (24hrs) and the vertical axis has the exposure bin variables. The exposures are highest, as expected, for the milder temperatures 15°C to 24°C, and lowest for extreme temperatures for both samples. The hottest bin shows greater variation for the irrigated sample.

Figure 6: Temperature Exposure Variation across Irrigation Status



The dryland wheat is cultivated in the northern parts of Punjab called the *Barani* region. The Barani region is characterized by lower temperatures and higher rainfall. The temperatures tend to increase, and rainfall decrease from North to South. Whereas the central and southern parts of Punjab are predominantly irrigated. This is reflected by higher exposure days for the low-temperature bin for the dryland sample as compared to the irrigated sample in Figure 6. Moreover, the precipitation density curve in Figure 7 also shows a higher density of heavy rainfall in the dryland as compared to the irrigated plots.

Figure 7: Precipitation Density Curve



Linking Weather and Agricultural Data

To link the agricultural data with the weather data, the geographic coordinates of each plot were collected and linked with the weather data. Since the weather data is on a grid level of 0.5x0.5 resolution, which is usually larger than a typical village area, there is a possibility of multiple villages in one grid, thus containing the same weather information across the grid. Therefore, the spatial variation of the weather data comes at the Tehsil level and not the plot or village level.

Methods

The study dataset provides sufficient in-sample variation to support a robust estimation of wheat yield response to different weather conditions. It varies spatially across plot locations, wheat varieties, and production types (irrigation, dryland) and temporally across growing seasons. We control for the unobserved time-invariant factors such as soil quality, that may vary across locations, using location fixed effects. We expect changes in technology over time, particularly through breeding efforts as newer varieties are generally associated with higher mean yields. To address this, we use variety fixed effects that capture genetic gains over time. A quadratic time trend is also included to control for changes in best management practices. The regression model is specified as:

$$y_{ivt} = \sum_{k=1}^{8} \delta_k \, bin_{ikt} + \beta_1 t + \beta_2 t^2 + \beta_3 \, p_{it} + \beta_4 \, p_{it}^2 + \alpha_h + \alpha_v + \varepsilon_{ivt}$$

where y_{ivt} is log wheat yield for variety v, at farm i, in year t. $\sum_{k=1}^{8} \delta_k \, bin_{ikvt}$ are the eight exposure bins with 5°C intervals including the *freeze* bin that measures exposures below 0°C and the highest temperature bin of >35 °C measuring the extreme heat. These bins are a measure of exposure in days to respective temperatures and capture the effects of weather on wheat yields. The linear and quadratic approximation of the trend and precipitation is denoted by t_t , t_t^2 and p_{it} and p_{it}^2 respectively. α_h and α_v are location and variety fixed effects.

Due to the nature of the dataset, it is plausible that the error terms ε_{ivt} exhibit spatial dependence which potentially violates the independence assumption. Therefore, we use the multiway framework which clusters standard errors by year-division. This allows for errors to be heteroskedastic, spatially correlated within each year, and temporally correlated within each division. This is an important consideration as the standard errors are found to be 3.1 times larger relative to heteroskedastic robust errors. With 9 divisions, it is the highest spatial classification available in the dataset, providing 54 clusters. We do not cluster by year alone due to the limited temporal resolution of the dataset.

The warming impacts were obtained by uniformly shifting the entire distribution of observed historic temperatures for each of the three scenarios and expressed as the percentage change in yield relative to baseline climate. To do this, we simulate new exposure bins for each +1°C increase in the observed daily minimum and maximum temperature up to +3°C. The warming impact for each scenario is then calculated by $100\left\{e^{\hat{\beta}(bin^1 - bin^0)} - 1\right\}$ where *bin* is a vector of exposure bins for shifted (1) and baseline (0) climate and $\hat{\beta}$ are the parameter estimates from the regression model. The estimation follows the delta method of asymptotic approximation for large samples which takes the nonlinear transformations of the estimated parameter vector and apply the delta method to make calculations of variance, standard errors, and other statistics. It is implemented through the *nlcom* command in Stata 17.0. Precipitation remains constant at historical averages.

To estimate the heterogeneity of the extreme heat (exposure > 35°C) across wheat varieties, we used a multilevel model where the impact of temperature > 35°C was allowed to vary across wheat varieties. This leads to the following modification in the regression model:

$$y_{ivt} = \sum_{k=1}^{9} \delta_k \, bin_{ikt} + \mu_v bin_{iv9t} + \beta_1 t + \beta_2 t^2 + \beta_3 \, p_{it} + \beta_4 \, p_{it}^2 + \alpha_h + \alpha_v + \varepsilon_{ivt}$$

where (μ_v) is included as the random slope that varies across wheat varieties for only the 9th exposure bin representing extreme heat. The random part of the model thus includes only the exposures > 35°C. Best linear unbiased predictions (BLUPs) were calculated for these random effects using the *reffects* option of the *predict* command in Stata 17.0. The heat resilience for each variety is calculated by adding the estimated fixed coefficient of exposure >35°C and the predicted random coefficient, given by $\delta_9\ bin_{i9vt}+\ \mu_v$. Since we focus only on varieties with more than ten location-years, the number of clusters is limited (17 for irrigated and 8 for dryland). The lower number of clusters (<50) exacerbates the downward bias of estimated variance parameters inherent in the maximum likelihood estimator. Therefore, we use a restricted maximum likelihood estimator (REML) that considers the loss of degrees of freedom from the estimation of regression parameters and produces unbiased estimates particularly when the number of clusters is small (Snijders & Bosker, 2011). The adjusted mean yield for each wheat variety was calculated keeping the weather covariates fixed at the mean level. This was implemented using the *margins* command in Stata 17.0.

Results

The main regression model specifies log yield as a function of location and variety fixed effects, a quadratic time trend and cumulative precipitation, and the exposure bins. The parameter estimates for the regression model are reported in the Table 9. Our main interest is in estimating the yield response of the net effect of warming temperatures. Therefore, these parameter estimates serve as an input for the calculation of the warming impacts for the three warming scenarios.

Table 9: Regression Output of Base Model

Variables	Irrigated	Dryland
Freeze	-0.079	-0.111
	(0.111)	(0.105)
Exposure 0-4C	0.026***	-0.034
	(0.006)	(0.023)
Exposure 5-9C	0.026***	0.021
	(0.005)	(0.014)
Exposure 10-14C	0.018***	0.006
	(0.005)	(0.017)
Exposure 15-19C	0.011*	-0.017
	(0.006)	(0.014)
Exposure 25-29C	0.02***	0.003
	(0.005)	(0.018)
Exposure 30-34C	0.014**	-0.015
	(0.005)	(0.016)
Exposure >35C	0.013***	-0.02
	(0.003)	(0.013)
Constant	-1.685**	2.956
	(0.804)	(2.501)
No. of Obs.	31,291	2,330
R-squared	0.205	0.399
Joint Test (p-value)	0.0000	0.0035
Locations	124	44
Varieties	25	19

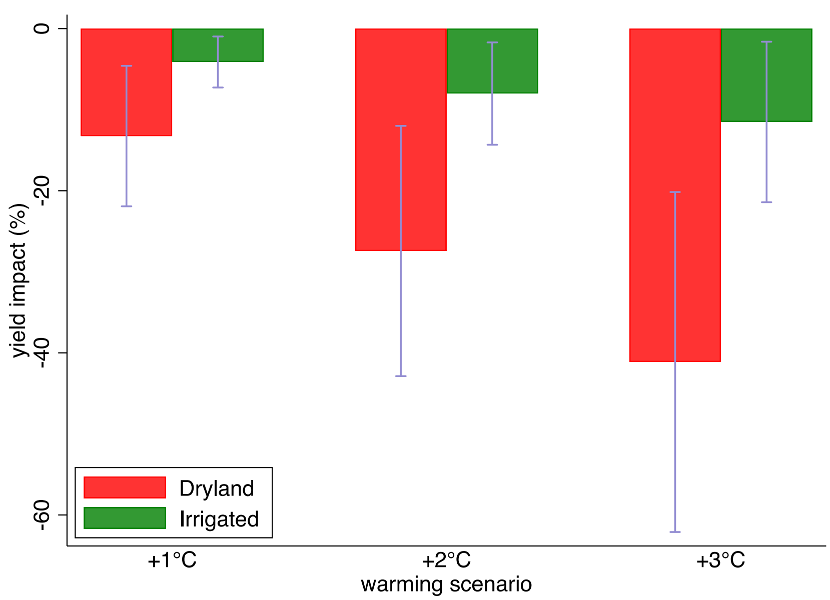
*Notes: Tehsil and variety fixed effects included in both models. Standard errors clustered by division-year are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.*

Irrigation Provides Substantial Protection from Heat Stress under Uniform Warming Scenarios.

The yield impacts across three uniform warming scenarios for both the irrigated and dryland samples are shown in Figure 8. The predicted yield impact expressed as percentage change is on the vertical axis and the three warming scenarios on the horizontal axis. Each two-bar cluster

shows estimates for dryland and irrigation samples using parameter estimates from the regression model. Bars show 95% confidence intervals using standard errors clustered by division-year.

Figure 8: Predicted Yield Impacts of Future Warming Scenarios by Irrigation Status

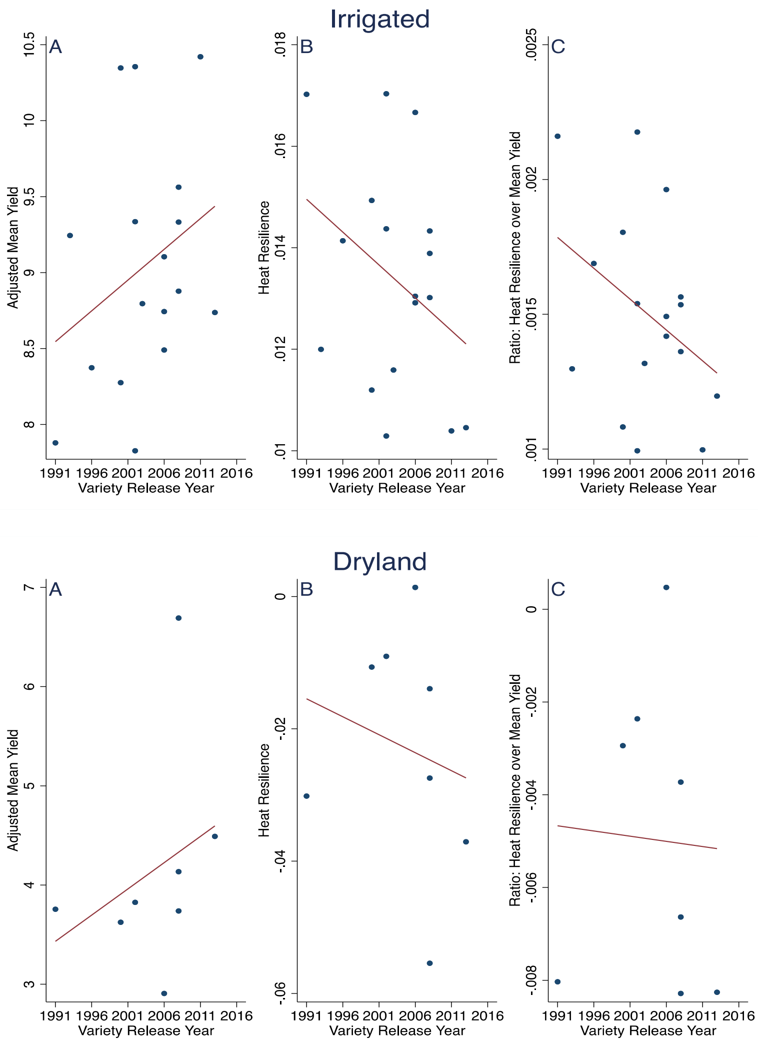


The results show that irrigation provides considerable protection against warming temperatures. All scenarios suggest that warming is associated with net yield reductions ($p < 0.02$). Under the conservative +1°C scenario, the yield reduction is predicted to be 13% for the dryland and 4% for the irrigated samples. This reflects a 69.2% lesser yield reduction in the irrigated sample as compared to the dryland sample, which increases slightly to 70.4% and 70.7% under +2°C and +3°C scenarios respectively.

Newer Varieties Suggest Improvement in Mean Yields but the Yield Gains are Offset by Lower Resistance to Heat.

The dataset includes information on irrigation status and wheat varieties with commercial release years ranging from 1991 through 2013. This allows us to assess genotype-by-environmental interactions in both the dryland and irrigated settings. We use a varying slope multilevel model where the fixed part of the model takes the form of the regression model, except effect of extreme heat (exposure >35°C) is allowed to vary randomly across wheat varieties. We plot both the adjusted mean yields, predicted under average weather conditions, and the variety-specific heat resilience against release year for both dryland and irrigated samples in Figure 9. The mean yields (Panel A) are predicted using restricted maximum likelihood (REML) estimation of the multilevel model with the weather variables held constant at their sample average. Heat resilience (Panel B) is measured as the percentage impact on mean yield from an additional degree day above 35°C. The heat resilience estimates are the release-year specific best linear unbiased predictor (BLUP) estimates for the random effects of exposures above 35°C obtained from a multilevel model of log yields. Panel C shows the ratio given by heat resilience over mean yield. The varieties with a presence of fewer than ten location-years were not included in this analysis.

Figure 9: Variety Specific Mean Yield and Heat Resilience by Irrigation Status



The plot trends suggest that newer varieties have higher mean yields. However, the heat resilience plot shows a decreasing resilience for the newer varieties. This indicates the success of the breeding efforts in terms of increasing mean yields over time, however potentially at the expense of greater sensitivity to extreme heat.

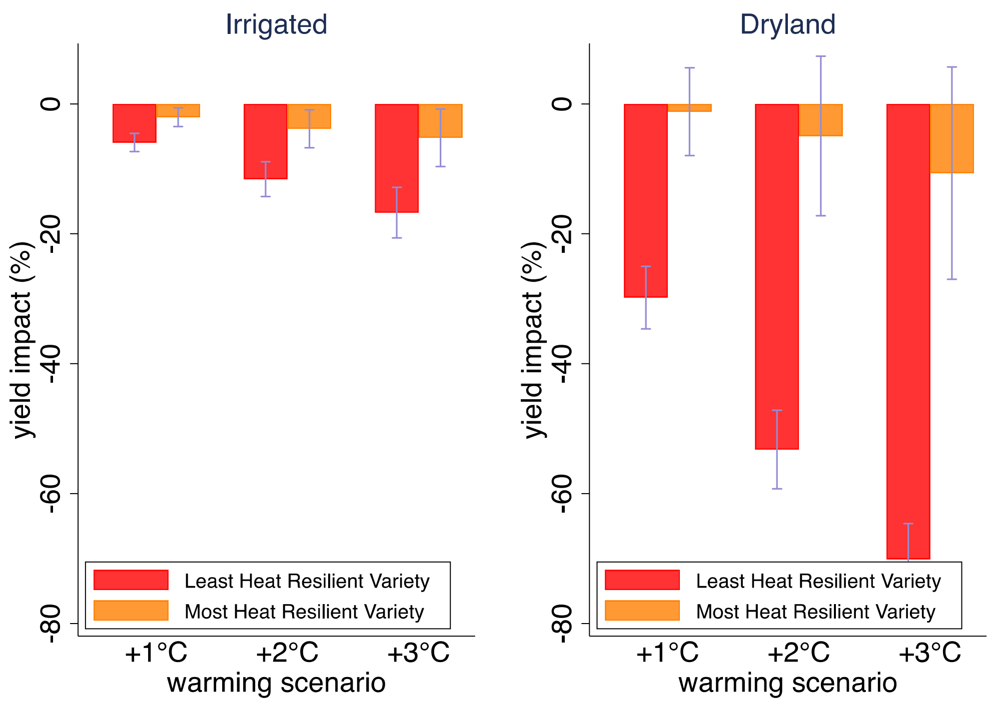
The tradeoff between mean yields and heat resilience is similar across both the dryland and irrigation settings. The correlation coefficient between adjusted mean yields and heat resilience is -0.89 for dryland and -0.76 for irrigated plots. This suggests a strong negative relationship where the varieties with the highest mean yields have the lowest heat resilience. Panel C shows that for newer varieties, the yield loss from decreased heat resilience is higher than the yield gain from increased mean yields making producers worse off, particularly in the irrigated sample.

There is Extensive Adaptation Potential for Reducing Warming Impacts by Switching to Heat-Resilient Varieties.

The heat resilience estimates show evidence of extensive heterogeneity across wheat varieties with the differences in estimates being as large as three times for varieties at each extreme in the pooled sample. This suggests a potential path toward adaptation through selective breeding and variety selection. We estimated the warming impacts for the most heat-resilient variety (MHRV) and the least heat-resilient variety (LHRV) for both irrigated and dryland samples and found evidence that variety selection provides extensive protection from heat stress. The results are shown in Figure 10. Impacts are reported as the percentage change in mean yield under +1 to +3°C warming scenarios relative to historical climate. Bars show 95% confidence intervals using standard errors clustered by division-year.

Under the conservative scenario of +1°C in the irrigated sample, the MHRV shows approximately 65% lesser yield reduction as compared to the LHRV, which increases to 96% for the dryland sample. The LHRV estimates also show major differences across irrigation status which implies that irrigation significantly reduces the reliance on variety selection, although variety selection still provides extensive protection in the irrigated sample. Thus, the combination of irrigation and optimal variety selection could be a doubly-effective management strategy for mitigating the adverse effects of warming temperatures. However, the tradeoff between heat resilience and mean yields (Fig. 9) across varieties suggests that extensive protection might come at the cost of reduced mean yields.

Figure 10: Comparison of Variety Selection and Irrigation as Adaptation Measures



Conclusion

Climate change is causing an increase in global temperatures which poses a challenge to agricultural production in general and grain production in particular. Pakistan is currently battling with the adverse impacts of extreme weather events such as droughts, floods, and intense heat waves, and it is considered one of the top ten countries affected by climate change. With the extreme vulnerability to climate-related calamities and heavy reliance on wheat production for its food security, understanding the impacts of warming temperatures on wheat yields and possible adaptation measures is an important and relevant topic of research for Pakistan.

Therefore, the purpose of this research is to estimate the impact of warming temperatures on wheat yields in Pakistan and to provide an assessment of adaptation measures of irrigation and variety selection. Utilizing a unique dataset of farm-level observations linked with the daily observation of weather variables, the study finds that warming temperatures have a substantial and negative impact on the wheat yields of Pakistan. Moreover, this impact is more pronounced in dryland areas as irrigation provides significant coverage against heat stress. The study also finds that these warming impacts show considerable heterogeneity across wheat varieties where the newer varieties show higher mean yield and lower heat resilience. Finally, the study shows that both variety selection and irrigation protect against the negative effects of warming temperatures and presents a case in favor of employing a combination of both adaptation measures to ensure the most protection. The evidence proposes policy intervention geared towards an enhanced focus on improving and extending irrigation coverage for the wheat crops as well as facilitation of developing heat tolerant and yield-enhancing wheat varieties.

This research extends the existing knowledge by addressing the research gap in estimating the interaction of irrigation and variety selection as adaptation measures against the warming temperatures which were otherwise addressed separately. A better understanding of the relationship between weather and agricultural production allows us to better prepare to respond to the potential future increase in temperature. This knowledge also provides a starting point for the wheat variety breeders to identify genetic traits that provide increased heat resilience and thus, inform their breeding efforts accordingly. The creation of knowledge on making staple crops more climate resilient, particularly for countries that are extremely vulnerable to climate change, holds the key to ensure the food security of millions of people.

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