Climate Volatility, Wheat Productivity and Food Security: A Quantile Regression Analysis

BABAR HUSSAIN[1], USMAN ALI[2], SANIA SHAHEEN[3], LAL K.ALMAS[4]
[1]School of Economics, IIIE, International Islamic University,
ISLAMABAD

[2]Government Graduate College,
Shorkot City, Punjab,
PAKISTAN

[3]International Institute of Islamic Economics (IIIE),
International Islamic University Islamabad,
PAKISTAN

[4]Department of Agricultural Sciences, Paul Engler College of Agriculture & Natural Sciences, West Texas A&M University (WTAMU),
Canyon, Texas,
USA

Abstract: - Climate change's effects on food crop production are a serious concern due to its linkages with food insecurity. This study attempts to investigate the question of whether and to what extend climate volatility has affected the yield of a major staple crop, the wheat, in the District Faisalabad, the largest agricultural city in Pakistan. Daily base data of temperature and rainfall over the past 33 years is collected, and the average and volatility measures of climate conditions are calculated for the whole crop period as well as for the vegetative and reproductive stages of crop growth. The quantile regression technique is utilized to estimate the influence of climate volatility on wheat yield distribution. The results provide convincing evidence that climate volatility is more damaging to food crops as compared to the gradual changes in rainfall and temperature. Besides, climate volatility is found to have significant effects on both the vegetative and reproductive stages of wheat crop growth. This research unravels the heterogeneous impact of temperature and rainfall across the vegetative and reproductive stages of wheat crop growth. It is hoped that the findings are important to guide policymakers to cope with uncertain climate shocks.

Key-Words: - Climate volatility, temperature, rainfall, food security, quantile

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1 Introduction

Environmental degradation and climate change issues are considered the greatest threat to human lives and natural resources, [1], [2]. It is regarded as the first intercontinental problem shaped by the concentration of CO_2 and *Greenhouse Gases* (GHG) emissions in the atmosphere, [2], [3], [4]. Greenhouse gases make the earth warm which ultimately damages natural resources, energy resources, and agriculture production, [4], [5]. Climate change impacts are global in scope and unprecedented in scale, [6], [7].

The repercussions of such climatic changes are visible from the intolerable weather conditions, more frequent floods, episodes of extreme temperature and rainfall, food shortage, etc, [8]. It is anticipated that the concentration of GHGs will increase by three times by the end of the 21st century to the level of the pre-industrial era, and this will cause a rise in Earth's temperature from 3°C to 10°C, [9].

This will bring more devastating implications for the human ecosystem, especially for those sectors that depend heavily on climatic conditions and would be more susceptible to the adverse effects of such variations. For instance, temperature rise, changes in rainfall and precipitation patterns, and other extreme weather events may disrupt agriculture productivity, food availability, and quality,

[10], [11].

The issue of climate change has become even more serious for under-developed agrarian countries of the world, such as South Asia, as it is threatening not only food security, [12], but also promoting poverty and inequality in this agriculture-dependent region, [13]. For policy and planning purposes, comprehending the impacts of climatic variability on food crop production is indispensable to adopting preventive measures. As observed in the 5th report of IPCC (the Intergovernmental Panel on Climate Change, [7], climate change in the last three decades has negatively affected crops, reducing production by up to 5%, and climate volatility is the main responsible factor driving food price instability in recent years. However, despite the importance of the topic, very limited research is devoted to exploring this research area. The extant literature has mostly focused on the quantitative assessment of the climate-food nexus based on the average climatic indicators, [14], [15], [16], [17]. Although these studies provided important insights and guidelines for future research, the main shortcoming is that they ignore the unprotected changes or the volatile nature of environmental variables, such as sudden rainfall during the harvesting period or a lack of temperature. The recent climatic changes are more volatile and require a fresh investigation of the relationship between climate volatility and food crop productivity.

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This study is intended to inquire about a case from Pakistan to spotlight the vulnerability of a major staple crop in particular, and the agriculture sector in general. The contribution of the agriculture sector to GDP is about 24% of GDP. This sector employs half of the total labor force in the country and is the third-largest source of foreign exchange earnings. The sensitivity of Pakistan to climate change is obvious from, for example, extreme weather events such as temperature hikes and rainfall volatility, devastating floods, and food insecurity arising from reduced food crop productivity. Adversative impacts of climatic conditions are appearing in Pakistan for the last two decades, [18], [19], [20].

The shortage of food stuffs along with increasing population growth pressure began to create food insecurity in the country, [21]. The frequent incidence of floods has not only damaged the market infrastructure but also reduced food availability, making the country's population food-insecure, [22]. A more serious cause of concern is that food insecurity is becoming more severe in rural areas that are already facing higher food prices and shortages in the country, [23].

This study contributes to the broader debate on the climate change-food security nexus by exploring whether and to what extent the capricious pattern of environmental indicators exerts an effect on wheat productivity, a major food crop not only in Pakistan but also in other regions of the world. This paper has several distinctive features. First, we calculate climatic volatility (rainfall and temperature) to examine its effect on wheat productivity and also compare it with average climatic indicators. Second, we divided the wheat crop season into the vegetative and reproductive stages to have an in-depth analysis. We collect daily basis primary data on climatic indicators daily to calculate average and volatility measures of rainfall and temperature from the largest agriculture-producing district of Pakistan, Faisalabad. Methodologically, we utilized the quantile regression (QR) approach. This method has an advantage over the other existing techniques as it helps to explain the relationship among the variables at the different points of data distribution, rather than focusing only on the single *average* parameter estimation.

The reaming of the paper is structured as follows: the next section provides a brief review of relevant studies. The section hereafter describes variables, data sources, and econometric methodology. Section 4 presents the results and their discussion; while Section 5 concludes the whole discussion.

2 Literature Review

Climate change is defined as the changes in climatic patterns, caused by nature or anthropogenic activities, which persist for a longer time period, [24]. Rise in Population size, deforestation, and GHGs emissions are the known factors causing climate change, [9], [25].

Though there might still be a debate on the degree and sources of climate change, its actuality has mainly been accepted on a scientific basis, [24], [26].

Climate change instigated a shift in seasons, a rise in temperature and sea level, and thus resulting in punishing weather events like floods, storms, and heat waves, [15]. Such variations in climatic conditions are closely related to the global socio-economic and ecological systems in several ways. Its global coverage has drawn the attention of research scholars and has resulted in a plethora of research papers in the field, [3], [27], [28], [29].

Agriculture is one of the basic economic activities that not only provides food to human beings but also a source of industrial raw materials. Unfortunately, agriculture is one of the vulnerable sectors to climate change owing to its greater dependence on weather and climatic conditions, [30]. The vulnerability of the agriculture sector is associated with several interrelated factors, such as variations in rainfall patterns, sunshine hours, temperature, humidity, droughts, and storms etc. Some of these parameters have a direct impact on crop productivity, e.g., rainfall, sunshine intensity, and temperature; while others exert an influence on productivity indirectly through droughts and CO_2, weeds, pests and management, water supply etc.,

[24], [31], [32], noted that food-crop production is exposed to population pressure and several climatic factors including changes in rainfall and temperature patterns, harvesting time, and water stress. All these factors have the potential to alter agriculture productivity and yield, and thus have substantial implications for food security, [33], [34], [35].

Recent quantitative research in this field utilizes different methods and climatic indicators to empirically examine the food crop response to changing climate conditions but provides mixed results. For instance, [36], preferred QR analysis to inspect the influence of climate change on crop yield by accounting for overall crop yield distribution. The study concludes that the crops which are monsoon-dependent are more responsive to any change in climatic conditions. [37], study the effects of rainfall and temperature on agriculture productivity using Ethiopian household survey data. The findings show that the temperature's effects are significant and nonlinear; while the impact of precipitation on productivity is less prominent as compared to temperature. Besides, the effects of temperature are not the same across food crops, indicating the crop-specific effects of climatic indicators. [38], conclude that the average temperature is increasing in March which is shortening the grain filling rate. [39], study finds that climate-related seasonal droughts are resulting in a reduction of the crop sown area and a substantial loss of China's grain production. [17], predicted about 32% fall in wheat productivity in Mexico due to changes in rainfall patterns. More recently, [40], finds that the changes in the weather, air, and sea temperature have a significant effect on food insecurity in the Caribbean.

In the particular context of Pakistan, it is observed that environmental degradation and climate hazards have made the country's population food-insecure by affecting food crops' productivity directly or indirectly through changes in temperature, rainfall, precipitation, and other related conditions, [41], [23], [42], [43], use metrological data of rainfall, temperature, sunshine hours, and relative humidity to show that all these factors have a favorable impact on productivity during the reproductive stage.

[9], use 50 years' time series data and find no negative effect of climate change on wheat yield. [32], utilize primary data of district Rawalpindi in a Ricardian framework and report the positive effects of rainfall on agriculture productivity. Using panel data of Punjab province, [44], find that the impacts of temperature and rainfall are changing with respect to time and crop stages, and their impact is different across different crops and districts in the province.

[45], employ average monthly data to show that the temperature has significantly positive impacts on both the vegetative and reproductive stages of the rice crop; while the rainfall is harmful only for the reproductive phase. [46], utilize annual time series data of 19 districts of Pakistan and report a negative effect of temperature hikes on wheat yield. [47], collected primary data from 442 farmers and concluded that they are aware of the negative consequences of climate change but are unable to adopt preventive measures. Using survey data from 240 farmers, [48], find a negative impact of heat stress on major food crop yield in Pakistan.

[49], collected cross-sectional data from 400 wheat farmers to show a negative impact of temperature rise on mean wheat yield. [50], conducted a survey of 150 farmers from a province of Pakistan and found that the wheat yield response to changing climatic conditions is different across the districts in the province. More recently, [45], shows that temperature anomaly has a significantly negative effect on the economic efficiency of rainfed wheat farmers; while rainfall appears to exert a significantly positive effect.

In summary, the extant literature provides very useful insights into the relationship by using different methods and climatic indicators. However, the results of these studies remain largely ambiguous as some report negative, [38], [48], while others conclude a positive impact of climate change on food-crop yield, [9], [32], [47].

Besides, these studies are based on the cross-sectional primary data focusing on a selected sample of the farmers, [48], [51].

Although some studies have utilized time series data, their analysis is susceptible to aggregation bias as they use monthly-averaged, [52], or even annually-averaged measures, [53], of the climatic variables. Different from previous studies, this study collected daily base data of climatic conditions and calculated their average and volatility measures to examine if it is the climate volatility that matters the most to food-crop yield. In addition, a non-parametric QR approach is utilized to quantify the impact of climate volatility on food security by focusing on wheat yield.

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3 Data and Methodology

Previous studies emphasize rainfall and temperature as the two most important indicators of climate change, [15], [53]. This study also took these two parameters along with some other non-climatic factors to quantify the impact of climate volatility on the wheat crop - the major staple food in Pakistan. The initial daily base data during 1981-2013 for district Faisalabad is collected from the Pakistan Meteorological Department, Faisalabad station. This daily-based data is utilized to calculate the average and volatility measures of rainfall and temperature. Following, [27], we assess rainfall volatility (RV) and temperature volatility (TV) from the coefficient variation i.e., the standard deviation of the rainfall series divided by the mean of the rainfall over the month. Specifically,

Rainfall (x) volatility,

$$RV = 1/\bar{x}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

Temperature (y) Volatility,

$$TV = 1/\bar{y}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

It should be noted that we sort out the data duration by including only those months that encompass the duration of the wheat crop in the Faisalabad region. In other words, the total duration of the wheat crop in the district is from 16 November to 15 April. Therefore, daily base data is considered only for this period due to its relevance with the crop duration, while the remaining period is eliminated. In addition to calculating average and volatility measures during the whole crop period, two further phases are also created given the requirements of the crop. Specifically, data is divided into the vegetative stage of the wheat crop i.e., from 16 November to 31st January; and the reproductive stage from 1st February to 15 April, [54]. For each stage of the crop growth, average and volatility measures are recalculated from the original daily basis data.

Table 1. Definitions of the variables

Variable	Description
Yield	Average yield 40 kilograms per hectare
Trend	Time trend
AUC	Area under cultivation
Rain	Average rainfall in millimeters (mm)
Tem	Average temperature in centigrade (°C)
TV	Temperature Volatility
RV	Rainfall Volatility
Veg_Tem	Average vegetative stage temperature
Veg_Rain	Average vegetative stage rainfall
RP_Tem	Average reproductive stage temperature
RP_Rain	Average reproductive stage rainfall
Veg_TV	Temperature volatility at the vegetative stage
Veg_VR	Rainfall volatility at the vegetative stage
RP_TV	Temperature volatility at the reproductive stage
RP_RV	Rainfall volatility at the reproductive stage

Data for the dependent variable, wheat yield per hectare, for district Faisalabad during 1981-2013 is gathered from different sources, such as the Pakistan Economic Survey, Agricultural Statistics of Pakistan, and Punjab Development Statistics. Besides, we also include the area under wheat cultivation (AUC) as a regressor. Being a basic and central factor, AUC cannot be ignored when analyzing the dynamics of crop growth. AUC also accounts for various omitted economic variables. For instance, if the farmer expects a higher price for wheat, they tend to devote more area for wheat cultivation, and, on the other hand, the higher cost of input might prevent the farmers from substituting the field for another alternative. Therefore, a rise in AUC indicates positive economic conditions for wheat growers. Furthermore, our regression also includes time trends as an additional regressor to avoid spurious regression, [55], [56]. A description of the variables is given in Table 1.

Table 2. Descriptive statistics

Variables	Minimum	Maximum	SD	Mean
Yield	34.51	79.08	13.46	56.46
AUC	238.4	303.00	12.77	261.42
Tem	23.18	27.25	0.97	25.65
Rain	0.21	0.91	0.19	0.43
TV	0.19	0.31	0.03	0.24
RV	3.47	7.71	0.93	5.32

Note: Authors' calculations

Table 2 demonstrates the basic descriptive statistics of the variables. Of these variables, average rainfall and temperature volatility have the lowest average, i.e., 0.24 and 0.43 respectively, while the highest average values appeared for the AUC and wheat yield i.e., 261.42 and 56.46, respectively. For volatility measures, the rainfall volatility is higher than that of the temperature for the average year. The temperature volatility is the lowest one but its annual mean value is the highest as compared to the rainfall. The standard deviation shows that the wheat yield has the highest dispersion, which also indicates the extent of volatility in wheat yield. Figure 1 displays the historic trend in rainfall, wheat yield, and temperature. As depicted, the trend of these variables exhibits a complex and weave pattern. Wheat yield (panel a) depicts an upward trend but with some instabilities over time. The Rainfall (panel c) points out more ambiguous variations during the period, while the temperature variations (panel b), reveal an increasing trend over time with relatively fewer disturbances as compared to the rainfall.

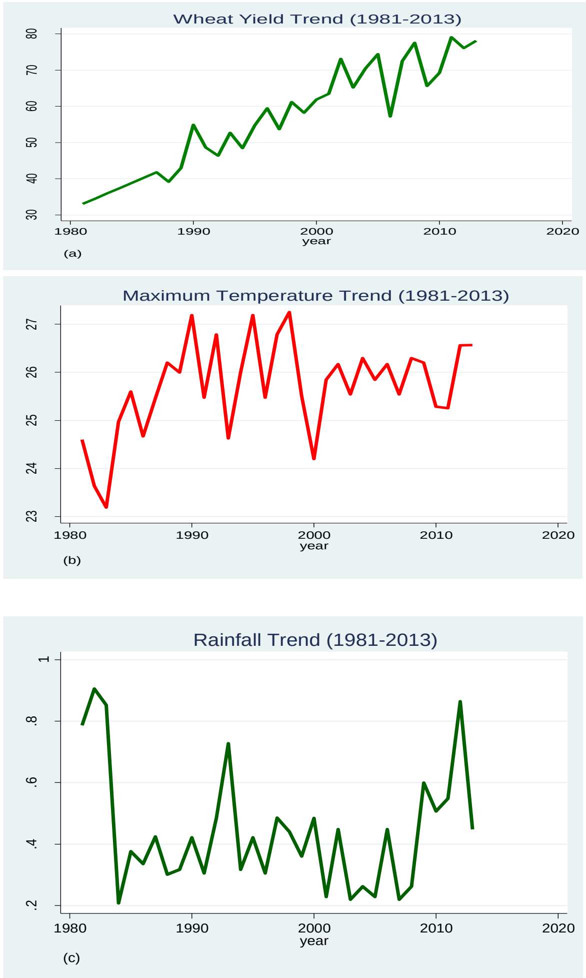

Fig. 1: Historical trends of climatic indicators and wheat yield

3.1 Model Specification

Our empirical strategy is to estimate two different models. First, we consider average measures of temperature and rainfall along with other non-climatic factors such as AUC and trend variables. Secondly, we replace volatility measures for the average of climatic indicators. This separation aims to examine if it is an average climate or climate shock (i.e., volatility) that matters the most for the food yield.

To quantify the impact of climate change on wheat yield, we specify the following production function:

$$Yield_t = Q(C_t, AUC_t, A_t) \quad (1)$$

where $Yield_t$ is wheat crop yield or productivity; C_t is a vector of climatic factors. AUC_t and A_t represent annual trends and AUC, respectively. The model specifications to estimate the impact of average climate change and volatility are as follows:

$$Yield_t = \beta_0 + \beta_t Trend_t + B_\alpha AUC_t + \beta_r Rain_t + \beta_m Tem_t + u_t \tag{2}$$

$$Yield_t = \sigma_0 + \sigma_t \, Trend_t + \sigma_\alpha \, AUC_t + \sigma_r \, VR_t + + \sigma_m VM_t + ȩ_t \tag{3}$$

where *Yield*$_t$ is the wheat yield per hectare, *Trend* captures the annual time trend, and *AUC* is the area under wheat cultivation. *Rain* and *Tem* represent the average of rainfall and temperature, respectively, during the whole crop duration; while *VR* and *VT* respectively are the volatility measures of rainfall temperature. As aforementioned, we have also made a separation in the wheat crop growth period i.e., *vegetative* and *reproductive* stages. Therefore, four further models are estimated using the average and volatility specifications for the vegetative and reproductive stages as follows:

$$Yield_t = \beta_0 + \beta_t Trend_t + B_\alpha AUC_t + \beta_r \, Veg\_Rain_t + \beta_m Veg\_Tem_t + u_t \tag{4}$$

$$\text{Yield}_t = \sigma_0 + \sigma_t \, Trend_t + \sigma_\alpha \, AUC_t + \sigma_r \, Veg\_VR_t + \sigma m \; Veg\_TM + ȩ_t \tag{5}$$

$$Yield_t = \beta_0 + \beta_t Trend_t + B_\alpha AUC_t + \beta_r \, RP\_Rain_t + \beta_m RP\_Tem_t + u_t \tag{6}$$

$$\text{Yield}_t = \sigma_0 + \sigma_t \, Trend_t + \sigma_\alpha \, AUC_t + \sigma_r \, RP\_VR_t + \sigma m \; RP\_TM + ȩ_t \tag{7}$$

Definitions of all these variables are given in Table 1.

3.2 Quantile Regression

This study employs the QR approach to analyze the impact of climatic variations on wheat yield distribution. This methodology helps analyze the differential impact of climatic indicators across the different points of wheat yield distribution and also facilitates computing the marginal effects of other regressors on the conditional distribution of the respondent variable. In reality, several phenomena require analysis of the differential distributional impact of independent actors on the behavior of the outcome variable. In other words, instead of considering only the average effect as usual, it might be more important to estimate the whole quantiles of a distribution to study the impact on the tails of the distribution. This is in contrast to the traditional 'average-based' regressions which yield a calculation of the impact of the independent variable on the average or mean value of the respondent, implicitly assuming that the relationship is throughout the whole distribution. The QR approach provides estimation based on the conditional percentiles or quantiles of yield distribution.

In this particular context, the QR is more appropriate to study the effects of fluctuations in climatic variables on the different conditional distributions of wheat yield because different stages of the crop growth might require different levels of temperature and rainfall, [15]. Besides, the QR is found to address the issue of heteroscedasticity by estimating different coefficients for the quantiles, [2]. The distortion arising from the outliers in data is also reduced when making different quantiles, indicating that the QR keeps efficiency in case of highly skewed distribution in error terms. Another advantage of the QR approach is that it does not put restrictions on the specifications i.e., how changes in variance are related to the mean, [57]. Thus, the QR provides a very malleable tool to inspect the association between the variables, without placing any constraints on the functional form. Following, [57], the QR model is written as,

$$y_i = x_i^{'}\beta_\theta + u_{\theta i} \quad \text{with Quant}_\theta\,(y_i|x_i) = x_i^{'}\beta_\theta \qquad (i = 1,2,\ldots..n)$$

where x is the vector of independent variables, β denotes the vector of parameters and u_θ denotes the error term. $\text{Quant}_\theta\,(y_i|x_i)$ is the θth conditional quantile for y given x. Distinct from the traditional least square methods, the QR minimizes the absolute sum of the error for a particular quantile of y. The θth QR as a solution to the problem is defined as;

$$\min\left[\sum_{i:y_i \ge x_i^{'}\beta} \theta \left| y_i - x_i^{'}\beta_\theta \right| + \sum_{i:y_i < x_i^{'}\beta} (1-\theta) \left| y_i - x_i^{'}\beta_\theta \right| \right] \qquad 0 < \theta < 1$$

By changing the level of θ, we can obtain any conditional quantile of the distribution of the response variable. Please note that we use β_θ instead of β to indicate that the parameter might yield different values against any given value of θ.

The linear programming technique is utilized to solve the problem by using the whole sample. The QR production function in the present context can be written as;

$$\text{yield}_i = \mathrm{x}_i^{'}\beta_\theta + \mathrm{u}_{\theta i} \quad \text{with Quant}_\theta\,(\text{yield}_i|\mathrm{x}_i) = \mathrm{x}_i^{'}\beta_\theta$$

where the θth conditional quantile of wheat yield is given by $\text{Quant}_\theta\,(\text{yield}_t|\mathrm{x}_t)$, X denotes the set of explanatory variables. In this study, we estimate a vector of coefficients, β_θ, for the four quantiles, i.e., θ=25th, 50th, 75th and 95th for each specified model.

4 Results and Discussion

Given the long-term time dimensions of our data, it is considered necessary to test time series properties a priori to get reliable estimates. We utilized the two most common unit root tests, namely the Augmented Dicky Fuller (ADF) and Philips Perron (PP) tests to confirm the stationary of the observed series. From the results given in Table 3, it is revealed that yield, rainfall, vegetative stage rainfall, and reproductive stage temperature are stationary at the level at 1% level of significance; while average temperature, rainfall for the whole crop period, and the vegetative stage temperature are stationary at the 5% level of significance. The results of the remaining variable also show that all variables are stationary at the level either at the 1 percent or 5 percent level of significance. Thus, we conclude that our series are stationary at the level and there is no need to take their first differences.

Table 3. Unit root test results

Var.	ADF	PP
Yield	-6.41*	-6.48*
AUC	-4.32*	-4.26**
Tem	-4.24**	-4.21**
Rain	-3.98**	-3.89**
Veg_Tem	-3.81**	-3.85**
Veg_Rain	-4.69*	-4.71*
RP_Tem	-4.88*	-4.91*
RP_Rain	-4.72*	-4.66*
TV	-4.26**	-4.23**
RV	-4.33*	-4.26**
Veg_TV	-4.56*	-4.58*
Veg_RV	-4.81*	-4.78*
RP_TV	-7.27*	-7.18*
RP_RV	-4.67*	-4.62*

*Note: * and ** represent the 1 % and 5% level of significance.*

Before proceeding to the main QR analysis, it is useful to draw some non-parametric evidence by using graphs. Figure 2 displays a linear relationship between wheat yield and average maximum temperature (panel a) and between yield and average rainfall (panel b).

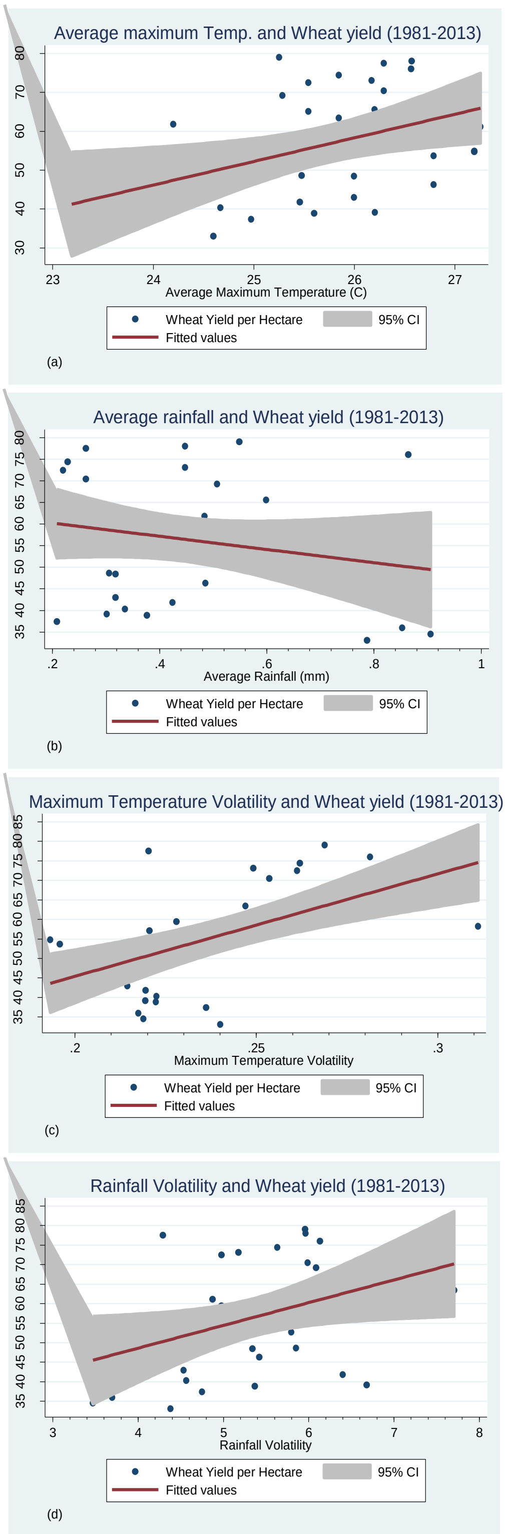

Fig. 2: Linear regression lines between climate change and wheat yield

Rainfall is a crucial input and an important driving force behind the wheat crop growth in the rain-fed as well as in the irrigated settings. In the irrigated fields, rain delivers a clean and healthy ecosystem to support the finest photographic activity for improved biomass and grain yield. However, the curve displays a negative association between wheat yield and rainfall. A possible reason might be that the rainfall at the reproductive stage, when the crop is ready to be harvested, is harmful to crop productivity because, at that time the sunshine hours and maximum temperature are needed for the crop ripeness; while rainfall at this ripening stage deteriorates grain quality, such as damaged grains or viviparous germination. Therefore, we separated the whole crop growth duration and hence metrological data into two parts, the vegetative stage and reproductive stage, to get a clearer picture of these effects.

From the above figures, we observe a positive link between the average maximum temperature and wheat yield, indicating the significance of higher temperature during the crop growth stages. In the lower panels c and d, the volatility measures of rainfall and temperature are displayed to observe their association with wheat yield. It reveals that the volatility of both rainfall and temperature is favorably related to yield, suggesting that the volatility of climatic conditions is desirable rather than their permanent existence or absence.

Turning to the regression estimations, Table 4 represents the results of coefficient estimation for the 25th, 50th, 75th, and 95th percentiles of the yield distribution. The estimates reveal that wheat yield responds differently to climate change across the different quantiles. The value of Pseudo-R^2 throughout the QR is greater than 0.70, demonstrating the model is well enough to explain the variation in the response variable. The Highest quantile reflects the highest yield during the study period. It represents the wheat yield of the last decade as there has been a substantial increase in wheat yield per hectare for the last ten to fifteen years (see also Figure 1). The results reveal a negative relationship between wheat yield and average maximum temperature at the lowest quantile, although insignificant; while the coefficient of temperature becomes positive at the 95th quantile. Specifically, the impact of average temperature is significantly greater and positive for the highest quantile, indicating a rise of about 2.68 mounds in wheat yield per hectare due to a degree rise in average temperature during the whole crop growth period. Since the lowest quantile (i.e., 25 percentile of data) mostly represents the initial period of the study and the highest quantile captures the more recent wheat yield trends, the findings suggest that average temperature is not a threat to contemporary wheat yield, [58].

Table 4. Wheat yield response to average climatic parameters

Quantiles	AUC	Trend	Rain	Tem	Pseudo R^2
$\theta = 0.25$	-0.12 (-0.99)	1.50* (9.86)	-2.45 (-0.54)	-1.17 (-1.08)	0.76
$\theta = 0.50$	-0.19* (-2.47)	1.56* (14.69)	-1.09 (-0.31)	-0.16 (-0.19)	0.78
$\theta = 0.75$	-0.10 (-0.66)	1.629* (6.57)	-0.15 (-0.02)	0.06 (0.03)	0.76
$\theta = 0.95$	-0.04* (-2.53)	1.69* (71.91)	8.04* (8.95)	2.68* (14.42)	0.71

*Note. * implies that the estimate is significant at the 1 percent level. t- Statistics are in brackets ().*

The coefficient of rainfall is also significant and positive only at the 95th quantile, suggesting an increase of about 8 mounds in yield due to a millimeter upsurge in rainfall during the period of study. The findings that temperature and rainfall vary across different quantiles are in line with, [58], for Ghana. The authors conclude that the effects of climate change on maize production are different across the different quantiles of crop distribution. Comparison of the coefficients from the least square regression with those of the QR in Kenya, [59], showed that the different quantiles of rice are disproportionally associated with agriculture extension and ecology. Besides, the size of the coefficient is increasing with higher quantile; while it is insignificant for the lowest yield distribution.

Regarding control variables, we observe a significantly positive effect of *Trend* on yield throughout the quantiles. It shows that wheat yield tends to increase every year which can be explained by some other factors not explicitly accounted for in the model. The *Trend* variable also captures the effect of technology change, [53], [60]. It has been a common practice of economists to include time variables to control for the effects stemming from technology and management style. Therefore, a positive impact of *the Trend* is not surprising, given that this effect is due to technical changes.

The sign of the coefficients of AUC remains negative throughout the four quantiles, indicating a decline in wheat yield per hectare with a rise in the area harvested. This result supports existing studies that report similar results, [58], [61], [62],. It is argued that the diminishing return to scale is the reason behind the negative association between AUC and crop yield. It has been noted that the small farmers are risk-averse, take more care of their resources by devoting most of their time on land to maximize output, and thus avoid a diminishing return to scale. On the other hand, large farmers use wage laborers and also face greater uncertainty and production loss due to extreme weather events. Therefore, the higher the AUC, the lower the yield per hectare.

Table 5 reports the QR results obtained by using the volatility measures of climatic indicators. As aforementioned, climate volatility is a different concept than the average climatic change, as the former represents uncertain variations in weather; while the latter is related to the gradual changes in weather captured through averaging the parameters. This is also depicted from the results in Table 5 which are different from those of Table 4. The difference is seen not only from the magnitude but also from the signs of coefficients. The results show significantly negative coefficients of both rainfall and temperature at the highest quantile, while negative but insignificant for most of the lowest quantiles, indicating that climatic volatility is harmful to wheat crop productivity, see also, [63].

These findings are in contrast to those of Table 4 where we observed that average climate change (i.e., a gradual change in the weather) is beneficial for the crop. Besides, as we move from the lower to the upper quantile, the size, and sign of the maximum temperature coefficient are also changing; while the coefficient of rainfall is negatively associated with every quantile and its magnitude is the highest for the highest quantile, as also concluded by, [36].

In other words, the volatility in climatic factors i.e., maximum temperature and rainfall is highly and negatively associated with wheat yield in the last decade as compared to its impact on the previous decades.

Table 5. Wheat yield response to volatility of climatic parameters

Quantiles	AUC	Trend	RV	TV	Pseudo R^2
θ = 0.25	-0. 16 (-0.93)	1.47* (6.11)	-0.82 (-0.43)	33.29 (0.41)	0.75
θ = 0.50	-0.14* (-2.97)	1.58* (18.49)	-0.18 (-0.27)	-26.21 (-1.27)	0.77
θ = 0.75	-0.09 (-0.59)	1.67* (6.64)	-0.51 (-0.25)	-20.05 (-0.47)	0.74
θ = 0.95	-0.06* (-3.47)	1. 96* (55.46)	-2.84* (-11.91)	-23.38* (-15.17)	0.73

*Note. * Implies that the estimate is significant at the 1 percent level. t- Statistics are in brackets ().*

4.1 Stage-wise Breakdown of Climate Volatility and Wheat Yield Analysis

The results discussed so far (Table 4 and Table 5) were based on the overall wheat crop growth period, and there is a caveat that the estimations might be sensitive due to ignoring the different stages of wheat crop growth. That is, the temperature and rainfall requirements of the wheat crop are different for the vegetative and reproductive stages. Therefore, to overcome this issue to the possible extent, we redo all the estimation by dividing the study data into two main stages of wheat crop i.e., vegetative and reproductive phases, and the results are given in Table 6 and Table 7.

Starting from the average measures, the results reported in Table 6 show that the rainfall is significant and positive only at the highest quantile for both the vegetative and reproductive stages, confirming our previous findings that average rainfall is positively associated with wheat yield. However, the impact of temperature across the crop growth stages is not the same. It is significantly positive for the vegetative stage but negative for the reproductive stage. Specifically, the vegetative stage average temperature indicates that a rise of 1°C in temperature increases wheat yield by about 3.151 mounds per hectare. However, the same rise in temperature at the reproductive stage reduces wheat yield by about 1.06 mounds per hectare. These findings reveal that the requirements of wheat crops are not the same for the vegetative and reproductive stages. Similarly, we found a greater effect of rain at the vegetative stage than that of the reproductive stage. A millimeter rise in rainfall at the vegetative stage increases yield by about 5.8; while the same change at the reproductive stage brings only a 0.6 mounds increase. This indicates that the rainfall is more beneficial at the early stages of the crop growth period i.e., the flowering stage. Nonetheless, these estimations are based on the average measures of climate indicators, and therefore the results might be sensitive to the aggregation bias.

Table 6. Wheat yield response to climatic parameters at different stages of the crop

Quantiles	RP_ Tem	Veg_ Tem	RP_ Rain	Veg_ Rain	Pseudo R^2
θ = 0.25	-0.38 (-0.60)	-0.07 (-0.07)	-2.45 (-1.77)	3.50 (0.97)	0.77
θ = 0.50	-0.33 (-0.38)	-0.17 (-0.14)	0.21 (0.11)	1.18 (0.22)	0.79
θ = 0.75	-0.21 (-0.25)	1.08 (1.19)	1.57 (0.89)	1.89 (0.37)	0.74
θ = 0.95	-1.06* (-19.36)	3.15* (40.59)	0.60* (4.29)	5.78* (15.18)	0.76

*Note: * indicates the level of significance at 1 percent. t- Statistics are in brackets ()*

The results obtained using the volatility measures of rainfall and temperature at different stages of the crop growth period are reported in Table 7. In the case of the lowest quantile, we find a negative, albeit insignificant effect of temperature volatility on wheat yield per hectare; while at the reproductive stage, temperature volatility appears to be positive. This is in contrast to the results of the overall crop growth period volatility which indicates a positive effect of temperature on yield. More valid results are observed for the highest quantile, where the temperature volatility is highly and positively related to yield at the reproductive stage or the second phase of crop maturity. The results for the rainfall volatility during both stages of crop growth at the lowest quantiles are against that of the previous estimated model where we incorporate the overall crop growth period. For the highest quantile, we observe a negatively significant impact of rainfall volatility on wheat yield. It implies that the unpredictable shocks in rainfall are more harmful to crop development, irrespective of the stages of growth.

Table 7. Wheat yield response to climate volatility at different stages of the crop

Quantiles	Veg_TV	RP_TV	Veg_RV	RP_RV	Pseudo R^2
θ = 0.25	-15.78 (-0.23)	34.68 (0.36)	0.13 (0.11)	0.98 (0.32)	0.78
θ = 0.50	-20.98 (-0.54)	-6.53 (-0.17)	-0.16 (-0.29)	0.45 (0.31)	0.77
θ = 0.75	-15.76 (-0.23)	1.89 (0.03)	-0.20 (-0.19)	-0.18 (-0.05)	0.71
θ = 0.95	2.99 (0.12)	8.27* (3.16)	-1.22* (-3.57)	-1.46* (-2.00)	0.76

*Note: * indicates the level of significance at 1 percent. t-Statistics are in brackets ()*

Combining all the findings, it can be obtained that though both temperature and rainfall are important for crop growth, their impacts are not the same across the whole crop growth period. Besides, a shock in the climatic conditions in terms of the sudden change in rainfall or temperature is also harmful to wheat yield. More importantly, we observe that the volatility of climatic factors exerts a different impact on the wheat yield when different stages of crop growth are accounted for in the analysis. Based on these findings, it can be argued that climate volatility is more damaging for food crops as compared to the gradual change (i.e., average measures) in climate conditions.

5 Conclusions

This study aimed to investigate the heterogeneous effects of climate volatility on the conditional distribution of wheat yield focusing on the rainfall and temperature that are the basic determining factors of wheat crop. The study explores a case from Pakistan by selecting a district from Punjab province, namely Faisalabad, and a key staple crop i.e., wheat. We collected daily-base data on climatic conditions for the past 33 years and utilized a quantile regression method to enumerate the diverse climatic impacts. Moreover, we employed alternative definitions of rainfall and temperature to examine if they have different influences on wheat yield. For this, the average and volatility measures of rainfall and temperature are calculated for the whole crop period as well as for the two main stages using different models.

Overall results indicate strong evidence that the volatility of climatic conditions is more harmful for the staple crop as compared to its mean values i.e., a gradual change in the rainfall and temperature. The QR estimates reveal a negative connection between climatic parameters and wheat yield distribution. Our findings call for government policies to focus on the development of new high-yielding varieties that are resistant to volatile climatic conditions, such as heavy spells of rain, heat stress, drought, and other related diseases. It can be suggested that to ensure a sustained supply of food, there is a need to establish a well-managed and sustainable irrigation system. Changes in climate patterns may also interrupt the crop growth period. For this, the appropriate adjustment in the harvesting time of the crop may be helpful to minimize grain damage due to extreme weather shocks. This also requires developing a weather forecasting system and the timely spread of climatic information to the wheat growers is essential.

Future research can consider the sensitivity of the findings of this study to alternative estimation techniques and also extend our investigations to other food and non-food crops.

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All authors equally contributed in this research regarding the data collection, empirical analysis, and writing of the manuscript.

- Usman Ali and Sania Shaheen conceived the study idea, reviewed the literature, collected/organized the data, done empirical analysis and completed the writeup of this research.
- Babar Hussain and Lal K. Almas provided the technical support, model development, abstract, and suggested the policy recommendations.

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Conflict of Interest

The authors have no conflicts of interest to declare.