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Long Term Trends in Rainfall and Temperature Effects on Food Security in Pakistan: An Analysis of 75 Years (1947-2021)

Rabia Rehman [1] Shumaila Sadiq [2] Sifat Ullah Khan [3] Akhtar Gul [4]

Abstract: *This study investigates the rainfall and temperature impact on food security (Wheat production) in Pakistan. The data nature is quarterly, and the time period is from 1947 to 2021. Econometrics approach simple OLS used. The wheat production is based on January, March, and November rainfall and temperature. In the findings of model 1, the rainfall in January and wheat production are negatively correlated. Besides, temperature and wheat production are directly correlated with each other. In Model 2, the rainfall has a significant and positive impact on wheat production. In the same month, the temperature was insignificant. The combined effect of rainfall and temperature has a negative impact on wheat production. It suggests that the combined effect of March rainfall and March temperature has a significant impact on wheat production at 10%. In model 3, November rainfall and wheat production are negatively correlated. The combined impact of November rainfall and November temperature has a positive and significant impact on the dependent variable. The study suggested the government reduce CO2 emissions in various sectors as well as improve technology and hybrid seeds. Besides, the state also adopts long-term reduction policy such as other developing countries adopts.*

Key Words: Rainfall, Food Security, Pakistan, OLS

Background

The 21st century is an amalgamation of the previous centuries. The people of this century are facing various issues, and climate change is also included in this. The human race of the modern era is facing several issues and it many severe consequences. The lack of awareness about its deep-rooted impacts is intensifying efforts to address vulnerabilities in the environment. Climate-associated challenges are adversely affecting the fulfillment of basic human needs, particularly in the food system. Human actions are contributing to climate changes that, in turn, are disrupting nutritional requirements and leading to a growing problem of food insecurity (El Bilali et al., 2020). Climate-related events, i.e., floods, earthquakes, and storms, have devastating impacts on human activities and as surrounding environment. These natural threats are significant challenges to human health. Livestock, farms, and water resources are often destroyed by these events. On average, annual floods resulting from rising global temperatures lead to over 20 thousand fatalities, harm a number of flora and fauna, and displace more than 20 million people worldwide. Roughly estimated, approximately 3 billion people have suffered economic and cultural losses since 1990 due to these climate-related fluctuations (Kumar, 2012; Kasperson and Kasperson, 2021).

The issue of food security gained global attention among countries, institutions, and policymakers after the World Food Summit (1996). At the moment, approximately 815 million people are dying in developing countries (FAO, 2017). Currently, the Global Risks Report by the World Economic Forum (2018) defines "food crises" as the seventh most perilous global risk. It refers to a situation where people either lack access to sufficient and nutritious food, cannot afford it, or cannot rely on consistent access. According to the Global Report on Food Crisis (2018), approximately 124 million people worldwide are experiencing heightened food insecurity, primarily due to conflicts, political instability, and severe climate-related

[1] Horticulture, Department of Horticulture, Sichuan Agriculture University, Chengdu, China.
[2] Assistant Professor of Economics, Government Sadiq College Women University, Bahawalpur, Punjab, Pakistan.
[3] M.Phil. Scholar, Department of Economics, University of Sciences and Technology, Bannu, KP, Pakistan.
[4] M.Phil. Scholar, Department of Economics, University of Sciences and Technology, Bannu, KP, Pakistan.

- Corresponding Author: Akhtar Gul (akhtar.gul31@yahoo.com)
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events. Food security is defined as a condition in which all residents of a region have adequate food supplies to meet their nutritious needs (FAO, 2020). Therefore, food security is a situation where every individual consistently meets their nutritional requirements (FAO, 2004). In developing and advanced countries, agriculture systems and production are closely connected with climate change. Climatic factors such as increasing temperatures, prolonged floods, irregular precipitation patterns, and rainfall variations directly impact agriculture systems and production by altering the physical characteristics of the environment. Regions with weaker natural immunity and biological controls are more susceptible to these harmful species. Notably, 75% of the Himalayan glaciers have already melted, and there are forecasts that they may disappear by 2035. This rapid glacier melting is elevating the risk of frequent flooding in the surrounding areas (Cogley, 2011; Anthwal et al., 2006). Climate change is significantly affecting the essential factors for establishing food security in developing nations, mainly in Asia and Africa.

History Background of this Study

Pakistan has been facing several challenges since its inception. Poverty and hunger are two of them (Gul et al., 2020). The people of these countries heavily depend on their agricultural sectors. About 21% of the GDP and 43.5% of the total workforce were employed in 2019 (Zhang et al., 2020). In 2022–23, the agricultural share increased from 21% to 22.9% of GDP, while employment declined from 43.5% to 37.4% of the total labor force (ESP 2022-23). Despite this, the per capita income of Pakistan will be $1,399.1 in 2022–2023, which remains low compared to neighboring countries. It's remarkable that Pakistan is the 6th most populous country in the globe. About 61% and 39% of people live in rural and urban areas, despite a 4.4% growth rate in the agriculture sector. Pakistan, like other countries in the world, is achieving food security. The second goal of the SDGs is to eradicate world hunger by 2030. Numerous measures have been implemented to mitigate global food security risks, resulting in nearly 200 million people being lifted out of the threat of hunger from 1990-92. Despite world population growth aligning with past projections in recent decades, effective socioeconomic policies have played a significant role in continuing equality and mitigating climate-related vulnerabilities, which have been lower than expected (Fujimori et al., 2019). Since 2013, Pakistan has suffered 5-floods, and about 35 million people have been hurt (Rehman et al., 2016). As well, in the last decade, Pakistan faced the most severe floods (in 2010, 2013, and 2015) in the country's history.

Furthermore, the 2010 flood affected around 20 million people and resulted in approximately 2000 casualties (Ali & Rahut, 2019). Nevertheless, both Pakistan and India are still facing the issues of hunger and poverty. Approximately 216 million people in South Asia are living in extreme poverty. Pakistan's Human Development Index (HDI) ranking stands at 161 out of 192 and 0.544, which is below the world average score of 0.723 (Economic Survey, 2023). Projected 11.8 million people from November 2023 to January 2024, of which 32% of the population will face the food insecurity issue (IPC, 2023). Pakistan was also ranked 92nd out of 116 food-insecure countries globally. Similarly, 20.5% of the population is malnourished, 44% of children under five are stunted, and 207.7 million are in the total population (WFP report 2023). Climate change emerged as an essential factor in Pakistan's food security challenges with five key aspects: utilization, hygiene, access, distribution, and food production (FAO, 2004, 2021). This study mainly focuses on the food production dimension to contribute to the existing literature, aiming to evaluate the impact of climate change, particularly temperature and rainfall, on food security. In Pakistan, wheat is the most crucial and main food, with the majority of farmers engaged in its production. In the blow figures 1 and 2, Pakistan's rainfall and temperature history from 1947 to 2021 are shown.

Figure 1

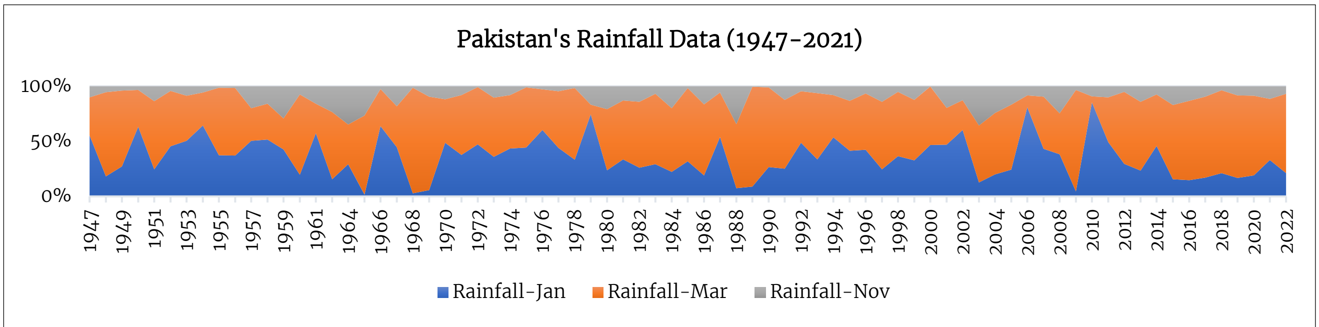
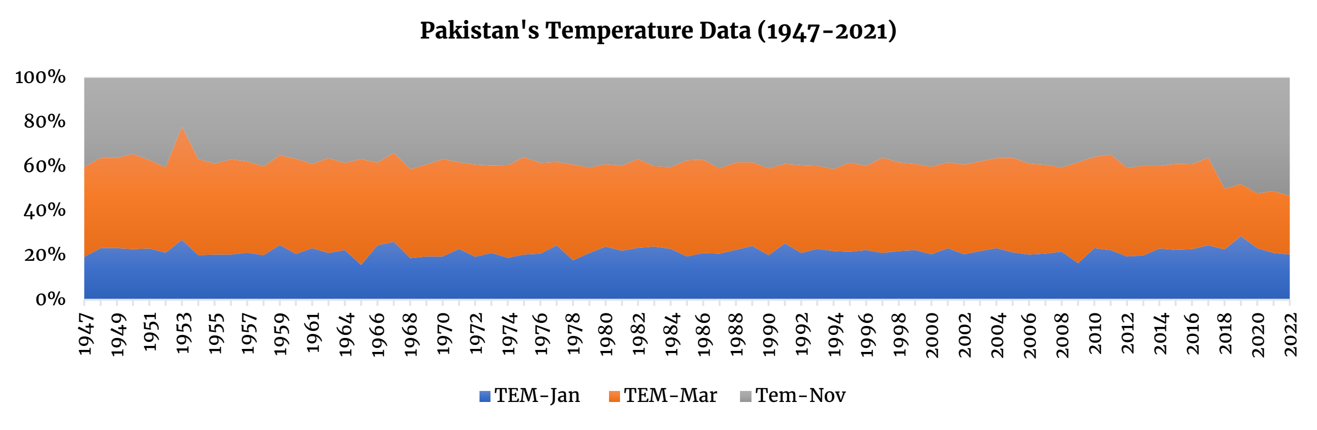


Figure 2



Literature Review

Numerous studies have been conducted by economists and environmentalists to investigate the impact of climate change on food security, with a particular focus on wheat and rice production. These studies consistently found a negative relationship between climate change and food security. Climate change poses a significant threat to the sustainability of our food system (Wheeler & Braun, 2013). Tariq et al. (2014) conducted that per capita wheat availability and essential food sources. The study examined climate change and its effects on production. The study used time series data from 1980 to 2012 and employed a simple regression (OLS) approach. The study found that in irrigated regions, rising temperatures in November and January were adversely associated with wheat production. On the contrary, low temperatures in March and November positively correlated with wheat production. Non-irrigated areas were significantly affected by minimum temperatures, and March rainfall exhibited a negative relationship with wheat production. Joyo et al. (2018) examine the climate-related risks on rice production and their implications for food security. They also examined the current state and growth of rice production in Sindh. In that study, time series was used along with the econometric approach VAR. Their study found a negative association between rice production and temperature and suggested that institutions adopt hybrid seeds and adapted varieties. Bocchiola et al. (2019) investigated the connection between climate change and food security in the Himalayas. They used from 1981 to 2010. Their study considered various variables, including daily temperature, rainfall, solar radiation, population figures, and a nutritional index based on daily calorie consumption.

The results found substantial decreases in wheat, rice, and maize production, 25%, 42%, and 46%, respectively. Furthermore, adapting land use at higher altitudes was recommended to mitigate a 38% reduction in wheat production and minor decreases in rice and maize production. Factors such as climate change, sown area, fertilizer usage intensity, and population size played pivotal roles in food security and agricultural output. Xu et al. (2019) examined the impacts of climate change and human interventions on agricultural production and food security. The time series data was used from 1990 to 2015, and applied the OLS approach. The study found that over one-fourth of counties in the Yangtze River Basin faced high food insecurity risks, with 19.4% to 27.4% of countries experiencing severe or moderate per capita food insufficiency since 1990. Multiple studies have been conducted on temperature's influence on agricultural production and food security (Saseendran et al., 2000; Peng et al., 2004; Xiao et al., 2008; Ye et al., 2014; Baldos & Hertel, 2014). For instance, Saseendran et al. (2000) reported that a one °C temperature increase reduced crop output by 6%, while Peng et al. (2004) found that a similar temperature increase led to a 10% drop in rice output in the Philippines. Baldos & Hertel's (2014) global food security forecast for 2050 indicated that increased agricultural productivity could enhance food security but emphasized the risks posed by climate change. Finally, Abrar and Maryiam (2023) investigated climate change's impact on Pakistan's food security and highlighted an increase in minimum temperature leading to an 8.87kg decline in wheat yield, eventually reducing food security in Pakistan.

Methodology

Data and Data Sources

This study investigates the heavy rainfall and temperature impact on wheat production. The data nature is time series and time period from 1947 to 2021. The data is taken from different sources, i.e., Agricultural Statistics of Pakistan, the Pakistan Meteorological Department, and the Economic Survey of Pakistan. Three variables are also used. Wheat production is the dependent variable, while rainfall (MM) and temperature (Celsius) are independent variables.

Model Specification

$$\boldsymbol{LNWHEAT - Jan = f(Rainfall - Jan, Temperature - Jan, Rainfall - Jan * Temperature - Jan \ldots (1)}$$

$$LNWHEAT - Mar = f(Rainfall - Mar, Temperature - Mar, ainfall - Mar * Temperature - Mar \ldots (2)$$

$$LNWHEAT - Nov = f(Rainfall - Nov, Temperature - Nov, ainfall - Nov * Temperature - Nov \ldots (3)$$

Models 1 to 3 represent the mathematical or exact models. In this model, the variable wheat is transformed into a log form. In other words, models 1 to 3 are also called semi-log models.

Econometric Model

$$\boldsymbol{LNW - Jan_t = a_1 + \beta_1 RF - Jan_t + \beta_2 TEM - jan_t + \beta_3 RF - Jan_t * TEM - Jan_t + \varepsilon_t \ \ldots (1a)}$$

DV*	IVs				
LNW-Jan =	a_1+	$\beta_1 RF - Jan_t$	$+\beta_2 TEM - jan_t$	$+\beta_3 RF - Jan_t * TEM - Jan_t$	ε_t
	Constant	$\beta_1$coefficient $\beta_1 < 0$	$\beta_1$coefficient $\beta_2 > 0$	$\beta_1$coefficient $\beta_3 > 0$	Error term

$$LNW - Mar_t = a_1 + \beta_1 RF - Mar_t + \beta_2 TEM - Mar_t + \beta_3 RF - Mar_t * TEM - Mar_t + \varepsilon_t \ \ldots (1b)$$

DV*	IVs				
LNW-mar =	a_1+	$\beta_1 RF - mar_t$	$+\beta_2 TEM - mar_t$	$+\beta_3 RF - mar_t * TEM - mar_t$	ε_t
	Constant	$\beta_1$coefficient $\beta_1 > 0$	$\beta_1$coefficient $\beta_2 > 0$	$\beta_1$coefficient $\beta_3 < 0$	Error term

$$LNW - Nov_t = a_1 + \beta_1 RF - Nov_t + \beta_1 TEM - Nov_t + \beta_3 RF - Nov_t * TEM - Nov_t + \varepsilon_t \ldots (1c)$$

DV*	IVs				
LNW-Nov =	a_1+	$\beta_1 RF - Nov_t$	$+\beta_2 TEM - Nov_t$	$+\beta_3 RF - Jan_t * TEM - mar_t$	ε_t
	Constant	$\beta_1$coefficient $\beta_1 < 0$	$\beta_1$coefficient $\beta_2 > 0$	$\beta_1$coefficient $\beta_3 > 0$	Error term

Author's calculations

The model 1a to 1c show the econometric or inexact model. It is also called a probabilistic model. Therefore, a_1 and $\beta_i$are parameters, which are further divided into intercepts and coefficients. The a_1 shows the constant while β_1 and $\beta_2$are shows the coefficients of W_t and RFt, respectively. The β_3 is the coefficient of the interaction term (or variable) of the rainfall and temperature (Rainfall*Temperature). Parallel Jan, Mar, and Nov show the months such as Jan =January, Mar =March, and Nov= November, respectively. Similarly, W indicates wheat production, while RT and TEM represent Rainfall and Temperature, respectively.

Unit Root Test

A unit root test is a statistical test used in time series analysis to determine whether a time series data set has a unit root or is stationary. Stationarity is a crucial assumption in many time series models because it implies that the statistical properties of the data, such as the mean and variance, do not vary over time. Non-stationary data can lead to unreliable model results and wrong conclusions (Gul and Khan 2021).

There are many unit root tests such as ADF, PP, KPSS, and so on. This study used ADF and PP unit root tests.

Augmented Dickey-Fuller (ADF)

The ADF test is a common statistical test used in time series analysis to determine whether a univariate time series dataset has a unit root or not. The H_0 of the ADF series has a trend, and the H_A of the ADF test series does not have a trend. The below equation represents the ADF equation:

$$\Delta Y_t = a_i + \beta_i Y_{t-1} + \gamma \Delta Y_{t-1} + \delta_1 \Delta Y_{t-2} + \delta_2 \Delta Y_{t-3} + \cdots + \delta_{p-1} \Delta Y_{t-p+3} + \epsilon_t$$

Where, ΔY_t Represents the 1st difference of the time series at time t. it is defined as $\Delta Y_t = \Delta Y_t - Y_{t-1}$. Y_{t-1} is represents the lagged value of the original time series, ΔY_{t-1} is represents the lagged first difference of the time series. δ_1, $\delta_2 .... \delta_{p-1}$ represent coefficients related to the lagged differences of Yt. The number of lags (p) is determined using criteria like AIC or BIC. The error term is represented as ϵ_t Is the error term. The H0 being tested is whether the time series has a unit root, implying it is non-stationary, typically represented as β=0, indicating the presence of a trend. On the other hand, the H1 proposes that the time series does not have a unit root, indicating stationarity (β≠0), signifying the absence of a trend.

Ordinary Least Square (OLS)

The OLS is a fundamental and widely used method in econometrics and statistics for estimating the parameters of a linear regression model. In econometrics, OLS is used to analyze and model relationships between variables, understand the effects of one or more independent variables on a dependent variable, and make predictions or infer causal relationships. The overview of OLS in econometrics. In econometrics, a linear regression model is expressed as:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \epsilon_i$$

Where: Y_i is the dependent variable for the ith observation, $X_{1i} + X_{1i}, \ldots, X_{ki}$ are the independent variables (explanatory variables) for the ith observation, β_0 is the intercept (constant term), $\beta_1, \beta_2, and\ \beta_k$ Are the coefficients associated with the independent variables and $\epsilon_i\ is$ the error term.

Results and Discussion

Table 1

Remsey RESET TEST

Model 1: $\boldsymbol{LNW - Jan_t = a_1 + \beta_1 RF - Jan_t + \beta_2 TEM - jan_t + \beta_3 RF - Jan_t * TEM - Jan_t + \varepsilon_t \ \ldots (1a)}$			
Omitted Variables: Squares of fitted Values			
Specification Variables: LAN-JAN Rainfall-JAN TEM-JAN C			
Tests	Value "Coefficient"	Df [], ()	Prob.
t-statistics	1.464710	71	0.1522
F-statistics	1.514835	(1,71) *	0.1391
Likelihood Ratio	1.313463	1	0.1978
FITTED^2	0.761338	[0.4485], (1.6975)	0.0990***
Model 2: $LNW - Mar_t = a_1 + \beta_1 RF - Mar_t + \beta_2 TEM - Mar_t + \beta_3 RF - Mar_t * TEM - Mar_t + \varepsilon_t \ \ldots (1b)$			
Omitted Variables: Squares of fitted Values			
Specification Variables: LAN-MAR Rainfall-MAR TEM-MAR C			
Tests	Value "Coefficient"	Df [], ()	Prob.
t-statistics	1.558478	71	0.1290
F-statistics	1.351342	(1,71) *	0.1861
Likelihood Ratio	0.084430	1	0.7714
FITTED^2	0.985110	[2.9514], (-0.7223)	0.1290***
Model.3. $LNW - Nov_t = a_1 + \beta_1 RF - Nov_t + \beta_1 TEM - Nov_t + \beta_3 RF - Nov_t * TEM - Nov_t + \varepsilon_t \ldots (1c)$			
Omitted Variables: Squares of fitted Values			
Specification Variables: LAN-NOV Rainfall-NOV TEM-NOV C			
Tests	Value "Coefficient"	Df [], ()	Prob.
t-statistics	0.730414	71	0.4675

F-statistics	0.533507	(1,71) *	0.3543
Likelihood Ratio	0.561457	1	0.4537
FITTED^2	0.810403	[0.044], (1.810)	0.07***

Author's calculations

() *, (), ***, [], "Indicates df, t-statistics value, the insignificant level at 5% (P>0.05, here we take a decision on 5%), Std-error values, coefficient value respectively.

First of all, it is necessary to check the validity of a model. For these purposes, econometricians developed a number of tests, and Ramsey's RESET (Regression Specification Error Test) is one of them. Ramsey's RESET test (1969, 1974) was used to check the validity of a regression model. It helps to examine whether the relationship between the independent variables and the dependent variable is correctly specified in a linear regression model or not. H0: The linear regression model is correctly specified, and HA: The linear regression model is not correctly specified (misspecification of the model). In these models, the t-statistics (show the significant value of individual variables), F-statistics (show the significant level of the whole model), and likelihood ratio probability values are greater than 0.05, which means do not reject the null hypothesis and accept the null hypothesis. Our null hypothesis is that the model is correctly specified (no misspecification of the model). Similarly, the FITTED^2 value of all models is higher than 0.05, which also shows that there is no misspecification of the model. The results conclude that the regression model is valid for estimation and policy forecasting.

Table 2

Descriptive statistics

Model 1: $LNW-Jan_t = a_1 + \beta_1 RF-Jan_t + \beta_2 TEM-jan_t + \beta_3 RF-Jan_t * TEM-Jan_t + \varepsilon_t \;...(1a)$			
Basic statistics	Variable		
	LNW-Jan	Rainfall-Jan	TEM-Jan
Mean	8.396239	15.80281	8.828751
Median	8.504815	13.40810	8.702610
Maximum	9.017066	22.08620	12.14350
Minimum	7.576610	0.997730	5.913450
Std. Dev.	0.378361	13.56111	1.048274
Skewness	-0.564627	0.673902	0.556166
Kurtosis	2.279390	3.303930	4.493400
Prob. value of Jarque-Bera	0.060574	0.080654	0.094436
Model 2: $LNW-Mar_t = a_1 + \beta_1 RF-Mar_t + \beta_2 TEM-Mar_t + \beta_3 RF-Mar_t * TEM-Mar_t + \varepsilon_t \;...\;(1b)$			
	LNW-Mar	Rainfall-Mar	TEM-Jan
Mean	8.409567	34.77340	15.94552
Median	8.494555	33.51640	15.91932
Maximum	9.075802	76.03290	22.73770
Minimum	7.637716	2.835106	9.716620
Std. Dev.	0.379841	16.81556	2.068973
Skewness	-0.403994	0.315422	-0.439600
Kurtosis	2.167206	2.514261	6.5117371
Prob. value of Jarque-Bera	0.122000	0.317399	0.0000153
Model 2: $LNW-Nov_t = a_1 + \beta_1 RF-Nov_t + \beta_1 TEM-Nov_t + \beta_3 RF-Nov_t * TEM-Nov_t + \varepsilon_t \;...(1c)$			
	LNW-Nov	Rainfall-Nov	TEM-Nov
Mean	8.414115	7.088937	15.68994
Median	8.504815	5.248330	15.58770
Maximum	9.075815	26.15420	22.36780
Minimum	7.576610	0.161850	9.798860
Std. Dev.	0.375790	6.250958	1.811240

Skewness	-0.497846	1.454573	1.144989
Kurtosis	2.256980	4.792932	7.395706
Prob. value of Jarque-Bera	0.089664	0.140212	0.342112

Author's calculations

Table 2 describes the basic information about the specific data. The mean value of model 1 is 8.39, 15.80, and 8.82 for wheat, rainfall, and temperature in January, respectively. The mean value of model 2 is 8.40, 34.55, and 15.94 for wheat rainfall and temperature in March, respectively. Similarly, 8.41, 7.08, and 15.68 values of the mean of the wheat, rainfall, and temperature of November, respectively. The median value represents the middle value of the variables. Therefore, the maximum and minimum values show the highest and lowest values of the models. The standard deviation of wheat is the minimum in all models. The skewness value is >+1.0 or <-1.0, which are considered skewed distributions, and the kurtosis value is -3 to +3 (Gul et al., 2023).

Table 3

Correlations

Model 1: $LNW-Jan_t = a_1 + \beta_1 RF-Jan_t + \beta_2 TEM-jan_t + \beta_3 RF-Jan_t * TEM-Jan_t + \varepsilon_t$ ...(1a)				
		Variable		
		LNW-Jan	Rainfall-Mar	TEM-Nov
Variable	LNW-Jan	1		
	Rainfall-Mar	-0.197582 [0.0893] ***	1	
	TEM-Nov	0.340190 [0.0028] *	0.060011 [0.6090]	1
Model 2: $LNW-Mar_t = a_1 + \beta_1 RF-Mar_t + \beta_2 TEM-Mar_t + \beta_3 RF-Mar_t * TEM-Mar_t + \varepsilon_t$ ... (1b)				
		LNW-Jan	Rainfall-Mar	TEM-Nov
Variable	LNW-Jan	1		
	Rainfall-Mar	0.102491 [0.3816]	1	
	TEM-Nov	-0.149861 [0.0158] *	-0.205605 [0.0768] ***	1
Model 3: $LNW-Nov_t = a_1 + \beta_1 RF-Nov_t + \beta_1 TEM-Nov_t + \beta_3 RF-Nov_t * TEM-Nov_t + \varepsilon_t$ ...(1c)				
		LNW-Jan	Rainfall-Mar	TEM-Nov
Variable	LNW-Jan	1		
	Rainfall-Mar	-0.107163 [0.3601]	1	
	TEM-Nov	0.530214 [0.0000] *	-0.096067 [0.0271] **	1

Author's calculations
*, **, and *** represent 1%, 5%, and 10% significant levels respectively.

Table 3 shows the association between projected variables. The minus sign represents a negative association, while the plus sign indicates a positive association. In the above model 1, rainfall and wheat have a negative association, while wheat is positively correlated with temperature. Rainfall and temperature are also positively correlated. Similarly, in model 2, wheat and rainfall are positive, while wheat and temperature are negative. The rainfall and temperature in January were also negatively correlated with each other. The story is not different in Model 3. The rainfall is negatively correlated with wheat and temperature, while wheat has a positive association with temperature.

Table 4

The Results of Unit Root Tests

Variable	ADF				PP			
	Level				Level			
	Constant		Trend & Intercept		Constant		Trend & Intercept	
	t-test	P-value	t-test	P-value	t-test	P-value	t-test	P-value
W-Jan	-1.8240	0.366	-3.9374	0.0152*	-2.4832	0.123	-4.211	0.007*

W-Mar	-2.2457	0.192	-3.6979	0.0286**	-2.2230	0.200	-3.829	0.020**
W-Nov	-1.1283	0.700	-3.5324	0.0432**	-1.9524	0.307	-3.532	0.043**
RF-Jan	-7.4853	0.000*	-	-	-7.485	0.000*	-	-
RF-Mar	-6.9044	0.000*	-	-	-6.9047	0.000*	-	-
RF-Nov	-8.7098	0.000*	-	-	-8.7179	0.000*	-	-
TEM-Jan	-9.1374	0.000*	-	-	-9.1284	0.000*	-	-
TEM-Mar	-4.8943	0.001*	-	-	-5.1049	0.000*	-	-
TEM-Nov	-0.9523	0.7658	-5.4350	0.000*	-3.7122	0.005*	-	-

Unit-Root Results

Model.1. $LNW - Jan_{t-stationary\,I(0)} = a_1 + \beta_1 RF - Jan_{t-StationaryI(0)} + \beta_2 TEM - jan_{t-stationary\,I(0)} + \beta_3 RF - Jan_t * TEM - Jan_{t-stationary\,I(0)} + \varepsilon_t$

Model.2. $LNW - Mar_{t-stationary\,I(0)} = a_1 + \beta_1 RF - Mar_{t-stationary\,I(0)} + \beta_2 TEM - Mar_{t-stationary\,I(0)} + \beta_3 RF - Mar_t * TEM - Mar_{t-stationary\,I(0)} + \varepsilon_t$

Model.3. $LNW - Nov_{t-stationary\,I(0)} = a_1 + \beta_1 RF - Nov_{t-stationary\,I(0)} + \beta_1 TEM - Nov_{t-stationary\,I(0)} + \beta_3 RF - Nov_t * TEM - Nov_{t-stationary\,I(0)} + \varepsilon_t$

Author's calculations

*Indicates the significant level at 1%.

Before any estimation, we check if our variables are stationary or not. If any variables are non-stationary, then first convert them to stationary. Because non-stationary variables mislead results, for this purpose, statisticians and econometricians developed many unit root tests, and ADF and PP are two of them. Table 2 describes the ADF and PP results. In this table, all specific variables are stationary at level 1. When all variables are stationary at level 1, we use simple regression or OLS (Gul et al., 2023).

Table 5

Ordinary Least Square (OLS) results

Dependent Variable: LNW [Wheat Production]				
Model 1: $LNW - Jan_t = a_1 + \beta_1 RF - Jan_t + \beta_2 TEM - jan_t + \beta_3 RF - Jan_t * TEM - Jan_t + \varepsilon_t$ ... (1a)				
Variable	Coefficient	Std. Error	t-statistics	Prob. value
RF-Jan	-0.006104	0.003013	-2.026046	0.0465**
TEM-Jan	0.127526	0.0038976	3.271888	0.0016*
RF-Jan*TEM-Jan	0.151551	0.073571	2.059915	0.0431**
C	7.205315	0.635162	11.34407	0.0000*
Model 2: $LNW - Mar_t = a_1 + \beta_1 RF - Mar_t + \beta_2 TEM - Mar_t + \beta_3 RF - Mar_t * TEM - Mar_t + \varepsilon_t$ ... (1b)				
RF-Mar	0.032085	0.016609	1,931800	0.0574***
TEM-Mar	0.052396	0.046788	1.119849	0.2666
RF-Mar*TEM-Mar	-0.001967	0.001061	-1.853537	0.0680***
C	7.535290	0.752059	10.01954	0.0000
Model 3: $LNW - Nov_t = a_1 + \beta_1 RF - Nov_t + \beta_1 TEM - Nov_t + \beta_3 RF - Nov_t * TEM - Nov_t + \varepsilon_t$ ... (1c)				
RF-Nov	-0.164574	0.089405	-1.840782	0.0698***
TEM-Nov	0.057202	0.035169	1.626494	0.1083
RF-Nov*TEM-Nov	0.010452	0.005786	1.806598	0.0751***
C	7.531927	0.552984	13.62052	0.0000*

Author's calculations

In Model 1, both independent variables, rainfall and temperature, have a significant influence on the dependent variable. When 1 unit increases rainfall in January. As a result, wheat production declined by 0.006 percent in the same month. It indicates there is an inverse relationship between rainfall in January and wheat production in January. Besides, temperature and wheat production are directly correlated with each other. When there is a 1 unit increase in temperature in January, wheat production also increases by 0.12 percent in the same month. Now, check the interaction effect on wheat production in the same month. The positive coefficient of interaction terms suggests that the impact of January rainfall on wheat production depends on the level of January temperature. In other words, the effect of rainfall on wheat production is amplified or diminished based on temperature. It also means that when January rainfall is high, and the January temperature is also high, the effect on wheat production is significantly positive, indicating that favorable conditions in both rainfall and temperature contribute to increased wheat production. Similarly, in model 2, the rainfall has a significant and positive impact on wheat production. When there was a 1 unit increase in rainfall in March, as a result, wheat production also increased by 0.03 percent. In the same month, the temperature is insignificant. It means temperature does not impact wheat production. The interaction term "RF-Mar*TEM-Mar" coefficient is -0.001, representing a negative relationship with the dependent variable (wheat production). It suggests that the combined effect of March rainfall and March temperature has a significant impact on wheat production at 10%. In model 3, rainfall and interaction terms are significant at 10%, while temperature is insignificant. November rainfall and wheat production are negatively correlated. When rainfall increases by one unit in November, Pakistan's wheat production falls by -0.16%. The interaction between November rainfall and November temperature (RF-Nov*TEM-Nov) has a positive and significant impact on the dependent variable. When both rainfall and temperature increase in November, there is a modest positive influence on the dependent variable. A number of previous studies found parallel and contradictory outcomes. Janjua et al. (2014) finding contradict this study. They found that Climate change does not negatively impact wheat production in Pakistan. A parallel study conducted by Hussain and Mudasser (2007) and Rashid and Rasul (2011) finds rainfall has a negative impact on wheat yield and other crops.

Table 6

Heteroscedasticity Test Bruesch-Pagan-Godfrey

Model 1: $LNW - Jan_t = a_1 + \beta_1 RF - Jan_t + \beta_2 TEM - jan_t + \beta_3 RF - Jan_t * TEM - Jan_t + \varepsilon_t$ ... (1a)			
H0: Homoskedasticity			
F-statistics	1.158613	P.F(2,72)	0.3197
Obs*R^2	2.338514	P. X^2(2)	0.3106
Scaled Explained SS	1.620368	P. X^2(2)	0.4448
Model 2: $LNW - Mar_t = a_1 + \beta_1 RF - Mar_t + \beta_2 TEM - Mar_t + \beta_3 RF - Mar_t * TEM - Mar_t + \varepsilon_t$ ... (1b)			
F-statistics	4.113296	P.F(2,72)	0.2321
Obs*R^2	7.690647	P. X^2(2)	0.2348
Scaled Explained SS	4.506756	P. X^2()	0.1050
Model 3: $LNW - Nov_t = a_1 + \beta_1 RF - Nov_t + \beta_1 TEM - Nov_t + \beta_3 RF - Nov_t * TEM - Nov_t + \varepsilon_t$ ... (1c)			
F-statistics	1.772427	P.F(2,72)	0.1773
Obs*R^2	3.519287	P. X^2(2)	0.1721
Scaled Explained SS	1.919822	P. X^2(2)	0.3829

Table 6 shows the outcome of the heteroscedasticity of the three models. In all models, the value of Prob. of X^2 is higher than 0.05. When p-value >0.05, thus cannot reject H_0, and rather than accept H0 and H0, the model is homoscedastic or free from heteroskedasticity.

Normality [Histogram]

The stability of the model was checked through the Jarque-Bera value. Figures 1 to 3 describe the stability of the models. In all models, the probability value of Jarque-Bera exceeds 0.05, which means we accept the null hypothesis, and our null hypothesis the model is stable.

Model.1. $LNW - Jan_t = a_1 + \beta_1 RF - Jan_t + \beta_2 TEM - jan_t + \beta_3 RF - Jan_t * TEM - Jan_t + \varepsilon_t$ ... (1a)

Figure 1

Model 2: $LNW - Mar_t = a_1 + \beta_1 RF - Mar_t + \beta_2 TEM - Mar_t + \beta_3 RF - Mar_t * TEM - Mar_t + \varepsilon_t$ ... $(1b)$

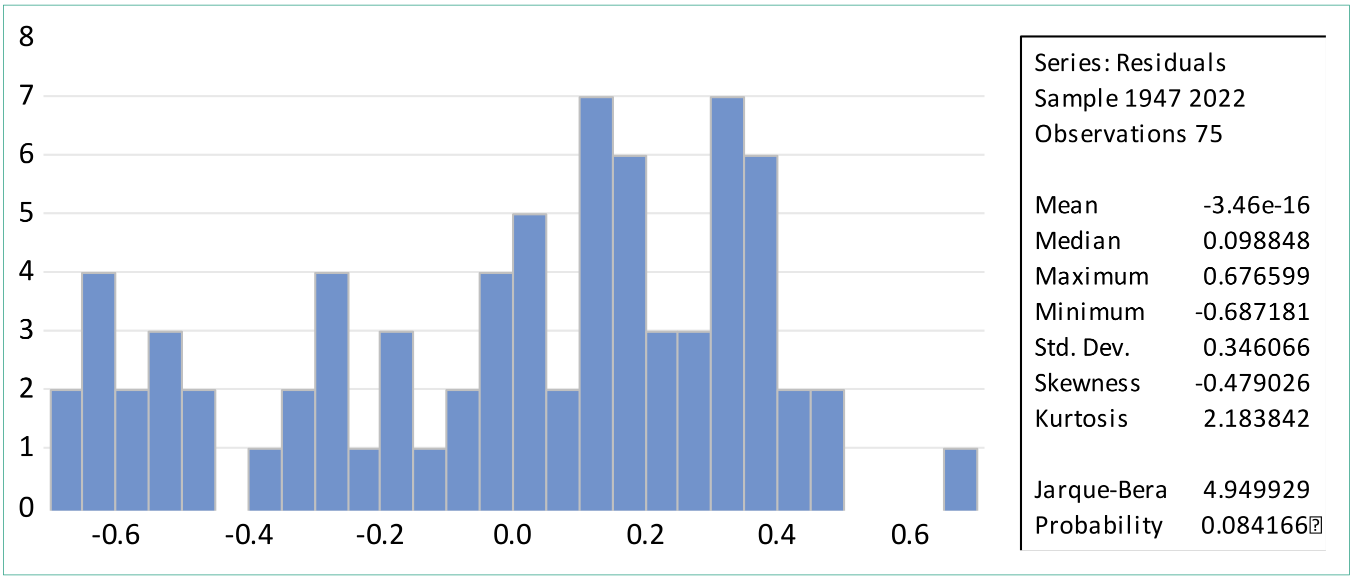


Figure 2

Model 3: $LNW - Nov_t = a_1 + \beta_1 RF - Nov_t + \beta_1 TEM - Nov_t + \beta_3 RF - Nov_t * TEM - Nov_t + \varepsilon_t$ ... $(1c)$

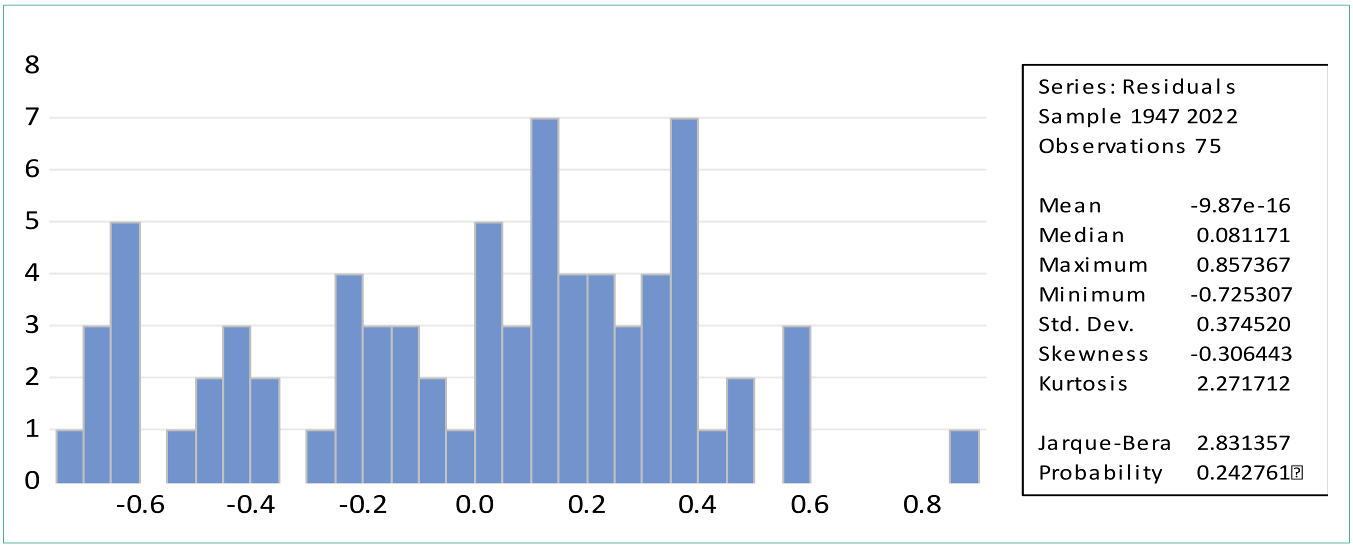
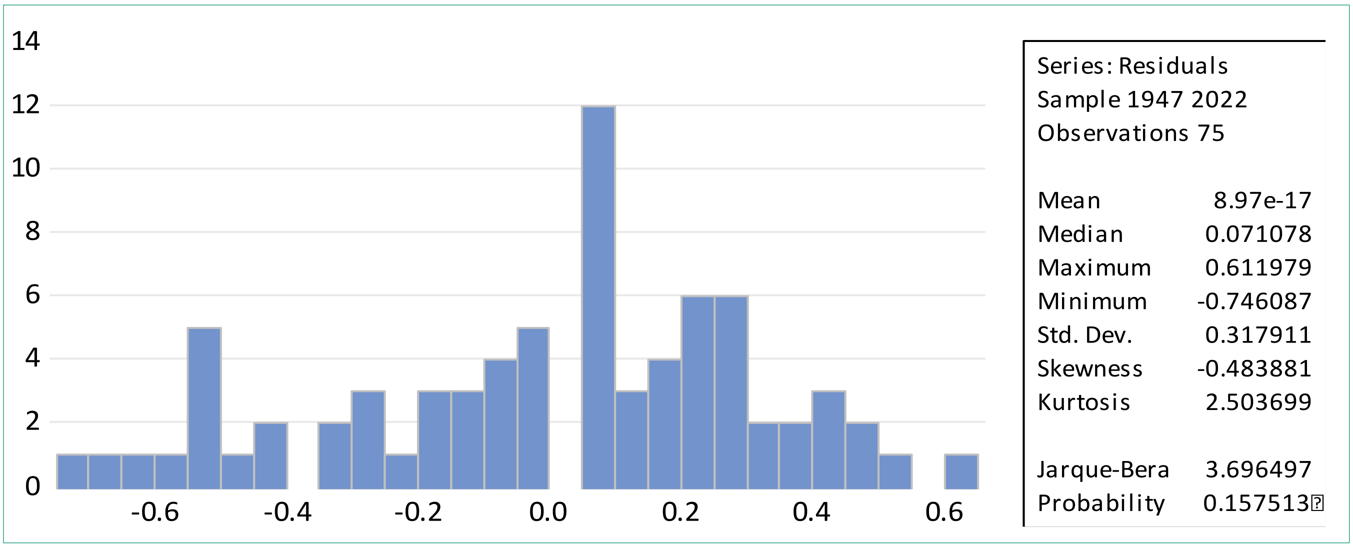


Figure 3

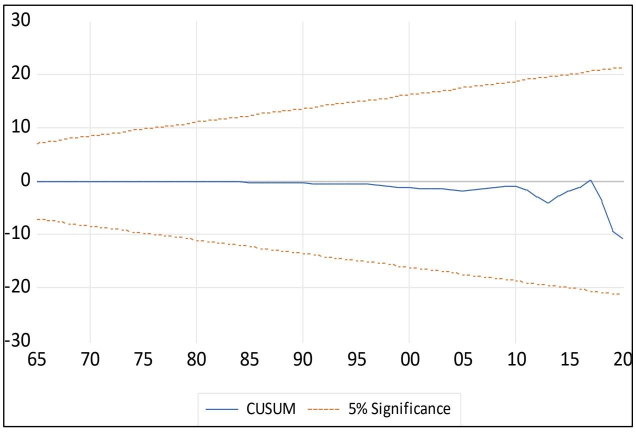


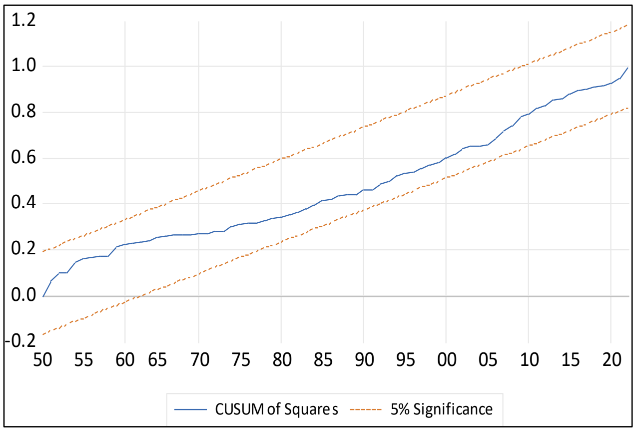
Stability OF Model

Model 1: $LNW - Jan_t = a_1 + \beta_1 RF - Jan_t + \beta_2 TEM - jan_t + \beta_3 RF - Jan_t * TEM - Jan_t + \varepsilon_t$

Figures 4 and 5

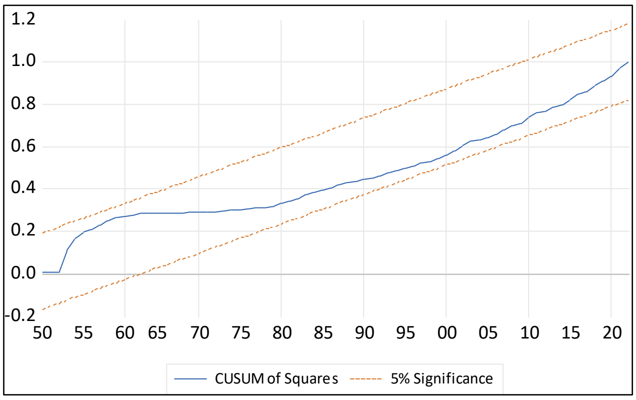
Model.2. $LNW - Mar_t = a_1 + \beta_1 RF - Mar_t + \beta_2 TEM - Mar_t + \beta_3 RF - Mar_t * TEM - Mar_t + \varepsilon_t$

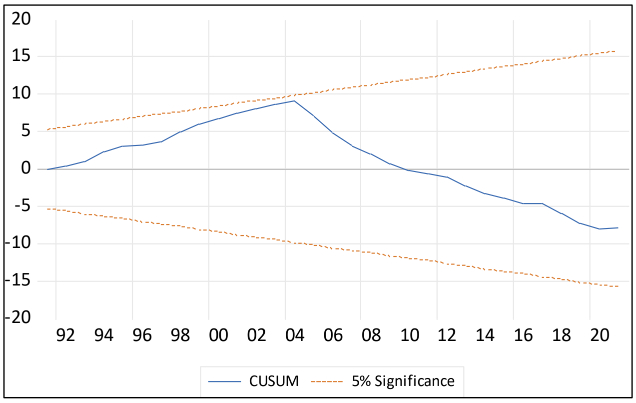




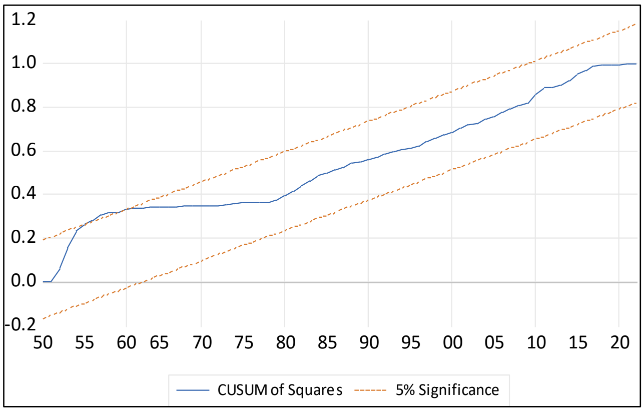
Figures 6 and 7

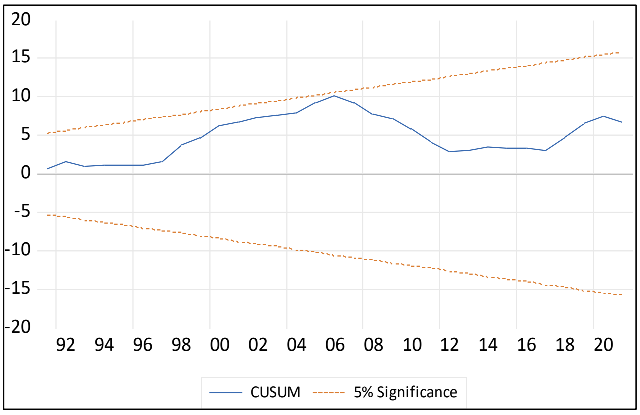
Model.3.$LNW - Nov_t = a_1 + \beta_1 RF - Nov_t + \beta_1 TEM - Nov_t + \beta_3 RF - Nov_t * TEM - Nov_t + \varepsilon_t \ldots (1c)$





Figures 8 and 9





The stability and validity of the model are necessary for a regression model. The CUSUM and CUSUM^2 tests check the stability of the model. Figures 4 to 9 describe the stability of a model. In all figures, the blue lines lie within the red line, as shown in Figure 8. When blue lines are within red lines, it shows the stability of the model. In Figure 8, the stability of model 3 is determined by the distribution in the case of CUSUM while stabilizing in CUSUM^2 tests. Thus, the long-run model is stable.

Table 7

Causality

Null hypothesis	Directional		F-statistic	Prob
	Uni-directional	Bi-directional		
Model 1: $LNW-Jan_t = a_1 + \beta_1 RF-Jan_t + \beta_2 TEM-jan_t + \beta_3 RF-Jan_t * TEM-Jan_t + \varepsilon_t$ ... (1a)				
Rainfall-Jan ↔ LNW-Jan			3.15439	0.0306^{WC}
			3.29423	0.025^{WC}
TEM-Jan ↔ LAN-Jan			7.61807	0.0073^{SC}
			9.74244	0.0026^{SC}
TEM-Jan ----- Rainfall-Jan	X		0.59393	0.4435^{NC}
			0.71469	0.4007^{NC}
Model 2: $LNW-Mar_t = a_1 + \beta_1 RF-Mar_t + \beta_2 TEM-Mar_t + \beta_3 RF-Mar_t * TEM-Mar_t + \varepsilon_t$ ... (1b)				
TEM-Mar → LNW-Mar			7.59453	0.0002^{SC}
TEM-Mar ----- LNW-Mar	X		0.41672	0.7416^{NC}
TEM-Mar ↔ Rainfall-Mar			4.61541	0.0055^{SC}
			3.99747	0.0113^{WC}
Rainfall-Mar ----- LNW-Mar	X		0.88166	0.4553^{NC}
			0.86335	0.4647^{NC}
Model 3: $LNW-Nov_t = a_1 + \beta_1 RF-Nov_t + \beta_1 TEM-Nov_t + \beta_3 RF-Nov_t * TEM-Nov_t + \varepsilon_t$ ... (1c)				
Rainfall-Nov ----- LNW-Nov	X		0.32153	0.8981^{NC}
LNW-Nov → Rainfall-Nov			2.96883	0.0186^{WC}
TEM-Nov → LAW-Nov			5.67375	0.0002^{SC}
LNW-Nov ----- TEM-Nov	X		1.55405	1.1872^{NC}
TEM-Nov ----- Rainfall-Nov	X		4.32844	0.0076^{SC}
			2.74633	0.0500^{WC}

Author's calculations

Notes: →, ↔, and ---- represent unidirectional causality, bidirectional causality, and no causality, respectively. Therefore, WC, SC, and NC represent Weak, Strong, and No causality.

Table 7 describes the pairwise Granger causality test. The test used to study one variable can predict another variable based on time. It does not prove the causation of a true cause-and-effect association. It identifies statistical associations based on analytical estimation. In model 1, there is a bidirectional relationship between rainfall and wheat production. Parallelly, temperature and wheat also hold bidirectional associations. Besides, there is no causality between temperature and rainfall in January. In model 2, temperature and wheat have unidirectional causality. But temperature and rainfall have bidirectional causality, while rainfall and wheat production have no causality. In Model 3, rainfall and wheat production in November have no causality. At the same time, wheat production has unidirectional causality with rainfall. Similarly, wheat production has unidirectional causality with temperature, while temperature has no causality with wheat production. Temperature and rainfall have no causality in November with each other. So, the study results conclude that rainfall and temperature have uni- and bidirectional causality with wheat production.

Conclusion and Policy Recommendations

In this study, we investigate the impact of rainfall and temperature on wheat production. Developing countries, including Pakistan, mostly depend on wheat production. The rainfall and temperature significantly influence wheat production in Pakistan. The rainfall in January had a negative and significant impact on wheat production. Besides, temperature and wheat production are directly correlated with each other. Similarly, the positive coefficient of interaction terms suggests that the impact of January rainfall on wheat production depends on the level of January temperature. In other words, the effect of rainfall on wheat production is amplified or diminished based on temperature. It also means that when January rainfall is high, and the January temperature is also high, the effect on wheat production is significantly positive, indicating that favorable conditions in both rainfall and temperature contribute to increased wheat production. In Model 2, the rainfall has a significant and positive impact on wheat production. When there was an increase in rainfall in March, as a result, wheat production also increased by 0.03 percent. In the same month, the temperature was insignificant. It means temperature does not impact wheat production. The combined effect of rainfall and temperature has a negative impact on wheat production. It suggests that the combined effect of March rainfall and March temperature has a significant impact on wheat production at 10%. In model 3, rainfall and interaction terms are significant at 10%, while temperature is insignificant. November rainfall and wheat production are negatively correlated. When rainfall increases in November, Pakistan's wheat production falls. The combined impact of November rainfall and November temperature has a positive and significant impact on the dependent variable. When both rainfall and temperature increase in November, there is a modest positive influence on the dependent variable. Thus, the study concludes that rainfall and temperature separate and collectively affect wheat production in Pakistan. The study suggested the government reduce CO2 emissions in various sectors as well as improve technology and hybrid seeds. Besides, the state also adopts long-term reduction policy such as other developing countries adopts.

References

Abrar, M. A., & Maryiam, M. (2023). Climate change impact on food security in Pakistan . *Pakistan Journal of Multidisciplinary Research*, 4(1), 131-146. https://pjmr.org/pjmr/article/view/359

Ali, A., & Rahut, D. B. (2019). Localized floods, poverty and food security: Empirical evidence from rural Pakistan. *Hydrology*, 7(1), 2. https://doi.org/10.3390/hydrology7010002

Anthwal, A., Joshi, V., Sharma, A., & Anthwal, S. (2006). Retreat of Himalayan glaciers–indicator of climate change. *Nature and Science*, 4(4), 53-59.

Armitage, S., & Brzeszczynski, J. (2011). Heteroscedasticity and interval effects in estimating beta: UK evidence. *Applied Financial Economics*, *21*(20), 1525-1538. https://doi.org/10.1080/09603107.2011.581208

Baldos, U. L., & Hertel, T. W. (2014). Global food security in 2050: The role of agricultural productivity and climate change. *Australian Journal of Agricultural and Resource Economics*, *58*(4), 554-570. https://doi.org/10.1111/1467-8489.12048

Baltagi, B. H., Heun Song, S., Cheol Jung, B., & Koh, W. (2007). Testing for serial correlation, spatial autocorrelation and random effects using panel data. *Journal of Econometrics*, *140*(1), 5-51. https://doi.org/10.1016/j.jeconom.2006.09.001

Bocchiola, D., Brunetti, L., Soncini, A., Polinelli, F., & Gianinetto, M. (2019). Impact of climate change on agricultural productivity and food security in the Himalayas: A case study in Nepal. *Agricultural systems*, *171*, 113-125. https://doi.org/10.1016/j.agsy.2019.01.008

Burton, A. L. (2021). OLS (Linear) regression. *The Encyclopedia of Research Methods in Criminology and Criminal Justice*, 509-514. https://doi.org/10.1002/9781119111931.ch104

Cogley, J. G. (2011). Present and future states of Himalaya and Karakoram glaciers. *Annals of Glaciology*, *52*(59), 69-73. https://doi.org/10.3189/172756411799096277

Durbin, J., & Watson, G. S. (1992). Testing for serial correlation in least squares regression. I. *Springer Series in Statistics*, 237-259. https://doi.org/10.1007/978-1-4612-4380-9_20

El Bilali, H., Bassole, I. H. N., Dambo, L., & Berjan, S. (2020). Climate change and food security. *The Journal "Agriculture and Forestry"*, *66*(3). https://doi.org/10.17707/agricultforest.66.3.16

Fujimori, S., Hasegawa, T., Krey, V., Riahi, K., Bertram, C., Bodirsky, B. L., ... & van Vuuren, D. (2019). A multi-model assessment of food security implications of climate change mitigation. *Nature Sustainability*, 2(5), 386-396. https://doi.org/10.1038/s41893-019-0286-2

Gul, A., & Khan, A. W. (2021). The Effect of Small-Scale Industries on Employment Level in Pakistan. *Journal of Research and Reviews in Social Sciences Pakistan*, 4(2), 1393-1404.

Gul, A., Khan, S. U., & Abbasi, R. A. (2023). Vicious Circle of Health Expenditure: Time Series Evidence from Pakistan. *Journal of Contemporary Macroeconomic Issues*, 4(1), 57-77. https://ojs.scekr.org/index.php/jcmi/article/view/99

Hussain, S. S., & Mudasser, M. (2007). Prospects for wheat production under changing climate in mountain areas of Pakistan – An econometric analysis. *Agricultural Systems*, *94*(2), 494–501. https://doi.org/10.1016/j.agsy.2006.12.001

Joyo, M., Ram, N., & Magsi, H. (2018). Risk assessment of climate variability on rice productivity in sindh province of Pakistan: Department of Agricultural Economics, Sindh Agriculture University, Tandojam, Pakistan. *Pakistan Journal of Agriculture, Agricultural Engineering and Veterinary Sciences*, *34*(1), 68-77. https://pjaaevs.sau.edu.pk/index.php/ojs/article/view/257

Kasperson, R.E., & Kasperson, J. (2005). Social Contours of Risk: Volume I: Publics, Risk Communication and the Social (1st ed.). Routledge. https://doi.org/10.4324/9781849772549

Kumar, P. (2021). Climate change and cities: Challenges ahead. *Frontiers in Sustainable Cities*, *3*. https://doi.org/10.3389/frsc.2021.645613

Lin, Y., Xin, X., Zhang, H., & Wang, X. (2015). The implications of serial correlation and time-lag effects for the impact study of climate change on vegetation dynamics – a case study with Hulunber meadow steppe, Inner Mongolia. *International Journal of Remote Sensing*, *36*(19-20), 5031-5044. https://doi.org/10.1080/01431161.2015.1093196

Marcoulides, K. M., & Raykov, T. (2018). Evaluation of variance inflation factors in regression models using latent variable modeling methods. *Educational and Psychological Measurement*, *79*(5), 874-882. https://doi.org/10.1177/0013164418817803

Nwakuya, M. T., & Nwabueze, J. C. (2018). Application of box-cox transformation as a corrective measure to heteroscedasticity using an economic data. *American Journal of Mathematics and statistics*, *8*(1), 8-12. https://doi.org/10.5923/j.ajms.20180801.02

Paul, R. K. (2006). Multicollinearity: Causes, effects and remedies. *IASRI, New Delhi*, *1*(1), 58-65.

Peng, S., Huang, J., Sheehy, J. E., Laza, R. C., Visperas, R. M., Zhong, X., Centeno, G. S., Khush, G. S., & Cassman, K. G. (2004). Rice yields decline with higher night temperature from global warming. *Proceedings of the National Academy of Sciences*, *101*(27), 9971-9975. https://doi.org/10.1073/pnas.0403720101

Phillips, G. D., & Harvey, A. C. (1974). A simple test for serial correlation in regression analysis. *Journal of the American Statistical Association*, *69*(348), 935-939. https://doi.org/10.1080/01621459.1974.10480231

Ramsey, J. B. (1969). Tests for specification errors in classical linear least-squares regression analysis. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *31*(2), 350-371.https://www.jstor.org/stable/2984219

Ramsey, J. B. (1974). Classical model selection through specification error tests. *Frontiers in econometrics*, *1*, 13-47.

Rashid, K., & Rasul, G. (2011). Rainfall variability and maize production over the Potohar Plateau of Pakistan. *Pakistan Journal of Meteorology*, *8*(15), 63-74.

Rehman, A., Jingdong, L., Du, Y., Khatoon, R., Wagan, S. A., & Nisar, S. K. (2016). Flood disaster in Pakistan and its impact on agriculture growth (a review). *Environ Dev Econ*, *6*(23), 39-42.

Rosopa, P. J., Schaffer, M. M., & Schroeder, A. N. (2013). Managing heteroscedasticity in general linear models. *Psychological Methods*, *18*(3), 335-351. https://doi.org/10.1037/a0032553

Saseendran, S. A., Singh, K. K., Rathore, L. S., Singh, S. V., & Sinha, S. K. (2000). Effects of climate change on rice production in the tropical humid climate of Kerala, India. *Climatic Change*, *44*, 495-514.

Senaviratna, N. A., & A. Cooray, T. M. (2019). Diagnosing multicollinearity of logistic regression model. *Asian Journal of Probability and Statistics*, 1-9. https://doi.org/10.9734/ajpas/2019/v5i230132

Thomas, D. R., Hughes, E., & Zumbo, B. D. (1998). On Variable Importance in Linear Regression. *Social Indicators Research*, *45*(1/3), 253–275. http://www.jstor.org/stable/27522344

Vu, D., Muttaqi, K., & Agalgaonkar, A. (2015). A variance inflation factor and backward elimination based robust regression model for forecasting monthly electricity demand using climatic variables. *Applied Energy*, *140*, 385-394. https://doi.org/10.1016/j.apenergy.2014.12.011

Wheeler, T., & Von Braun, J. (2013). Climate change impacts on global food security. *Science*, *341*(6145), 508-513. https://doi.org/10.1126/science.1239402

Xiao, G., Zhang, Q., Yao, Y., Zhao, H., Wang, R., Bai, H., & Zhang, F. (2008). Impact of recent climatic change on the yield of winter wheat at low and high altitudes in semi-arid northwestern China. *Agriculture, Ecosystems & Environment*, *127*(1-2), 37-42. https://doi.org/10.1016/j.agee.2008.02.007

Xu, X., Hu, H., Tan, Y., Yang, G., Zhu, P., & Jiang, B. (2019). Quantifying the impacts of climate variability and human interventions on crop production and food security in the Yangtze River basin, China, 1990–2015. *Science of The Total Environment*, *665*, 379-389. https://doi.org/10.1016/j.scitotenv.2019.02.118

Ye, L., Tang, H., Wu, W., Yang, P., Nelson, G. C., Mason-D'Croz, D., & Palazzo, A. (2014). Chinese food security and climate change: Agriculture futures. *Economics*, *8*(1). https://doi.org/10.5018/economics-ejournal.ja.2014-1

Zahra, F., Gul, A., Iqbal, A., Ghafoor, T., & Ambreen, A. (2020). The impact of COVID-19 on rural areas students of Pakistan: Moderating role of HEC policy and internet service. *Asian Journal of Contemporary Education*, *4*(2), 69-79. https://doi.org/10.18488/journal.137.2020.42.69.79

Zhang, T., Zhou, X., & Liu, X. (2020). Reliability analysis of slopes using the improved stochastic response surface methods with multicollinearity. *Engineering Geology*, *271*, 105617. https://doi.org/10.1016/j.enggeo.2020.105617