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Research Article

ANALYSING THE NEXUS OF WEATHER ON COTTON PRODUCTION IN SINDH PAKISTAN: USING ARDL BOUND TEST

Adnan Nazir[1], Abdul Salam Lodhi*[1], Shoaib Akhtar[2], Akbar Khan Khajjak[3, 4]

[1]*Department of Economics, University College Zhob, BUITEMS, Zhob, Pakistan*
[2]*Department of Agriculture Business and Marketing, Faculty of Agricultural Sciences and Technology, Bahauddin Zakariya University, Multan, Pakistan*
[3]*Department of Agricultural Economics, Faculty of Agricultural Social Sciences, Sindh Agriculture University, Tando Jam, Pakistan.*
[4]*Directorate of water management and HEIS, Agriculture Research Institute, Quetta*

*Corresponding author: **salam@buitms.edu.pk***

Abstract

Climate change is expected to have impacts on plants, crops, and insect pests, and pose substantial pressures to sustainable food security. This research investigates the impact of weather changes on the production of cotton crops in Sindh, Pakistan by analyzing both short-term and long-term effects. Hence by employing annual time-series data of 58 years from 1961 to 2018 to explore the causal relationship between climate variables and specifically cotton production. For this purpose the Augmented Dickey-Fuller (ADF) test was applied and was significantly stationary at 1st difference, ensuring robust econometric analysis. In addition to understanding the long-run and short-run effects, the Autoregressive Distributed Lag (ARDL) bounds test was applied. Short-term findings reveal that a 1% increase in logged annual cotton area (CA) leads to a 0.671% rise in cotton production (CP), and a similar 1% increment in logged annual rainfall in kharif (R) results in a 0.224% increase in cotton production. The long-term relationships between weather variables and cotton yields were confirmed through the Johansen cointegration test, suggesting persistent climate impacts over time. It is recommended that authorities identify and promote the cultivation of temperature variation-tolerant cotton varieties and enhance the focus on agricultural research and technological innovation. To support these initiatives, timely and farm-specific climate change information should be disseminated. Adoption of advanced, cost-effective agricultural technologies can significantly improve crop yields. These strategic responses are essential to mitigate the adverse effects of climate variability on agriculture in Sindh, ensuring sustainable cotton production and economic stability for cotton farming communities.

Keywords:
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1. INTRODUCTION

Climatic change is defined as "long-term climate change caused by human activity and natural environmental changes" (Solomon et al., 2007). It is widely assumed that disruption of the climate's seasonal regime, as evidenced by an increase in temperature and a poor distribution of intra- and inter-seasonal precipitation in Pakistan's climate, could have an impact on agricultural crop productivity and quality, particularly in areas with a regular cycle, such as the south of the country near the Arabian Sea. The economy of Pakistan mainly depends upon agriculture and contributes 18.23 percent to the GDP (GoP, 2023), more than 65-70 percent of the population depends on agriculture for its livelihood. It sources 38.5 percent of people for employment and provides raw materials to many industries. Diminishing arable land, water scarcity, climate change, and increasing populace and migration labour from countryside to urban zones have decelerated growth in the agricultural sector. As a result, new techniques for increasing agricultural output are required (GOP, 2021). There is a great role of agriculture in national development, food security, and poverty alleviation. The urban population of Pakistan is increasing fast and with the fast-growing urban population, the demand for vegetables, fruits, meat, and milk is at a simultaneous increase. The government is emphasizing increased yields for growers by developing infrastructure investment for supply chains of the modern business world. The China-Pakistan Economic Corridor (CPEC) the supply chain and enhancement of agribusiness benefits are expected. In the year 2016-17, the agriculture sector succeeded in growing 3.46 percent against a target growth of 3.5 percent compared to a tiny growth of 0.27 percent in the last year (2015-16). The growth target in agriculture was achieved by harvesting greater crop yields by ensuring the timely availability of inputs required for crop production, better credit facilities, and irrigation water availability. The growth rate of crops remained at 3.02 percent in the year 2016-17 against -4.97 percent growth in the year 2015-16. The cotton sector grew at a 4.12 percent rate. The growth rate of Livestock, Forestry, and Fisheries remained at 3.43, 14.49, and 1.23 percent, respectively; due to enhancement in yields (GoP, 2017).

Cotton is considered the mainstay of Pakistan's agrarian economy as a most important cash crop. It shares 0.3% of the country's GDP and shares 1.4% in value-added agriculture (GoP, 2023). Pakistan is the 4th leading cotton yarn exporter globally, and the 5th leading producer (Khaskheli & Ali, 2023). The export of cotton textile products has contributed an overall 60% to the country's exports (Khan et al., 2020). The present the tariff is based on a free trade policy with no restrictions on cotton export and import. About 1.3 million farmers grow cotton on 2.147 million ha, covering 15% of the cultivable area. During 2020-21 the cotton production in Pakistan was 4.90 million bales (170 kg) against the target of 10.5 million bales. The key reasons behind this drop were high temperature, unprecedented rainfalls and floods causing loss in flower shedding, and pest attacks of whiteflies, and pink bollworms (GoP, 2022).

Climate change is projected to have a significant impact on cotton crop output around the world, particularly in developing countries (Jans et al., 2020). Responses to climate change occurrences, cotton crop production in many nations, and agricultural production obstacles in climate changes are all being studied to better understand the effects of climate variability on crop production and to recommend ways to minimize the consequences of climate changes while also improving agriculture long-term viability (Iqbal et al., 2022).

Weather factors such as temperature and precipitation are direct inputs into agriculture productivity, making agriculture the most vulnerable to environmental variations (Deschênes & Greenstone, 2012). Weather variability and climate change have been researched in agriculture across the world, especially in Pakistan (Lohano, 2018). Pakistan is particularly vulnerable to such effects. Agriculture has strong backward and forward connections to other industries (GOP, 2016). Agro-based businesses, such as textile and food processing, are directly or indirectly tied to it. Furthermore, while household consumer demand is reliant on agro-related income, other sectors are harmed as well. As a result, weather factors affect the economy both directly and indirectly through agriculture.

In Pakistan, like other South Asian countries, a substantial portion of its economy is built on climate-sensitive agriculture, it's indeed vulnerable to climate change. Due to climate change, there is an increase in monsoon variability; flood and drought risks are increased, and severe water-stressed conditions. Due to weather changes happening of the decline of Glaciers is reported; The capacity of natural reservoirs has been reduced as the snowline has risen; upstream infiltration of saline water has been observed in the Indus delta; and threats to mangroves, coral reefs, and fish breeding sites have been documented. The last three decades are supposed to be warmer than the past centuries (Lashari et al., 2021). Moreover, Weather change has caused sluggish growth in the agriculture sector (Mobeen et al., 2017). In natural science, there are primarily two approaches for determining the influence of climate change on agriculture. In the discipline of economics, empirical models are commonly used (panel data model, regression model) (Demeke & Zeller, 2012; Hsiao, 2014) and economic models (yield function and Ricardian models) (Xu et al., 2021; Zhang et al., 2017) based on statistical data to cover the impact of climate fluctuation Such methods are used to diagnose model uncertainty and reduce the model's reliance on field observations (Nasrullah et al., 2021). The statistical method is derived from data gathered from many metrological/experimental sites (Wang et al., 2017), or advanced technology (Tsui et al., 2015). Climate change and agricultural technology, on the other hand, have received less empirical research attention (Ayinde et al., 2011).

Theoretical Framework

Investigating the influence of climatic factors on agricultural production in Sindh, Pakistan, integrating several key theories and models explored the complex interactions between climate variables and cotton production (Lohano et al., 2019). The Autoregressive Distributed Lag (ARDL) model is specifically useful in identifying short-term and long-term relationships between climatic changes and agricultural outputs (Jordan & Philips, 2018). These models help in examining long-term equilibrium relationships and short-term dynamics between climatic factors and crop production, (Engle & Granger, 1987), also proposed by (Nkoro & Uko, 2016) respectively. Over five decades (1961-2010), valuable insights have been gleaned from longitudinal data on key crops such as cotton. Researchers across nations like Pakistan, Ghana, and Europe have lauded ARDL methodology's effectiveness in conducting empirical studies that explore this link between climate change and agriculture. A major strength of ARDL is its ability to identify both long-term and short-term links among variables - a significant improvement over previous methods deployed for similar purposes since governments' collaborative efforts with research institutions are crucial components underpinning successful analysis. Consequently, the ARDL approach is frequently utilized for detecting variable integrations as well as assessing data suitability when sample size is limited. Studies on the relationship between weather and its impact on cotton output are needed to close the knowledge gap. In order to investigate the impact of weather effects the cotton production, the study was designed to examine short and long term impact of weather on cotton production in Sindh Pakistan. The agricultural development as a whole established on systematic investigation and in assessment of the research findings the associated strategies are designed.

2. Materials and Methods

For this study, annual data of area under cotton crop and total production of cotton crop and weather-related variables of annual rainfall in millimeters and annual temperature in centigrade were considered for Sindh province of Pakistan for 1961–2018. The data for different variables were obtained from the Government of Pakistan Metrological Department and Agricultural Statistics of Pakistan.

2.1. Model Specification

Cotton production (dependent variable) was compared to the area under a certain crop, rainfall, rainfall standard deviation, temperature, and temperature standard deviation, all of which were independent factors in this study. The following is an example of an econometric description of the variables under study:

Table 1: Description of variables under study

Variables	Symbols	Units	Resource point
Cotton Production	*CP*	Production in tonnes	AMIS.Pk
Cotton Area	*CA*	Area in Acres	AMIS.Pk
Temperature Kharif	*T*	Mean temperature (^oC)	GOP-Met
Temperature Kharif Standard Deviation	*TSD*	Mean temperature (^oC)	GOP-Met
Rainfall Kharif	*R*	Mean Rainfall (mm)	GOP-Met
Rainfall Kharif Standard Deviation	*RSD*	Mean Rainfall (mm)	GOP-Met

$$CP = f(CA, R, RSD, T, TSD) \quad (1)$$

The logarithmic linear model, according to (Shahbaz et al., 2012), provides more useful findings than basic linear models. For that purpose, following the research of Ali et al., (2021), equations 1 is transformed as follows:

2.2. Variables for Weather and Cotton

The data was obtained from the Pakistan Meteorological Department on average temperature and rainfall for each month between 1961 and 2018 for several stations in Sindh province. Pakistan's climate consists of two primary seasons for cropping, seasonally *Rabi* season period consists of November to April and the *Kharif* season consists of May to October. However, in the *Kharif* season cotton is cultivated.

$$lnCP_t = \beta_0 + \beta_1 lnCA_t + \beta_2 lnR_t + \beta_3 lnRSD_t + \beta_4 lnT_t + \beta_5 lnTSD_t + \varepsilon_t \quad (2)$$

All the variables under research are transformed into natural log format (*ln*). The parameters in Eq. (2), $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$, are the long-run elasticity coefficient of CP_t cotton production in thousand tonnes and CA_t indicates the area under cotton crop in thousand acres. Where R_t indicates annual rainfall in millimeters in the Kharif season, RSD_t indicates the standard deviation of annual rainfall in millimeters in the Kharif season, T_t indicates annual $_{\text{mean}}$ temperature in centigrade in the Kharif season, TSD_t indicates the standard deviation of annual temperature in centigrade in *Kharif* season, and ε_t is the error term.

3. Results and Discussion

3.1. Summary statistics

The descriptive statistics of the variables are meant to reveal the main features of the variables under research. In the empirical outcomes of mean, median, maximum, minimum, (J-B) Jarque-Bera values, standard deviation, skewness, and kurtosis are shown (Table 2). The skewness determines a peaked inference in the order of dispersion, whereas the kurtosis measures the degree of disparity in data collection. The skewness values are presented in three different ways: (1) equal to zero indicating it is regular, (2) extended rightward tails that is to say positive, and (3) extended leftward tails as a result negative. These findings are in line with (Sharif et al., 2023).

The J-B test was performed to determine the normality of all variables. Because the Jarque-Bera values for all of the variables at a 5% level of significance were highly insignificant, the test indicates that the residuals for all of the variables were normal. Similarly, kurtosis can be classified as (a) platykurtic (b) leptokurtic, or (c) mesokurtic. Table 2 shows that the kurtosis values is more than 3 since CA and TSD are leptokurtic. The remaining variables are platykurtic, with a kurtosis value of less than three. Comparable results were also reported by (Ali et al., 2017).

3.2. Relationship between variables

Table 3 quantifies correlation analysis for all research variables to determine the relationship between two variables. Outcomes divulge that the mean temperature in the Kharif season (T) 49% correlates with cotton production, rainfall in Kharif 4.7% (R), rainfall standard deviation in Kharif season 2.9% (RSD) and cotton area 57.9% with cotton production

Table 2: Descriptive statistics of variables used for analysis

	CP	CA	T	TSD	R	RSD
Mean	12.45	14.07	3.46	0.84	6.48	5.18
Median	12.40	14.12	3.46	0.86	6.67	5.35
Max	13.50	14.32	3.50	1.12	8.07	6.94
Min	11.24	13.37	3.42	0.49	4.36	3.27
SD	0.59	0.20	0.02	0.12	0.92	0.86
Skewness	-0.07	-1.04	-0.10	-0.70	-0.68	-0.45
Kurtosis	2.05	4.08	2.86	3.77	2.95	2.55
J.Bera	2.21	13.26	0.14	6.15	4.46	2.42
Prob	0.33	0.00	0.93	0.05	0.11	0.30
Sum	722.00	815.90	200.45	48.87	375.67	300.61
Sum Sq. Dev.	19.72	2.20	0.01	0.85	48.69	41.85
Observations	58	58	58	58	58	58

Source: Authors' own calculation

Table 3: Correlation between cotton and weather variables

	CA	CP	R	RSD	T	TSD
CA	1.000					
CP	0.579	1.000				
R	0.016	0.047	1.000			
RSD	-0.027	0.029	0.975	1.000		
T	0.081	0.490	-0.198	-0.224	1.000	
TSD	0.105	-0.085	0.116	0.102	-0.301	1.000

Source: Authors' own calculation

Table 4: Augmented Dickey-Fuller Unit Root Test

Model	Level		1st diff	
	t-stat	Sig.	t-stat	Sig.
Intercept				
CP	-1.092	0.713	-12.632	0.000
CA	-3.642	0.008	-10.500	0.000
T	-2.368	0.155	-8.734	0.000
TSD	-6.506	0.000	-12.741	0.000
R	-7.745	0.000	-12.967	0.000
RSD	-7.807	0.000	-10.165	0.000
Intercept and trend				
CP	-4.853	0.001	-12.523	0.000
CA	-4.125	0.010	-10.403	0.000
T	-4.644	0.002	-6.559	0.000
TSD	-6.551	0.000	-12.636	0.000
R	-7.767	0.000	-12.841	0.000
RSD	-7.829	0.000	-10.073	0.000

Source: Authors' own calculation

respectively. Likewise, (Rashid et al., 2020) also reported similar findings.

3.3. Outcomes of Unit root test

Before estimating the ARDL bound procedure, the stationarity of all research variables must be determined. The augmented Dickey-Fuller (ADF) test, developed by Dickey and Fuller (1979), was used to check the stationarity of variables. The ADF unit root test requirements are utilized in this work to verify for regressor and stationarity of regressed variables. The findings of the unit root test are shown in Table 4. The findings demonstrate that almost all variables at level I(0) are not stationary, but that most

Table – 5. Unit Root Test (Breakpoint)

Model	Level			First diff		
	Break date	**t-stat**	**Prob**	**Break date**	**t-stat**	**Prob**
CP	1993	-3.282	0.514	2012	-13.725	< 0.01
CA	1976	-5.022	< 0.01	2012	-10.893	< 0.01
T	1997	-5.975	< 0.01	1989	-12.291	< 0.01
TSD	1999	-7.304	< 0.01	1967	-13.892	< 0.01
R	1974	-8.396	< 0.01	1970	-13.677	< 0.01
RSD	1974	-8.472	< 0.01	1970	-12.905	< 0.01

Source: Authors' own calculation

Table 6: selection criteria VAR lag order

Lag	FPE	HQ	LR	AIC	LogL	SIC
0	3.28e-10	-4.725480	NA	-4.811255	133.4983	-4.588203
1	4.22e-11*	-6.270613*	157.2406	-6.871038*	224.0825	-5.309674*
2	7.55e-11	-5.225956	33.13938	-6.341031	246.0373	-3.441357
3	1.28e-10	-4.322951	32.98461	-5.952676	271.7459	-1.714690
4	2.31e-10	-3.501660	29.45179	-5.646035	299.6199	-0.069738
5	1.44e-10	-3.992232	52.00167*	-6.651257	362.2583	0.263352

Source: Authors' calculation

*Note: * indicates lag order selected by the criterion; FPE: Final prediction error; HQ: Hannan-Quinn information criterion; LR: sequential modified LR test statistic (each test at 5% level); AIC: Akaike information criterion; SIC: Schwarz information criterion.*

are stationary at I(1) first difference with a 5% significant characteristic. The unit root test indicated that there is no stationary variable at I(2) second difference. These findings support the use of the ARDL bound method to examine short- and long-run associations (Ali et al., 2019). If the data isn't stationary, the findings might become meaningless and misleading. Even the findings demonstrate that all of the chosen variables were highly significant, especially at first difference with intercept and intercept and trend.

3.4. Outcomes of breakpoint unit root test

Unless there are structural breaks in a time series, the power of the unit root test would be unreliable. As a result, the breakpoint unit root test was carried out sequentially. The null hypothesis of the unit root test cannot be rejected in level form for most variables. In Table 5 findings indicate that at level almost 93% of structural breaks are to be found during 1967 to 1999s, and the remaining after 2000. Whereas approximately 64% of structural breaks are to be found during the late 1960s to the late 1980s, and the remaining 36% after 2000. These findings coincide with (Gul et al., 2022).

3.5. Selection criteria for lag order

In the ARDL technique, choosing the best lag length criteria is crucial. As a result, the unrestricted vector autoregression (VAR) lag selection criteria are used to find the optimal number of lags for the model. Likewise, Table 6 displays the estimates of SIC and AIC, the suitable lag “1” was chosen for all variables for the cotton crop. Previous studies (Abbas, 2020; Rashid et al., 2020) to detect the lag length in the ADF test also adopted the AIC criteria.

3.6. ARDL bound testing technique

ARDL bound testing method was applied, after performing the unit root test. The method of testing is commonly established on SIC and AIC results since these have a propensity to specify more parsimonious attributes. If the estimated F-stat value exceeds the upper critical limits, the null hypothesis of no co-integration is rejected. The null hypothesis is accepted when the estimated F value is smaller than the values of the lower critical limits. The outcome is inconclusive if the F value is set between the upper and lower critical values.

Similarly, the findings portrayed in Table 7 indicate that the F-statistic value (4.73) is higher than the lower bound and lies between upper bounds I(1) critical values at a 1% significance level (5.23) lying between the upper bound value, which supports that there is a long-run association between CP, CA, R, RSD, T, and TSD in Sindh province. The findings demonstrate that the null hypothesis, stating that there is no co-integration, is rejected, while the alternative hypothesis, indicating that there is co-integration, is accepted. Comparable outcomes were investigated in prior studies (Ali et al., 2021b; Gul et al., 2022).

3.8. Co-integration test (Johansen)

The cointegration approach was introduced by Johansen and Juselius (1990). This approach is employed to determine the long-run relationship among CP, CA, T, TSD, R, and RSD. Table 8 shows the cotton crop's Johansen cointegration test results. Trace statistical analyses indicate that two cointegration equations are statistically significant at the 5% level. Maximum eigenvalue tests reveal that one co-integration equation is statistically significant at the 5% level. The Trace statistics and maximum eigenvalue results both show that the research variables have a long-run relationship. Similarly, (Sharif et al., 2023) also adopted the Johansen co-integration rank test to reveal the significant level.

Table 7: Checking co-integration through ARDL Bound Test

Model	F Value	Sig %	Critical Bounds		Remarks
			Lower *I*(0)	Upper *I*(1)	
ARDL (3,1,3,3,0,2) k (5)	4.728768	10	2.75	3.79	Co-Integration
		5	3.12	4.25	
		2.5	3.49	4.67	
		1	3.93	5.23	

Source: Authors' own calculation

3.7. Model Selection Criteria Using AIC

Figure 1 depicts the top 20 likely and potential lags for the ARDL bound test for the cotton crop ARDL (1, 1, 1, 0, 0, 0) was determined using AIC. Likewise, findings are also depicted by (Rashid et al., 2020).

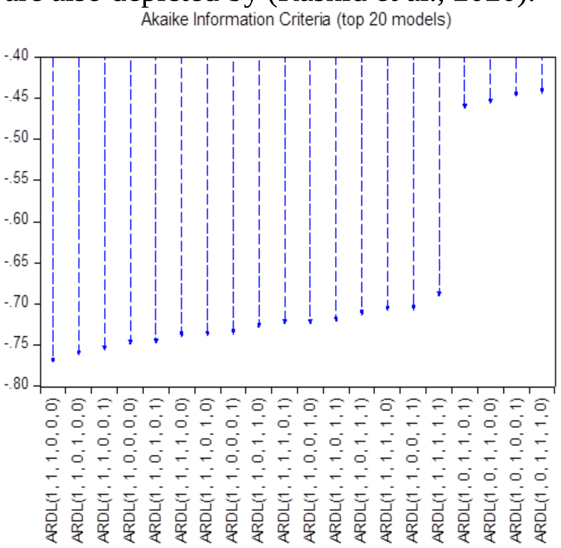

Figure 1: ARDL model selection criteria for Cotton

3.9. Long-run and short-run estimates

Table 9 shows the findings of long-run elasticities, which are determined as the first difference's predicted coefficients. Both D(CA) and RSD(-1) employ a positive significant impact on cotton production CP at a 1 percent level of significance. Similar results were also depicted by (Amin & Rahman, 2024).

The effect of CA on CP is positive and significant. The results of short-run estimates in Table 10 depict that a 1 percent increase in cotton area (CA) increases cotton production (CP) by 0.671 percent. Likewise, a 1 percent increase in R will increase cotton production (CP) by 0.224 percent. The value of ECT(-1) is negative and significant. Similar results were also depicted by (Amin & Rahman, 2024).

Table 8: Test results Johansen co-integration **(Rank Test)**

Trace				
# of CE(s) Assumed	Eigen value	Trace Statistic	CV 0.05	P **
None *	0.464	107.609	95.754	0.006
@ 1 *	0.393	72.688	69.819	0.029
@ 2	0.311	44.731	47.856	0.096
@ 3	0.257	23.886	29.797	0.205
@ 4	0.106	7.242	15.495	0.550
@ 5	0.017	0.950	3.841	0.330
Maximum Eigenvalue				
# of CE(s) Assumed	Eigen value	Max-Eigen Statistic	CV 0.05	P **
None	0.464	34.921	40.078	0.170
@ 1	0.393	27.957	33.877	0.216
@ 2	0.311	20.845	27.584	0.286
@ 3	0.257	16.644	21.132	0.190
@ 4	0.106	6.292	14.265	0.576
@ 5	0.017	0.950	3.841	0.330

*Note: * denotes rejection of the hypothesis at the 0.05 level; **MacKinnon-Haug-Michelis (1999) p-values. Trace test denoted 2 cointegrating eqn(s) at the 0.05 level; Max-eigenvalue test presents 2 cointegrating eqn(s) at the 0.05 level;*

Table 9: Long Run Form of ARDL Bounds Test: selected model (1, 1, 0, 0, 2, 0)

Variable	Coef.	SE	T-Stat	P-value*
C	0.152092	6.605196	0.023026	0.9817
CP(-1)*	-0.043759	0.054307	-0.805787	0.4245
CA(-1)	-0.000263	0.146535	-0.001794	0.9986
T**	0.009884	1.759370	0.005618	0.9955
TSD**	0.108902	0.175306	0.621213	0.5375
R(-1)	0.247712	0.108345	2.286330	0.0000
RSD**	-0.251211	0.121469	-2.068103	0.0443
D(CA)	0.670541	0.149363	4.489328	0.0000
D(R)	0.223584	0.110643	2.020780	0.0491
D(R(-1))	-0.056182	0.022649	-2.480540	0.0168

* p-value incompatible with t-bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

*EC = CP - (-0.0060*CA + 0.2259*T + 2.4887 *TSD + 5.6608*R -5.7407*RSD + 3.4756)*

Source: Authors' own calculation

Table 10: ARDL Short Run Form and Bounds Test: selected model (1, 1, 0, 0, 2, 0)

Variable	Coef.	SE	T-Stat	P-value*
D(CA)	0.670541	0.120716	5.554709	0.0000
D(R)	0.223584	0.073928	3.024354	0.0041
D(R(-1))	-0.056182	0.017302	-3.247119	0.0022
CointEq(-1)*	-0.043759	0.013246	-3.303477	0.0019

Source: Authors' own calculation

The effect of CA on CP is positive and significant. The results of short-run estimates in Table 10 depict that a 1 percent increase in cotton area (CA) increases cotton production (CP) by 0.671 percent. Likewise, a 1 percent increase in R will increase cotton production (CP) by 0.224 percent. The value of ECT(-1) is negative and significant. Similar results were also depicted by (Amin & Rahman, 2024).

Table 11: Diagnostic test results for cotton crop

Serial correlation LM test Breusch-Godfrey		
Cotton	F-statistic	0.3285
	Prob. F(2,38)	0.7220
	Prob. chi-square(2)	0.6267
	Obs* R-squared	0.9347
Heteroskedasticity test: Breusch-Pagan-Godfrey		
Cotton	F-statistic	1.5095
	Scaled explained SS	10.2000
	Prob. F(14,40)	0.1521
	Obs* R-squared	19.0127

Source: Authors own calculation

3.10. ARDL diagnostic tests

Several residual diagnostic tests, for instance, the serial correlation LM test and the heteroscedasticity test, are used to evaluate the quality of the chosen model, as shown in Table 11. Breusch-Godfrey serial correlation LM test has probability values above 5 % indicating that there is no serial correlation among the selected variables for cotton crop. Similarly, the heteroskedasticity test results portray a probability value, higher than 5%, this reveals that there is homoscedasticity in the variables used in the cotton production model. Similar tests were also used by (Amin & Rahman, 2024; Choudhary & Gupta, 2024).

3.11. Recursive estimates for cotton

For determining the model dependability the recursive residuals test cumulative sum of the square of the (CUSUMsq) and cumulative sum (CUSUM) was employed. Brown et al., (1975) introduced the CUSUM and CUSUMsq tests to assess the overall model's efficiency. Figure 2 demonstrates that all of the calculated parameters are stable during the selected period since the critical values were observed below the 5% significance threshold. As a result, the ARDL model has been proven to be fit and dependable. Similar tests were also used by (Choudhary & Gupta, 2024; Gul et al., 2022).

4. Conclusion and Suggestions

This study comprehensively analyzed the influence of climatic variations on the production of key agricultural crops i.e. cotton in the Sindh region of Pakistan. By analyzing data from 1961 to 2018 using advanced econometric methods such as the ARDL bounds test and Johansen co-integration test, our study demonstrates that both short-term weather changes and long-term climatic shifts significantly affect agricultural yields. Minor alterations in farming areas and precipitation patterns can have a considerable impact on cotton production. Our research also shows how agriculture quickly adjusts towards

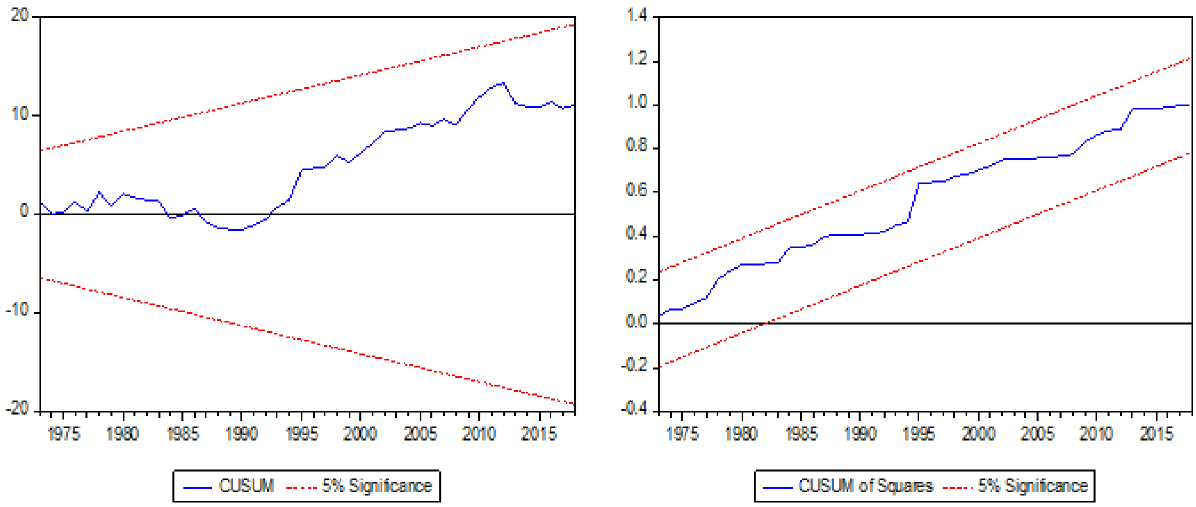

Figure 2: CUSUM and CUSUMSq for cotton

equilibrium following disruptions caused by climate variations - evident through the negative error correction term (ECT) present. The enduring connection between climatic factors and cotton output is demonstrated by our findings, underlining the need for strategic management of sustainable farming practices in response to these challenges. Collaborative efforts are essential among governments, and research institutions to find effective ways of developing resilient crop varieties capable of adapting to temperature fluctuations while efficiently utilizing water resources amidst varying climate conditions. Therefore increased investment responsive measures like efficient water usage techniques integration with stakeholders' coordination will provide an optimal solution mitigating any possible impacts on economically valuable crops like cotton due to climate change variation challenges posed upon us today.

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