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The Impact of Climate Variability and Socio-Economic Factors on Cereal Yield in Pakistan: An Empirical Analysis

Esha Tur-Razia[1], Khalid Zaman[2,*]

[1] Department of Economics, University of Haripur, Haripur Khyber Pakhtunkhwa 22620, Pakistan; eshaturrazia285@gmail.com; khalid_zaman786@yahoo.com.

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Abstract

This study examines how climate variability and key socio-economic factors influence Cereal Yield (CY) in Pakistan from 2000 to 2024. Using annual time-series data and an empirical framework grounded in the Cobb-Douglas production function and Climate Change Theory, the analysis applies the Autoregressive Distributed Lag (ARDL) technique with unit root, diagnostic, and stability tests to capture both short-run and long-run dynamics. Results show that short-run agricultural factors exert a stronger influence on CY yield than long-run relationships. Irrigated land significantly enhances productivity, whereas Fertilizer Consumption (FC), domestic credit, and agricultural CO_2 emissions exhibit weak or negligible effects. The national-level focus limits regional interpretation, and important variables such as temperature, rainfall, soil quality, and technological adoption are not included. Nonlinear interactions and structural breaks may also fall outside the ARDL framework. Overall, the findings highlight the need to strengthen land management, improve irrigation efficiency, and enhance input utilization to raise agricultural productivity. Effective credit mechanisms and resource allocation are essential for supporting sustainable cereal production. By integrating climate and socio-economic variables, the study provides new evidence on the drivers of CY in Pakistan and offers insights for designing climate-resilient agricultural policies.

Keywords: Cereal yield, Agricultural CO_2 emissions, Irrigated agricultural land, Fertilizer consumption, Domestic credit to private sector, ARDL bounds test, Pakistan.

1 | Introduction

Global climate change, driven by a temperature rise of 0.8°C to 1.3°C since 1850, poses severe risks to agriculture, which contributes roughly 14.5% of global emissions. Methane from rice cultivation accounts for nearly 11%, while nitrous oxide from fertilizers has a warming potential 283 times greater than CO_2, intensifying heatwaves, droughts, and floods that disrupt food security and crop cycles. Agriculture is both a contributor to and victim of climate change, facing pest outbreaks, water scarcity, and soil degradation [1]. Evidence from China shows that extreme weather weakens agricultural resilience, though infrastructure and

Corresponding Author: khalid_zaman786@yahoo.com

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digital banking can mitigate these effects [2]. Similar patterns appear in South Africa, where floods, droughts, frost, hail, and strong winds damage roads, arable land, and erosion control systems, undermining market access and rural livelihoods [3]. Collectively, these studies highlight the growing vulnerability of agricultural systems to climate variability and the need for strengthened infrastructure and adaptive capacity. Recent environmental–economic research emphasizes that evaluating climate pressures requires multidimensional indicators, as composite environmental quality indices capture complex interactions more accurately than single measures [4].

The IPCC identifies Southern Africa as a climate hotspot, with projections indicating a temperature rise of about 1.6°C and a 10% decline in rainfall by 2050. These shifts have already reduced cereal production and increased food prices and import dependence [5]. Across Africa, climate change severely affects rain-fed agriculture, which supports over 25% of GDP and more than half of the labor force. Declining yields, such as the projected 10-16% drop in South Africa's maize and the 36–40% reduction in Ethiopia's wheat by 2050, reflect the consequences of shifting rainfall and temperature patterns [6]. Global evidence reinforces these trends: heat stress, drought, and irregular rainfall have significantly reduced crop productivity and farm income, particularly in developing countries [7]. IPCC [8] reports a global temperature increase of 1.1°C, and data from 31 major agricultural producers show a measurable decline in productivity growth, underscoring the need for adaptation [9]. Pakistan mirrors this vulnerability, with a warming trend of 11.2°C since 1901 and projections reaching 5.3°C under high-emission scenarios. Climate variability already affects agriculture, water resources, and rural livelihoods, and Punjabi rice-wheat farmers exhibit high vulnerability levels [10]. Evidence also shows that environmental sustainability and the causal links between trade openness, foreign investment, and economic growth can shape agricultural performance, particularly in countries facing climate-related stress [4].

High exposure and sensitivity, combined with limited adaptive capacity, make targeted adaptation strategies essential for Pakistan's farming systems [11]. Communities in Gilgit Baltistan already employ measures such as relocation, early-warning systems, and traditional coping practices, yet weak institutional support and limited resources continue to hinder effective adaptation [12]. Across Pakistan, most farmers report noticeable shifts in temperature and rainfall, prompting adjustments in cropping patterns and soil-water conservation practices that have improved wheat yields [13]. Recent evidence using deep learning further shows that rising temperatures and erratic rainfall pose increasing risks to rice production, with climate variables exerting strong predictive influence under high-emission scenarios [14]. Collectively, these findings highlight both the urgency of climate adaptation and the uneven capacity of farming communities to respond effectively.

The study aims to assess how socio-economic factors and climate variability shape Pakistan's agricultural productivity, measured through Cereal Yield (CY) (wheat, rice, and maize). CY serves as the dependent variable, while key explanatory variables capture both environmental and economic dimensions. Agricultural CO_2 emissions represent climate-related stressors that can reduce productivity, whereas irrigated land reflects water availability, which is essential for stabilizing crop output. Fertilizer Consumption (FC) indicates the intensity of chemical inputs affecting soil fertility and crop growth, and domestic credit to the private sector reflects farmers' financial capacity to adopt improved technologies and acquire inputs. Agricultural land, a fundamental production resource, captures the extent of land available for farming activities. Together, these variables form an integrated framework to evaluate how climate pressures and socio-economic support systems influence Pakistan's CY between 2000 and 2024. Recent empirical evidence also shows that improvements in energy efficiency, financial systems, and technological advancement can significantly mitigate CO_2 emissions, highlighting the importance of integrating environmental and economic dimensions in productivity analysis [15].

Climate variability poses significant challenges to Pakistan's agricultural sector, undermining food security and crop productivity through rising temperatures, erratic rainfall, floods, droughts, and other environmental stressors [16], [17]. Socio-economic factors, including agricultural land availability, CO_2 emissions, domestic credit, fertilizer use, and irrigation facilities, also play critical roles in shaping output. Despite these pressures, empirical research integrating climate and socio-economic determinants within a unified framework remains limited in Pakistan, with most studies focusing on general climate impacts rather than short- and long-run dynamics [18]. Recent time-series evidence is similarly scarce, leaving gaps in understanding how these variables interact over time [19], [20]. Addressing this gap, the present study evaluates how climate variability and key agricultural support factors influence CY between 2000 and 2024, providing insights that can guide policymakers in designing effective climate adaptation strategies for Pakistan's agricultural sector.

This study is essential for understanding how climate variability and socio-economic conditions jointly shape agricultural productivity in Pakistan, where CYs are increasingly affected by shifting temperatures, agricultural emissions, and changes in land and input use. By linking key environmental and economic factors, such as agricultural CO_2 emissions, irrigated land, FC, domestic credit, and agricultural land, to real production challenges, the study provides a comprehensive framework for evaluating productivity constraints. Its findings offer practical insights for policymakers and agricultural planners seeking to design effective climate adaptation strategies and sustainable agricultural policies. These insights are critical not only for improving CY but also for strengthening food security amid rising environmental and socio-economic pressures. Studies grounded in the Environmental Kuznets Curve framework further highlight that the relationship between economic growth and environmental degradation is nonlinear, underscoring the importance of analyzing climate impacts on agricultural productivity [21]. Based on this rationale, the study formulates the following research questions.

RQ1: How do agricultural CO_2 emissions and agricultural irrigated land influence CY in Pakistan?

Irrigated land and agricultural CO_2 emissions are two central factors shaping CY in Pakistan. Rising CO_2 emissions, driven by climate variability, higher temperatures, and environmental stress, consistently reduce crop productivity [22], [23]. In contrast, irrigation plays a stabilizing role by ensuring reliable water availability and supporting crop growth under increasingly unpredictable climatic conditions. Understanding how these variables interact is essential for designing effective irrigation management and climate adaptation strategies. Recent studies emphasize that while climate pressures continue to intensify, targeted adaptation measures remain critical for sustaining agricultural productivity [24], [25].

RQ2: To what extent do FC and domestic credit to the private sector contribute to CY in Pakistan?

Fertilizer use and domestic credit are key socio-economic drivers of CY in Pakistan. Fertilizer improves soil fertility and crop growth, while credit enables farmers to access modern inputs and technologies, strengthening production capacity. These support mechanisms are essential for sustainable agricultural development and food security. Understanding their role is therefore critical for designing effective socio-economic interventions. Recent studies highlight that adaptation strategies and improved farming practices remain central to enhancing productivity under climate pressures [26], [27].

RQ3: How does agricultural land affect CY in Pakistan?

Agricultural land remains a fundamental determinant of cereal output in Pakistan, yet its productivity is increasingly constrained by climate variability, environmental stress, and shifting land-use patterns. Understanding how land availability interacts with these pressures is essential for sustaining agricultural output and ensuring food security. Insights into this relationship can guide policymakers in developing climate-responsive land management and long-term planning strategies [28], [29].

Building upon the above research questions, the study's primary goal is to use an Autoregressive Distributed Lag (ARDL) technique to investigate the combined effects of climate variability and socio-economic factors on agricultural production (cereal output) in Pakistan between 2000 and 2024. The following particular goals are pursued by the study in order to accomplish this: 1) to investigate how Pakistan's CY is affected by agricultural CO_2 emissions and irrigated land, 2) to assess how Pakistan's CY is affected by FC and domestic credit to the private sector, and 3) to evaluate how Pakistan's cereal productivity is affected by agricultural land.

2 | Literature Review

2.1 | Agricultural CO_2 Emissions and Agricultural Irrigated Land

Climate variability, CO_2 emissions, and irrigation availability are central determinants of CY, as rising temperatures and environmental stress reduce crop growth while irrigation stabilizes production under climate pressure. A broad body of research highlights these dynamics across diverse regions. Tubiello et al. [30] showed that higher temperatures and CO_2 levels increase irrigation demand by 60-90% and reduce yields by 10-40% in Italy, while Holden et al. [31] found that climate change lowers potato yields but may enhance barley productivity in Ireland. Field experiments in China demonstrated that moderate CO_2 and temperature increases can improve wheat yield, though larger warming reduces output; irrigation consistently enhances stability [32]. Global assessments confirm that precipitation and water availability strongly shape productivity, and expanding irrigation can raise yields but may intensify environmental degradation [33], [34]. Additional studies show that intercropping, no-tillage practices, and improved water management reduce emissions and support yields [35], [36]. Long-term modeling reveals substantial climate-driven effects on global agriculture and economic performance [37]. Empirical evidence from Turkey confirms that CO_2 emissions and temperature reduce CY, while rainfall improves productivity [38]. Collectively, these studies underscore the strong and multifaceted influence of climate variability, CO_2 emissions, and irrigation on cereal production. According to the recent advances in environmental assessment, composite environmental quality indices, constructed through multi-criteria decision-making and principal component analysis, can provide a more robust understanding of how financial and climatic factors jointly influence agricultural systems [39]. Overall, research indicates that rising temperatures and environmental stress caused by agricultural CO_2 emissions often have a detrimental effect on cereal productivity (see *Table 1*). On the other hand, by enhancing crop stability and lowering moisture stress, irrigation and water availability have a positive impact on agricultural productivity. The results, however, vary depending on the environment, methodology, and geographic location. While there is little actual data for developing nations like Pakistan, the majority of studies are based on simulations or industrialized nations.

Hypothesis 1. Agricultural CO_2 emissions have a negative effect, while agricultural irrigated land has a positive effect on CY in Pakistan.

Table 1. Agricultural CO_2 emissions, agricultural irrigated land, and Cereal Yield in Pakistan.

Authors	Techniques	Results
Rehman et al. [40]	GMM, 2SLS	The study concluded that Climate factors strongly influence agricultural productivity in Pakistan; policy measures are needed to reduce emissions.
Khan & Wang [41]	ARDL	The study concluded that Climate and agronomic factors influence wheat yield results, useful for policy and adaptation strategies.
Jadoon et al. [42]	ARDL	The study concluded that Environmental degradation affects agriculture; improving inputs and irrigation can enhance productivity in Pakistan.
Khan et al. [43]	Linear and Non-linear ARDL	The study concluded that Climate change significantly affects food and crop production in Pakistan; climate-resilient adaptation measures are needed.
Anwar et al. [44]	ARDL	The study concluded that Climate change negatively affects wheat production in Pakistan; strong adaptation, water management, and flood control policies are required.

2.2 | Fertilizer Consumption and Domestic Credit to Private Sector

Fertilizer use and domestic credit are widely recognized as critical drivers of cereal productivity, as they enhance soil fertility, input adoption, and farmers' access to modern technologies. Evidence from multiple regions supports this relationship. In Bangladesh, input market liberalization increased rice output by improving access to fertilizers and seeds [45]. Studies in Sub-Saharan Africa similarly show that weak irrigation systems, low fertilizer use, and poor soil fertility suppress yields, highlighting the need for improved access to inputs [46]. Research on private-sector incentives indicates that supportive policies can stimulate agricultural innovation, though structural constraints limit technology adoption [47]. Empirical findings from India confirm that hybrid wheat adoption, strongly influenced by information and financing, significantly boosts cereal productivity [48]. Government support and fertilizer subsidies have also raised maize yields and strengthened food security in Africa [49]. Further evidence shows that fertilizer credit increases input use and crop yield in Ethiopia [50], while yield gaps in Russia stem partly from insufficient nitrogen fertilizer [51]. Studies from Brazil and Nepal demonstrate that market liberalization, credit access, and adaptation strategies enhance innovation and rice productivity [52], [53]. In Mozambique, fertilizer use remains constrained by high costs, limited finance, and low awareness, underscoring the need for stronger financial and input systems [54]. Collectively, these studies show that fertilizer access and agricultural credit are central to improving CY and sustaining productivity under climate stress. The literature generally shows that fertilizer use and agricultural credit positively influence CY, as fertilizer improves soil fertility and crop performance, while credit enables farmers to acquire modern inputs and technologies. However, results vary across countries, methodological approaches, and institutional settings. Most existing studies focus on emerging regions outside Pakistan, and rigorous econometric evidence for Pakistan remains limited, highlighting the need for updated empirical analysis (see *Table 2*). Empirical evidence also indicates that financial development, whether through money markets or capital markets, can alter the intensity of economic growth's impact on environmental performance, an important consideration for sustainable agricultural productivity [55]. Additional evidence from advanced economies indicates that financial development and digitalization can foster environmental sustainability by reducing carbon emissions, suggesting that financial access and technological adoption may also strengthen agricultural resilience. [56] .

Hypothesis 2. FC and domestic credit to the private sector positively affect CY in Pakistan.

Table 2. Fertilizer Consumption, domestic credit to private sector and Cereal Yield in Pakistan.

Authors	Techniques	Conclusion
Chaiya et al. [57]	Multiple regression	The study concluded that Formal agricultural credit improves productivity and input use, but proper monitoring is necessary.
Larik et al. [58]	ARDL	The study concluded that FC and agricultural credit significantly improve CY in Pakistan; however, better resource efficiency and policy support are required.
Hussain and Maharjan [59]	Difference-in-Differences (DID)	The study concluded that on-farm demonstrations and improved input use significantly increase wheat yield and profitability in Pakistan. However, further expansion of farmer training, extension services, and access to quality inputs is still needed for long-term productivity growth.
Ishfaq and Khalid [60]	ARDL	This study concluded that Agricultural productivity in Pakistan improves through fertilizer use and agricultural credit. However, population growth and urbanization create structural pressures that limit long-term productivity, highlighting the need for balanced agricultural policies.
Schlecht and Roessler [61]	Baseline survey	This study concluded that yak production in Gilgit-Baltistan is affected by limited feed availability, diseases, degraded grazing land, and financial constraints; therefore, improved support structures and stronger value chains are necessary for sustainable yak production in the region.

2.3 | Agricultural Land Impact on Cereal Yield

Agricultural land is a core determinant of CY, yet its productivity is shaped by land degradation, drought, climate variability, and management practices. Prior research consistently shows that sustainable land use, conservation measures, and technological improvements enhance cereal output, whereas climate stress and land fragmentation reduce performance. Global evidence highlights these dynamics across diverse contexts. Gregory & Ingram [62] found that land intensification boosts cereal production, but long-term expansion is constrained by limited land and climate uncertainty. European studies show mixed regional outcomes, with northern areas benefiting from land expansion and southern regions experiencing yield losses under climate stress [63]. Life Cycle Assessment research demonstrates that appropriate nitrogen management sustains wheat yield while minimizing environmental impacts [64]. Empirical findings from Italy and West Africa indicate that cooperatives, mulching, crop rotation, and green manure improve cereal productivity [65], [66]. Evidence from France shows that land fragmentation lowers yield and raises costs [67], while soil-quality improvements and residue management enhance wheat performance in India [68]. Integrated assessments from Finland and Morocco further confirm that land management, improved cultivars, and soil-moisture conditions positively influence cereal output under climate variability [69], [70]. Overall, the literature underscores that agricultural land quality, management, and climate interactions jointly shape cereal productivity. Evidence shows that agricultural land, sustainable land management, conservation practices, and technological improvements generally raise CY (see *Table 3*). In contrast, land degradation, drought, fragmentation, and climate variability reduce productivity. Most studies highlight the need for institutional support and sustainable land use, yet many remain region-specific or model-based, and Pakistan still lacks robust empirical and econometric evidence.

Hypothesis 3. Agricultural land has a significant positive impact on CY in Pakistan.

Table 3. Agricultural land and Cereal Yield in Pakistan.

Authors	Techniques	Results
Gul et al. [71]	ARDL	The study concluded that Agricultural land and non-climatic factors improve rice production in Pakistan; however, climate change reduces productivity. The study is limited to macro-level time-series analysis and requires farm-level and region-specific evidence.
Rahman et al. [72]	SEM BPCA, OLSR	The study concluded that agricultural drought and land use variations significantly affect crop yield in Pakistan; however, it is limited to remote sensing and model-based analysis and requires ground-level socio-economic data.
Ali &Mujahid [73]	ARDL	The study concluded that Agricultural land and climate factors significantly influence agricultural productivity in Pakistan. However, advanced econometric techniques and policy evaluation are still needed for better assessment.
Hafeez et al. [74]	Remote Sensing	The study concluded that flood exposure and land degradation reduce agricultural productivity in Pakistan. Therefore, flood risk management and satellite-based monitoring are important for sustainable agriculture.
Iqbal et al. [75]	ARDL	The study concluded that agricultural land expansion and input-intensive practices increase agricultural productivity in Pakistan; however, sustainable resource management and policy intervention are necessary to reduce environmental risks.

Note: Structural Equation Modeling (SEM), Bayesian Principal Component Analysis (BPCA), Ordinary Least Squares Regression (OLSR).

2.4 | Research Gap

Existing studies in Pakistan [40], [42], [43] mainly examine climate variables, temperature, rainfall, floods, and CO_2 emissions, while agricultural inputs such as fertilizer and irrigation are often analyzed in isolation. A clear gap remains: no integrated model has jointly assessed fertilizer use, domestic credit, CO_2 emissions, irrigated land, and agricultural land as a core production factor. Agricultural land, despite its central role, is frequently treated as a secondary variable, leaving its interaction with climate and socio-economic factors underexplored. Most international studies [33], [36] focus on developed regions or cross-country assessments, while Pakistani research is limited to specific provinces or single crops. Although various methods, ARDL, GMM, 2SLS, descriptive analysis, and remote sensing, have been used [40], [41], [72], they often fail to capture short- and long-run dynamics simultaneously. This limitation creates a methodological gap in analyzing climate, inputs, finance, and land within a unified ARDL framework. Furthermore, many studies rely on older or mixed time periods (1970-2018, 1990-2020, 1960-2014), despite rapidly evolving climate and agricultural conditions. Updated empirical evidence using 2000-2024 data is therefore essential for accurately assessing current climate variability and policy impacts. Given these conceptual, empirical, and methodological gaps, this study contributes by presenting the first integrated empirical model for Pakistan that jointly examines key socio-economic drivers, FC, domestic credit, agricultural land, irrigated land, alongside CO_2 emissions. It also uses updated data (2000-2024) and applies the ARDL framework to capture both short-run and long-run dynamics. These contributions strengthen empirical understanding of CY and support more effective policy design for improving Pakistan's agricultural productivity and food security.

3 | Data Source and Methodology

3.1 | Data Collection

This study uses annual time-series data for Pakistan from 2000-2024 obtained from the World Development Indicators (WDI). The dataset includes the dependent variable CY and the independent variables agricultural land, irrigated land, FC, domestic credit to the private sector, and agricultural CO_2 emissions, all expressed in consistent annual units suitable for empirical analysis. The operational definitions of variables are presented in *Table 4*.

Table 4. Operational definition of variables [76].

Variable	Symbol	Measurement	Source
CY	CY	Kilograms per hectare (kg/ha)	WDI
Agricultural CO_2e emissions	CO_2e	Mt CO_2e	WDI
Agricultural irrigated land	AIL	% of total agricultural land	WDI
FC	FC	Kilograms per hectare of arable land	WDI
Domestic credit to private sector	DCTPS	% of GDP	WDI
Agricultural land	AL	% of land area	WDI

3.2 | Methodology and Model Specification

This study investigates the impact of agricultural CO_2 emissions, irrigated land, FC, domestic credit to the private sector, and agricultural land on Pakistan's cereal production using annual time-series data for 2000-2024. To capture both short-run adjustments and long-run equilibrium relationships, the analysis employs a comprehensive econometric strategy implemented in EViews. The methodological procedure includes descriptive statistics to summarize data behavior, correlation analysis to explore initial associations, unit root testing to determine integration orders, and optimal lag selection to ensure model adequacy. The core empirical estimation relies on the ARDL framework, followed by bounds testing to verify long-run cointegration and an error-correction model to quantify short-run dynamics. Diagnostic tests are conducted to assess serial correlation, heteroskedasticity, functional form, and normality, while stability tests evaluate the robustness of parameter estimates. Multicollinearity analysis is also performed to ensure the reliability of coefficient interpretation within the multivariate structure. Grounded in the Cobb–Douglas Production Function and Climate Change Theory, the empirical model is specified as *Eq. (1)*:

$$CY_t = \beta_0 + \beta_1 CO2_t + \beta_2 AIL_t + \beta_3 FC_t + \beta_4 DCTPS_t + \beta_5 AL_t + \varepsilon_t \quad \textbf{(1)}$$

where CY denotes CY, CO_2 agricultural CO_2 emissions, AIL irrigated land, FC, DCTPS domestic credit to the private sector, and AL agricultural land. The parameter β_0 represents the constant term, β_1-β_5 are the coefficients of the explanatory variables, ε_t is the error term, and $t$denotes the time period. This model captures how environmental pressures and socio-economic inputs jointly influence Pakistan's CY, allowing the analysis to quantify the individual and combined effects of CO_2 emissions, irrigation availability, fertilizer use, financial access, and land resources on agricultural performance.

4 | Results

This section presents the empirical findings using descriptive statistics, correlation analysis, unit root testing, lag selection, ARDL estimation, bounds testing, long-run and short-run Error Correction Model (ECM) dynamics, and diagnostic and stability evaluations. These procedures collectively assess how agricultural CO_2 emissions, irrigated land, FC, domestic credit, and agricultural land influence Pakistan's CY from 2000 to 2024.

Table 5 summarizes the descriptive statistics. CY averages 2905.24 with moderate variation, while CO_2 emissions, Irrigated Land (AIL), FC, Domestic Credit (DCTPS), and Agricultural Land (AL) show stable mean values across the sample period. Skewness values fall within −1 to +1, indicating near-symmetry, and kurtosis values close to 3 suggest approximately normal distributions.

Table 5. Descriptive statistics [76].

Methods	CY	CO_2	AIL	DCTPS	FC	AL
Mean	2905.240	4.652	51.850	16.996	132.895	47.001
Maximum	3805.000	5.585	55.728	24.168	173.599	48.000
Minimum	2230.500	3.396	47.487	11.466	94.071	45.716
Std. Dev.	433.8265	0.669	2.270	3.452	22.244	0.671
Skewness	0.266227	-0.463	-0.161	0.616	-0.216	-0.197
Kurtosis	2.267226	2.059	2.034	2.413	2.121	2.398

Table 6 reports the correlation matrix. CY shows strong positive correlations with CO_2 emissions (0.808), AIL (0.413), and FC (0.923), highlighting the role of environmental pressure and input intensity in shaping yield outcomes. Negative correlations appear with DCTPS (−0.611) and AL (−0.113). CO_2 emissions correlate positively with AIL and FC but negatively with DCTPS and AL. AIL is positively associated with FC and DCTPS, while strongly negatively correlated with AL. DCTPS shows negative associations with FC and AL, and FC also exhibits a mild negative correlation with AL. These correlations provide preliminary insights into variable interactions prior to ARDL estimation.

Table 6. Correlation matrix [76].

variable	CY	CO_2	AIL	DCTPS	FC	AL
CY	1					
CO_2	0.808 (0.000)	1				
AIL	0.413 (0.039)	0.496 (0.011)	1			
DCTPS	-0.611 (0.001)	-0.287 (0.164)	0.245 (0.236)	1		
FC	0.923 (0.000)	0.892 (0.000)	0.511 (0.008)	-0.460 (0.020)	1	
AL	-0.113 (0.589)	-0.234 (0.260)	-0.846 (0.000)	-0.396 (0.049)	-0.201 (0.334)	1

P-value is presented in parentheses.

Table 7 presents the Augmented Dickey-Fuller (ADF) unit root results. All variables, CY, CO_2, AIL, FC, DCTPS, and AL, are non-stationary at level, as indicated by probability values above 0.05. After first differencing, each variable becomes stationary, confirming integration of order one, I(1). This result satisfies the requirements for applying the ARDL framework, which accommodates mixed integration orders and allows simultaneous estimation of short-run adjustments and long-run equilibrium relationships.

Table 7. Unit root test results (ADF Test).

Variables	Level Constant and Trend	First Difference	Decision
CY	0.923177 (0.993)	-8.611890 (0.000)	I(1)
CO_2	2.435639 (0.143)	-8.120835 (0.000)	I(1)
AIL	-2.035826 (0.270)	-4.211553 (0.003)	I(1)
FC	-1.394823 (0.565)	-4.667632 (0.001)	I(1)
DCTPS	-0.447949 (0.885)	-4.184126 (0.005)	I(1)
AL	-1.911165 (0.321)	-4.882084 (0.000)	I(1)

P-value is presented in parentheses.

Table 7 presents the Augmented Dickey–Fuller ADF unit root results. All variables (CY, CO_2, AIL, FC, DCTPS, and AL) are non-stationary at level, as indicated by probability values above 0.05. After first differencing, each variable becomes stationary, confirming integration of order one, I(1). This result satisfies the requirements for applying the ARDL framework, which accommodates mixed integration orders and allows simultaneous estimation of short-run adjustments and long-run equilibrium relationships. *Table 8* shows the optimal lag order for the VAR model based on Likelihood Ratio (LR), FPE, AIC, SC, and HQ criteria for the period 2000-2024.

Table 8. Lag length selection criteria.

Lag	Log L	LR	FPE	AIC	SC	HQ
0	-370.0221	NA	1636710.	31.33517	31.62968	31.41331
1	-290.4348	112.7487*	48063.45*	27.70290*	29.76449*	28.24984*

The results, reported in *Table 8*, show that lag 1 is selected as the optimal lag duration based on all selection criteria. The LR, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ) all indicate that lag 1 provides the optimal model specification when compared to lag 0. Based on all selection criteria, lag 1 is shown to be the optimal lag length for further econometric research. Table 9 shows the ARDL short-run estimation results.

Table 9. ARDL short-run estimation results.

Variables	Coefficient	Std. Error	t-Statistic	Prob.*
CY(-1)	0.684131	0.205461	3.329744	0.0050
CO_2	134.3556	79.54058	1.689145	0.1133
AIL	12.20281	28.71670	0.424938	0.6773
AIL(-1)	77.85296	29.33125	2.654267	0.0189
FC	2.502458	3.633473	0.688724	0.5023
FC(-1)	-3.764569	3.293383	-1.143071	0.2722
DCTPS	-17.82113	13.50478	-1.319617	0.2081
AL	111.8321	85.82132	1.303080	0.2136
AL(-1)	123.1093	79.27887	1.552864	0.1428
C	-14911.95	6629.853	-2.249212	0.0411

Table 9 reports the short-run results of the ARDL (1,0,1,1,0,1) model. The lagged dependent variable CY (–1) is positive and statistically significant, indicating short-run persistence in CY. AIL (–1) is also positive and significant, showing that previous irrigation conditions contribute to short-term yield gains. The constant term is negative and significant. In contrast, the short-run coefficients of CO_2, AIL, FC, FC (–1), DCTPS, AL, and AL (–1) are statistically insignificant, suggesting that these variables do not exert immediate short-run effects on CY during the sample period. Table 10 presents the long-run coefficients of the ARDL levels equation for Pakistan (2000-2024), with CY as the dependent variable.

Table 10. ARDL long-run estimation.

Variables	Coefficient	Std. Error	t-Statistic	Prob.
CO_2	425.3522	389.4944	1.092063	0.2932
AIL	285.1048	208.2474	1.369068	0.1925
FC	-3.995678	16.20684	-0.246543	0.8088
DCTPS	-56.41938	34.27181	-1.646233	0.1220
AL	743.7937	580.0462	1.282301	0.2206
C	-47209.28	37077.04	-1.273275	0.2237

Table 10 displays the long-term results of the ARDL model for Pakistan's CY between 2000 and 2024. The results show that CO_2 has a positive coefficient of 425.3522 with a p-value of 0.2932, and AIL has a positive coefficient of 285.1048 with a p-value of 0.1925. FC has a negative coefficient of -3.995678 and a p-value of 0.8088. DCTPS has a negative coefficient of -56.41938 and a p-value of 0.1220. AL has a positive coefficient of 743.7937 and a p-value of 0.2206. The constant term has a negative coefficient of -47209.28 and a p-value of 0.2237. All explanatory factors are statistically insignificant in the long run since their probability values are greater than 0.05. Long-run coefficients are only provided for directional interpretation since there is no statistically significant cointegration. *Table 11* displays the F-Bounds test data for determining the presence of a long- term relationship in Pakistan (2000-2024).

Table 11. F-bound test statistic table.

Test Statistic	Value	I(0)	I(1)
F-statistic	2.214101	2.39	3.38
K	5		

Table 11 shows F-Bound test results for cointegration in the ARDL model. At the chosen significance level, the F-statistic value of 2.214101 is compared to the lower bound I(0) value of 2.39 and the upper bound I(1) value of 3.38. Both the lower and upper bound critical values are exceeded by the computed F-statistic. The number of regressors, or K, is five. *Table 12* shows the short-run dynamics of the ECM regression for Pakistan (2000-2024), with CY as the dependent variable.

Table 12. Autoregressive Distributed Lag short-run Error Correction Model estimation.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(AIL)	12.20281	18.95935	0.643631	0.5302
D(FC)	2.502458	2.113834	1.183848	0.2562
D(AL)	111.8321	52.11477	2.145881	0.0499
CointEq(-1)*	-0.315869	0.067129	-4.705423	0.0003

Table 12 presents the short-run ECM results of the ARDL specification. The coefficient of D(AL) is positive and statistically significant, indicating that short-run changes in agricultural land contribute meaningfully to CY. In contrast, D(FC) and D(AIL) are statistically insignificant, suggesting no immediate short-run effects from fertilizer use or irrigation changes. The error correction term, CointEq (–1), is negative and highly significant, confirming the presence of short-run adjustment dynamics. Its magnitude implies that approximately 31.5% of deviations from equilibrium are corrected annually. However, because the bounds test does not confirm long-run cointegration, the ECM significance reflects only short-run correction rather than a stable long-run relationship. Thus, while short-run adjustments exist, no definitive long-run equilibrium can be inferred. *Table 13* reports the Breusch–Godfrey serial correlation diagnostic results. The result shows the Breusch- Godfrey serial correlation LM test. The probability value is 0.7274, and the F-statistic value is 0.326885. With a probability value of 0.5379, the Obs*R-squared value is 1.239983. Since both probability values are higher than 0.05, serial correlation is not present in the model.

Table 13. Breusch-Godfrey serial correlation LM test results.

Test Statistic	Value	Probability
F-statistic	0.326885	0.7274
Obs*R-squared	1.239983	0.5379

Table 14. Heteroskedasticity (breusch-pagan-godfrey) test.

Test Statistic	Value	Probability
F-statistic	2.702137	0.0465
Obs*R-squared	15.23156	0.0848
Scaled explained SS	5.365982	0.8013

The results, presented in *Table 14*, show the Breusch-Pagan-Godfrey heteroskedasticity test findings. The probability value is 0.0465, and the F-statistic value is 2.702137. The Scaled Explained SS value is 5.365982 with a probability value of 0.8013, and the Obs*R-squared value is 15.23156 with a probability value of 0.0848. Based on the F-statistic probability value, the results provide evidence of heteroskedasticity in the model. Since the model exhibits heteroskedasticity, White-Hinkley HC1 robust standard errors are used in the final ARDL estimation to guarantee consistent and trustworthy inference.

Table 15. Heteroskedasticity-consistent (white-hinkley HC1) standard errors.

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
CY(-1)	0.684131	0.242671	2.819171	0.0137
CO_2	134.3556	85.46279	1.572095	0.1382
AIL	12.20281	25.22648	0.483730	0.6361
AIL(-1)	77.85296	36.30458	2.144439	0.0500
FC	2.502458	2.631136	0.951094	0.3577
FC(-1)	-3.764569	4.354998	-0.864425	0.4019
DCTPS	-17.82113	11.52018	-1.546950	0.1442
AL	111.8321	93.11037	1.201070	0.2497
AL(-1)	123.1093	70.35207	1.749903	0.1020
C	-14911.95	6355.098	-2.346454	0.0342

Table 15 shows the Heteroskedasticity-robust ARDL Estimation Results (HC1-corrected standard errors). The findings show ARDL estimate results with heteroskedasticity-consistent (White-Hinkley HC1) standard errors. With a coefficient of 0.684131, the data demonstrate that CY(-1) is positive and statistically significant. With a coefficient of 77.85296, AIL(-1) is likewise positive and statistically significant. With a value of -14911.95 ($p = 0.0342$), the constant term is statistically significant and negative. CO_2, AIL, FC, FC(-1), DCTPS, AL, and AL(-1) are all statistically insignificant. *Fig. 1* shows the normality test of the residuals.

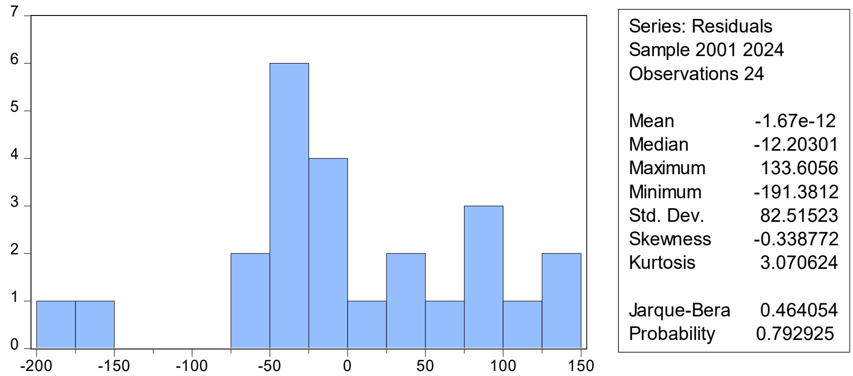

Fig. 1. Normality (Jarque-Bera) test.

The Jarque–Bera test was applied to assess the normality of the ARDL model residuals. The statistic's probability value is 0.7929, which is above the 0.05 significance threshold, indicating that the null hypothesis of normal distribution cannot be rejected. This finding confirms that the residuals follow a normal pattern and that the ARDL model satisfies the normality assumption. *Fig. 2* presents the CUSUM stability test.

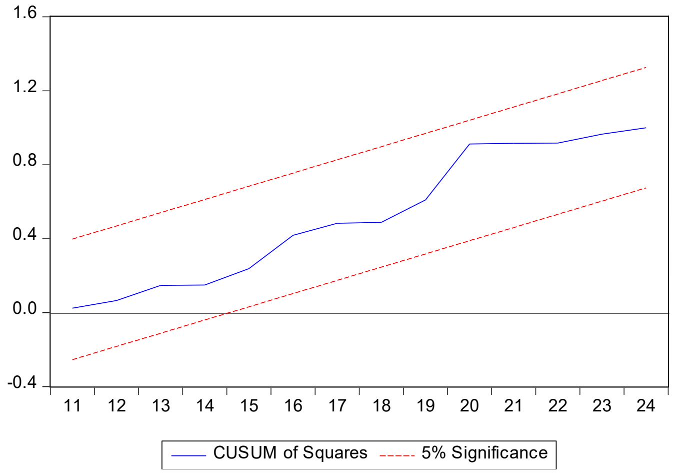

Fig. 2. Stability test (CUSUM) test

The CUSUM test using the calculated ARDL model was assessed stability. The findings demonstrate that during the sample period, the CUSUM statistic stays under the 5% critical boundaries. This suggests that during the course of the investigation, the calculated ARDL model is structurally stable. *Fig. 3* shows the CUSUM square test.

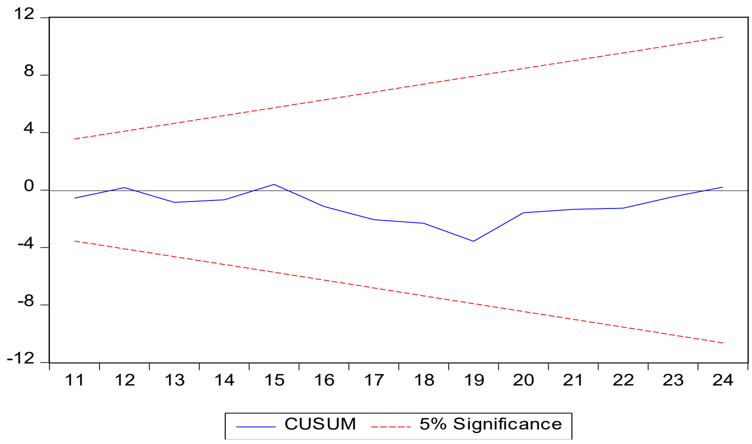

Fig. 3. Stability test (CUSUM of Squares).

The CUSUM of Squares (CUSUMSQ) test was applied to evaluate the structural stability of the ARDL model. The results show that the CUSUMSQ statistic remains within the 5% critical bounds throughout the sample period, indicating that the null hypothesis of parameter stability cannot be rejected. The finding confirms that the model is structurally stable over the study period.

Table 16. Ramsey RESET test.

Test statistic	Value	Probability
t-statistic	0.322544	0.7522
F-statistic	0.104035	0.7522

The Ramsey RESET test results in *Table 16* confirm the adequacy of the model specification. The F-statistic and t-statistic both exceed the 0.05 significance threshold, indicating no functional-form misspecification and supporting the correctness of the ARDL model structure.

Table 17. Variance Inflation Factor results.

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	37546825	41950.38	NA
CO2	11555.33	284.9911	5.552461
AIL	1288.883	3878.605	7.127403
FC	17.41809	352.9481	9.244262
DCTPS	183.2554	61.49233	2.343527
AL	9853.855	24326.49	4.764328

Table 17 reports the VIF results used to assess multicollinearity in the ARDL model. The centered VIF values are 5.55 for CO_2 emissions, 7.12 for irrigated land, 9.24 for FC, 2.34 for domestic credit, and 4.76 for agricultural land. These values fall within acceptable ranges, indicating no severe multicollinearity among the explanatory variables and confirming that the model's regressors are sufficiently independent for reliable estimation.

The ARDL bounds test provides only weak evidence of long-run relationships, as the F-statistic falls below the lower critical value. The result indicates the absence of a stable long-term equilibrium between CY and its determinants in Pakistan, suggesting that long-run coefficients should be interpreted only directionally. This weak cointegration aligns with structural challenges in Pakistan's agricultural sector, climate variability, water scarcity, inefficient input use, and institutional constraints, which, according to Climate Change Theory, undermine long-term productivity. Consequently, no firm theoretical conclusions can be drawn from the long-run estimates.

Short-run ARDL results offer more meaningful insights. The significant positive coefficient of CY(–1) confirms yield persistence, indicating that past output strongly influences current productivity. AIL also shows a significant short-run effect, consistent with the Cobb–Douglas Production Function and supported by studies such as Guoju et al. [32] and Kang et al. [33], partially validating

Hypothesis 1 Agricultural land contributes positively in the medium term, aligning with Ali & Mujahid [73] and Gul et al. [71], offering partial support for *Hypothesis 3* FC is insignificant, reflecting inefficient input use and contradicting production theory, consistent with Zavale et al. [54] and Ishfaq & Khalid [60], thus rejecting *Hypothesis 2* Domestic credit is also insignificant, suggesting weak financial support for agriculture, again consistent with Ishfaq & Khalid [60], rejecting H2. CO_2 emissions show a positive but insignificant effect, reflecting mixed climate impacts, similar to Jadoon et al. [42] and Anwar et al.[44]. Given the absence of cointegration, long-run results are only tentative. CO_2 emissions, irrigation, fertilizer use, domestic credit, and agricultural land all exhibit negligible long-run effects, indicating that structural instability prevents sustained productivity gains. These findings partially align with Climate Change Theory but contradict the Cobb-Douglas expectation of consistently positive input contributions.

5 | Conclusion and Policy Recommendations

5.1 | Conclusion

The primary goal of this study was to examine the effects of agricultural CO_2 emissions, irrigated land, FC, domestic credit to the private sector, and agricultural land on cereal output in Pakistan between 2000 and 2024. The study used the ARDL approach to examine the link between the chosen factors and CY, and it was based on the Cobb-Douglas Production Function and Climate Change Theory. The aggregate results indicate that stable, long-term structural factors have a smaller impact on Pakistani agricultural productivity than acute agricultural conditions. The findings emphasize how crucial it is to use resources productively in order to promote cereal production, especially the availability of agricultural land and water resources.

However, the results show that over the research period, advances in agricultural input management and financial support systems have not yet resulted in significant increases in production. There may be structural issues in the agriculture industry that could prevent long-term productivity growth, as indicated by the weak long-term correlation between the variables. By offering actual data on the connection between socio-economic and climate-related factors and CY in Pakistan, this study adds to the body of current work. By collectively analyzing these factors within a unified analytical framework for the years 2000-2024, it also fills a significant research gap. Overall, the results suggest that attaining sustainable agricultural productivity in Pakistan requires bolstering irrigation efficiency, expanding resource use, improving land management techniques, and encouraging climate-resilient agricultural solutions.

5.2 | Policy Recommendations

The study offers several policy implications and future research directions. Overall, Pakistan's agricultural policies should prioritize improved resource management, higher land productivity, and efficient water use, alongside promoting sustainable planning to mitigate climate variability. Given the strong short-run impact of irrigated land, investment in irrigation infrastructure, modern techniques, canal rehabilitation, and advanced water-management systems is essential. Since agricultural land also contributes positively, preventing land degradation and enhancing land productivity through better farming practices and conservation measures is crucial. The negligible role of domestic credit indicates weak financial support for farmers, highlighting the need for more transparent, accessible, and farmer-oriented financing mechanisms. Inefficient fertilizer use suggests the importance of soil testing, balanced application, and awareness programs to improve input efficiency. Although CO_2 emissions are statistically insignificant, climate fluctuations continue to challenge Pakistan's agriculture, making climate-smart practices, water conservation, and adaptation strategies vital. Future research should expand beyond Pakistan through cross-country panel studies to improve generalizability, and incorporate omitted variables such as rainfall, temperature, drought, soil quality, technology adoption, and subsidies for a more comprehensive understanding of yield determinants. Since no stable long-run cointegration was found, extending the time period or adding more explanatory variables may help uncover long-term dynamics. Using provincial, district, or farm-level data could capture regional variations more accurately. Methodologically, future studies may adopt advanced approaches such as NARDL, VAR, VECM, Panel ARDL, or nonlinear models to capture structural breaks and climate shocks better. Further work should also examine the effects of floods, droughts, extreme weather, and policy reforms to understand how climate variability and structural changes shape Pakistan's agricultural productivity.

5.3 | Limitations of the Study

This study, like all empirical research, faces several limitations that affect the interpretation and generalizability of its findings. The analysis relies solely on annual time-series data for Pakistan from 2000 to 2024, which restricts the applicability of the results to other countries or regions. The variable set is also limited, as key determinants such as rainfall, temperature, drought intensity, soil quality, technological adoption, and government agricultural support were not included, despite their potential influence on CY. Another limitation concerns the long-run relationship: the ARDL bounds test did not confirm stable cointegration, meaning the long-run coefficients cannot be treated as strong causal evidence. The study further depends on national-level aggregate data, preventing the capture of provincial or district-level variations in agricultural productivity. Methodologically, although the ARDL approach is suitable for mixed integration orders, it may not fully capture nonlinear dynamics, structural breaks, or climate-related shocks that characterize Pakistan's agricultural system.

Authors' Contributions

E. T. R.: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Writing-original draft, Visualization, and Validation. K. Z.: Formal analysis, Investigation, Supervision, Visualization, and Validation. The authors have read and agreed to the published version of the manuscript.

Data Availability

The data are available on request from the corresponding author.

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Conflict of Interest

There are no competing interests to declare.

Consent for Publication

The authors have given consent for the publication of this manuscript.

Ethics Approval and Consent to Participate

The authors confirm that this research did not involve human participants or animal subjects.

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