Available Online
Journal of Economic Impact
ISSN: 2664-9764 (Online), 2664-9756 (Print)
https://www.scienceimpactpub.com/jei

AGRICULTURE UNDER CLIMATE STRESS: DRIVERS AND POLICY IMPLICATIONS FOR SUSTAINABLE PRODUCTIVITY IN PUNJAB, PAKISTAN

Shagufta Rasheed *, Nazia Tabasam, Sarfraz Hassan, Almazea Fatima

Institute of Agricultural and Resource Economics, University of Agriculture Faisalabad, Pakistan

ARTICLE INFO

Article history
Received: August 19, 2024
Revised: November 27, 2024
Accepted: December 13, 2024

Keywords
Climate change
Agricultural productivity
Fertilizer
Precipitation
Fixed effects
Pakistan

ABSTRACT

Global warming is intensifying the impact of climate change on agricultural productivity. This study aims to assess the relationship between non-climatic and climatic variables like the area under cultivation, fertilizer consumption, tractor and tube well, and average minimum and maximum temperature, wind, and precipitation, and the effects of these variables on agricultural productivity between 1991 and 2021, in Punjab Pakistan. In the first phase, we used the unit root tests to verify that the panel data was stationary. A Fixed Effects model was employed to identify the dynamic linkages of climatic and non-climatic factors with agricultural productivity. The outcomes of the study revealed that temperature and precipitation have a diverse impact on productivity. While the cultivated area and fertilizer consumption have a positive and significant impact on agricultural productivity. The empirical findings also showed that in comparison to non-climatic factors, climatic parameters—such as average maximum temperature—have a greater impact on productivity. Few recommendations are offered to deal with the effects of climate change based on the study's findings. Create such agriculture-specific adaptation plans for farmers who are resilient and capable of addressing climate change. Agriculture-related research and development ought to concentrate on key temperature-tolerant food crop varieties. Because of these tactics, the agriculture sector will be able to maintain long-term production and distribution efficiency.

* *Email: shaguftarasheed57@gmail.com*
https://doi.org/10.52223/econimpact.2024.6311

INTRODUCTION

The term "climate" refers specifically to the state of the global environment as it is expressed through fluctuations in humidity, rainfall, and temperature. Thus, "climate change" refers to a change in the environment brought about by human activity and natural processes (Nath and Mandal 2018; Chandio et al., 2020a). Due to its long-term detrimental effects on food production, rural poverty livelihoods, water supplies, and agricultural productivity, climate change has drawn the attention of environmentalists and policymakers worldwide since the 1990s (Chavas et al., 2009; Below et al., 2010; Mohorji et al., 2017).

The cause of climate change is an increase in human activity on the land, such as land usage, deforestation, urbanization, population growth, and production and consumption activities to meet the need for food. The environment is always changing due to factors including global temperature, precipitation, and carbon emissions, which have a significant impact on agricultural productivity and development (Chandio et al., 2021a; Klutse et al., 2021). The primary causes of climate change, such as increased temperatures and precipitation, have resulted in a decline in agricultural production (Haile et al., 2017). The atmosphere's rising carbon concentration, mostly from the industrialized world's increased output, is to blame for the temperature's steady rise. However, the developing country, which is located in a tropical location and mostly depends on the agriculture sector, is primarily affected by rising temperatures, fluctuating rainfall, and frequent floods and droughts (Janjua et al., 2014).

In addition to being vulnerable to climate change, agriculture and its related industries also contribute to carbon emissions (Swaminathan and Kesavan, 2012). The production of agriculture is negatively impacted by climate change, and small and medium-sized farmers who primarily rely on agriculture and related industries for their livelihoods are more vulnerable (Zakaria et al., 2020). The effects of climate change may differ depending on one's geographic position from one region to another. While it improves agricultural output in affluent nations, it worsens the situation for the agricultural sector in underdeveloped nations (Nath and Behera, 2011; Janjua et al., 2014; Abbas, 2020).

Similarly, Abbas et al. (2022b) found that South Asia's food security and crop productivity have been greatly impacted by climate change throughout time. According to Swaminathan and Kesavan (2012), there has been a negative impact on food production due to climate change, and the primary food-producing areas may shift in position. Due to their greater reliance on the agricultural sector for a living, their lack of technical innovation, and their lack of strategies to adapt to climate change and its effects on agriculture production, poor nations are more vulnerable than developed ones (Praveen and Sharma, 2020; Warsame, 2021). However, according to Chandio et al. (2021b), Pakistan's cereal output is impacted both positively and negatively by rising temperatures and financial development, respectively. However, Ahsan et al. (2020) showed that CO_2 has a beneficial impact on agricultural productivity and that the primary determinants of agriculture productivity are labor force, cultivated area, energy consumption, and CO_2. Similarly, Warsame (2021) clarified how Somalia's agricultural productivity has been adversely affected by CO_2 and mean temperature. In a similar vein, Coulibaly et al. (2020) determined that the primary factors adversely affecting agricultural productivity are temperature and drought.

Other empirical studies discovered that climate change is negatively affecting agricultural productivity and predicted a very alarming situation in the coming days (Tubiello et al., 1995; Mendelsohn and Dinar, 1999; Chang, 2002; Tubiello et al., 2002; Luo et al., 2003; Ludwig and Asseng, 2006; Lobell and Field, 2007; You et al., 2009). Hanif et al. (2010) concluded that the impact of climate change varies by season (Rabi and Kharif) in Punjab. According to Suryabhagavan (2017) and Getachew et al. (2021), changes in the timing of monsoon seasons, as well as increased frequency of extreme weather events (floods and droughts), can have a significant impact on crop productivity. According to Ahmad et al. (2020), a 3.4°C rise in maximum temperature and 3.8°C rise in minimum temperature under hot/dry circumstances (RCP8.5) will result in a 28% decline in current productivity and a 29% decrease in future production by the mid-century (2050).

The rise in temperature had a detrimental influence on wheat yield in the short run, but a favorable effect in the long term. Increased precipitation has a negative impact on both runs. Both climate variables have a negative impact on cotton yield. Increased temperature has a negative impact on sugarcane productivity as well. Maize production is particularly vulnerable to drought stress and climate variability (Hafiza et al., 2022; Dahri et al., 2024), with changes in temperature and precipitation responsible for shortening the growing season and reducing yields (Ahmed et al., 2018; Osman et al., 2022).

Climate change adaptation is critical to agricultural sustainability. The most sustainable and environmentally friendly technique for mitigating the impacts of heat stress is to develop heat-tolerant wheat cultivars from a variety of genetic origins. Two essential adaptive procedures in heat-prone areas are cultivar selection and sowing date changes. The plant will undergo morphological changes to overcome the combined effects of heat and drought stress. The quick ground cover prevents water evaporation from the soil beneath the plant canopy. This enhances water availability for evapotranspiration and keeps the plant canopy cool during heat stress (Shashikumara et al., 2022). Crop diversification in location (substituting one crop for another) and time (changing crop rotation or cropping system) can be a reasonable and cost-effective strategy for increasing agricultural system resilience to climate change. The more diverse the agricultural systems, the better they are at improving food and nutritional security in the face of climate change. When planted in combinations of resistant types over broad expanses of land, had 89% higher yield and 94% less fungal blast incidence than when planted in monoculture (Aryal et al., 2020).

Considering the intricate relationship that exists between crop output and climate change, addressing climate change and its effects on agricultural productivity is a difficult task. Numerous earlier research has examined the effects of rising temperatures and shifting rainfall patterns during the twenty-first century using a variety of climate models (Bhatla et al., 2019). The current study employs the Random Effects technique to examine the dynamic relationship between agricultural productivity and both climatic and non-climatic factors across various districts in Punjab, Pakistan.

According to a study of the literature, the majority of research has looked at CO_2 emissions as a sign of environmental deterioration and climate change. A few studies that look at the effects of increased average annual temperature on certain crop output had varied results. Pakistan cultivates a wide range of crops, and further research is required to determine the overall impact of varying the average yearly temperature in addition to other explanatory factors on the performance of main food and cash crops in terms of production. Thus, the researchers hypothesize the following:

H_1. Agricultural productivity is negatively impacted by climate change

To the best of our knowledge, provincial Punjab has not been the subject of a thorough analysis, despite the abundance of studies on the impact of climate change on crop productivity. To close this gap, the researchers established this scholarship. Figure 1 illustrates the dynamic relationship between climatic, non-climatic, and agricultural productivity.

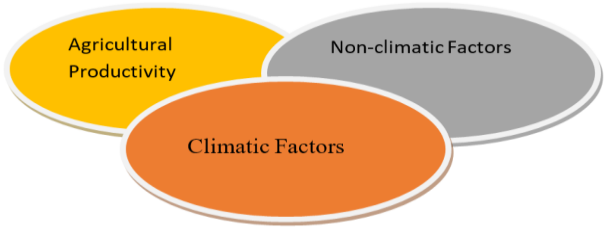

Figure 1. Dynamic connection of climatic and non-climatic factors with agriculture production.

METHODOLOGY

Study Area

Pakistan's province of Punjab (Figure 2) was the subject of the study. Punjab is the most populous province and the second largest in terms of land area, with 205,345 square kilometres (PBS, 2020). Punjab is home to more than half of Pakistan's population and generates more than 60% of the country's agricultural output. The Punjab province was selected because agriculture contributes more than half of the country's gross domestic product (GOP, 2022). Punjab province has 36 districts for administrative purposes. The Punjab province is located at 31.17 north latitudes and 72.70 east longitudes (Abbas et al., 2014). Generally speaking, Punjab province experiences harsh winters and lengthy, blistering summers. The monsoon winds in Punjab are mostly responsible for rainfall. Punjab province has the following climate classifications: extremely arid, arid, dry semi-arid, wet semi-arid, wet sub-humid, and dry sub-humid, according to the Pakistan Meteorological Department. The agricultural calendar's two main cropping seasons, Kharif (summer) and Rabi (winter) are determined by the combination of seasonal temperatures and rainfall. Wheat is a key crop in Rabi, but rice, cotton, maize, and sugarcane are major crops in Kharif (Hussain and Mudasser, 2007; Naheed and Rasul, 2010).

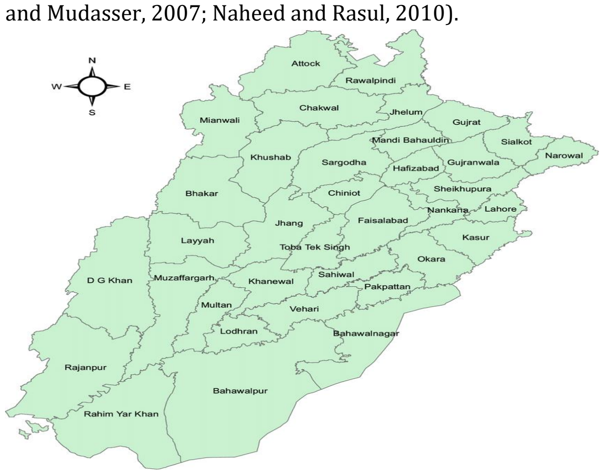

Figure 2. Punjab province map.

Data source

Cross-sectional time series, or panel data, are used to calculate the effects of climatic and non-climatic factors on agricultural productivity levels. Nine districts from Punjab are included in the panel set for the years 1991–2021. The data sources and descriptions are displayed in Table 1. There are two sets of variables in the dataset.

The first category consists of economic factors including total cultivated area, total number of tractors, fertilizer used, and number of tube wells. The second category is climate variables, which include wind, precipitation, and the minimum and maximum annual average temperature, make up the second group.

Agricultural productivity is used as a dependent variable. The yield of five (5) major crops (Wheat, Rice, Maize, Cotton, and Sugarcane) is used as a proxy for agricultural productivity. The Pakistan Metrological Department provided the climate data.

The description, measurement, and data sources of the undertaken antecedents are given in Table 1.

Table 1. The description, measurement, and data sources.

Sr. No.	Variable Data Source	Measurement Units	Data
1.	Agricultural productivity	(000)tons	PDS
	Non-climatic variables		
2.	Cultivated Area	(000)ha	PDS
3.	Fertilizer Consumption	(000)Nutrient tons	PDS
4.	Tractor	Number/Units	PDS
5.	Tube well	Number/Units	PDS
	Climatic variables		
6.	Average Min. Temperature	Degrees Celsius	PMD
7.	Average Max. Temperature	Degrees Celsius	PMD
8.	Precipitation	Millimeters	PMD
9.	Wind	Speed (km/h or m/s)	PMD

*PDS= Punjab Development Statistics; *PMD= Pakistan Metrological Department.

Model Specification

The current study examined the average minimum and average maximum temperature, precipitation, and wind as climatic factors, keeping in mind the studies of Ahsan et al. (2020), Kumar et al. (2021), Jan et al. (2021), Abbas et al. (2022b), and Gul et al. (2022). Additionally, this study made use of fertilizer, drawing from the most recent research conducted by Ali et al. (2021), and Chandio et al. (2021b). In addition, the article followed Baig et al. (2021), Jan et al. (2021), Abbas et al. (2022a), and Gul et al. (2022) in incorporating farmed area, number of tractors, and tubewells.

To assess the impact of climatic and non-climatic factors on agricultural productivity Fixed Effect Regression analysis was used for panel data (Edokpayi et al., 2015; Alboghdady and El-Hendawy, 2016).

$$Y_{it} = \alpha_i+\beta_1 CA_{it}+\beta_2 FC_{it}+\beta_3 TR_{it}+\beta_4 TW_{it}+\beta_5 MinTemp_{it}+\beta_6 MaxTemp_{it}+\beta_7 Precip_{it}+\beta_8 Wind_{it}+\epsilon_{it} \quad (1)$$

Yit = Agricultural productivity; αi = District-specific fixed effects (captures unobserved heterogeneity across districts); β1,β2,...,β8 = Coefficients for the explanatory variables; CAit = Cultivated area; FCit = Fertilizer consumption (in 000 nutrient tons); TRit = Number of tractors in the district; TWit = Number of tube wells in the district; MinTempit = Average minimum temperature; MaxTempit = Average maximum temperature; Precipit = Precipitation (in millimeters); Windit = Wind speed (in km/h or m/s); ϵit = Error term.

Figure 3 demonstrates the conceptual framework presenting climatic and non-climatic factors that may affect agricultural productivity.

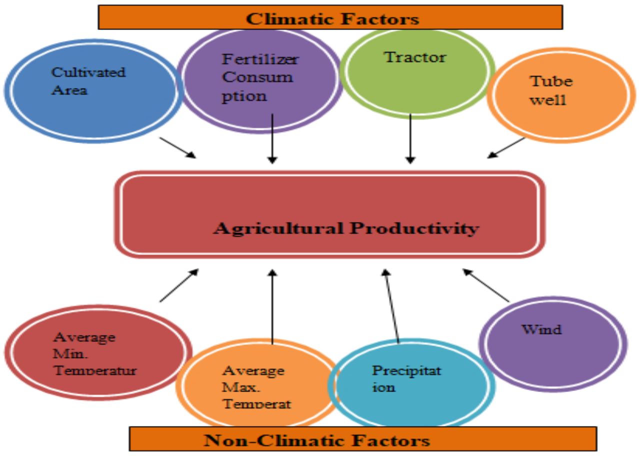

Figure 3. Conceptual framework of the study.

RESULTS AND DISCUSSION

Descriptive Analysis

Descriptive statistics are used to start the analysis of the study (Chandio et al., 2024). It provides a comprehensive summary of the vast amount of data. Table 2 presents the findings of the descriptive statistics. The dataset includes a wide range of agricultural techniques, weather patterns, and resource uses that might affect farming productivity and efficiency. It appears that agricultural techniques may need to be customized based on local conditions, resource availability, and climate variability. This is indicated by the high variability in most parameters and the evidence of non-normal distributions. Such analyses can support decision-making for increased sustainability and productivity.

Table 2. Descriptive statistics.

	PRODUCTION	AREA	FERTILIZER	TRACTORS	TUBEWELL	MIN_TEMP	MAX_TEMP	PRECIPITATION	WIND
Mean	120.1154	523.8521	87.47059	10806.65	21640.75	18.24132	33.02118	487.0795	1.320486
Median	112.9190	548.5000	84.00000	10163.00	16230.50	18.24000	31.60000	487.0800	1.320000
Maximum	206.7900	911.0000	264.0000	38599.00	73804.00	32.10000	445.6200	1651.200	3.300000
Minimum	19.99800	92.00000	1.000000	1189.000	619.0000	9.100000	17.90000	3.370000	0.100000
Std. Dev.	30.41906	228.9330	60.24163	6493.534	16665.64	1.502275	24.48023	321.4176	0.541417
Skewness	0.337313	-0.576366	0.745911	0.916235	1.061465	2.273861	16.70988	0.984024	0.961228
Jarque-Bera	6.243646	24.36433	27.91585	49.47642	57.07634	10480.63	948503.9	53.25244	90.57410
Probability	0.044077	0.000005	0.000001	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Correlation Coefficient Analysis for Selected Variables

The correlation matrix (Table 3) provides key insights into the connections between agricultural productivity and the climatic and non-climatic elements that influence it.

Production and Area have a somewhat positive association (0.4689) for non-climatic variables, indicating that increasing the amount of land under cultivation generally increases productivity. Fertilizer also has a large positive correlation (0.6327), indicating that it has a considerable influence on increasing yields. The significance of mechanization in enhancing agricultural results is highlighted by the strong correlation with tractors (0.7246), whilst the smaller connection with tube wells (0.3768) implies that irrigation facilities, although advantageous, have differing effects on different crops or regions.

A more nuanced picture emerges from the interaction between production and climatic factors. Moderate higher minimum temperature may help crops by lowering the risk of frost, according to a small positive connection with minimum temperature (0.2160). Nonetheless, the moderately negative association (-0.3403) with Max Temperature suggests that excessive heat can reduce productivity, most likely as a result of heat stress. Precipitation also exhibits a moderately negative correlation (-0.4401), indicating that too much rainfall could have negative consequences like crop disease or waterlogging. In this case, wind speed has little direct effect on productivity, as evidenced by the weak correlation with wind.

Other patterns are revealed by the interactions between variables. Fertilizer and Max Temperature have a substantial positive association (0.7503), which would suggest that warmer climates use more fertilizer to counteract nutrient loss. High-rainfall regions may have less cultivation, perhaps as a result of inadequate drainage or inappropriate terrain, according to the moderately negative association between precipitation and area (-0.5587).

These results have important ramifications for climate adaptation plans and agriculture policy. The need for better access to resources and need for climate-smart activities, such as the creation of drought-resistant crops and improved drainage systems, is highlighted by negative connections with climatic elements like precipitation and high temperatures. All things considered, the matrix highlights the complexity of agricultural productivity and shows how crucial it is to combine environmental management with technology breakthroughs in order to provide long-term results.

Unit Root test Results for Selected Variables

The stationary and order of integration of the chosen variables were examined in the current study using the augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips–Perron (PP) (Phillips, 1988) unit root tests. These tests are essential for determining if the series become stationary following differencing (I(1)) or remains stationary at their levels (I(0)). In regression analysis, maintaining stationary is essential to avoiding erroneous findings, particularly when dealing with time series or panel data. To identify potential deterministic trends in the data, trend, and intercept parameters were used for both the ADF and PP tests.

Crop production, average annual minimum and maximum temperatures, precipitation, wind speed, farmed area, fertilizer use, tractors, and tube wells are among the variables for which the unit root test results are shown in Tables 4 and 5. The findings show that the variables have varying degrees of integration. While some variables only become stationary after the first difference (I(1)), others are stationary at their levels (I(0)).

According to the results, some climatic and non-climatic variables are stationary at level (I(0)), including wind speed, precipitation, maximum temperature, area, fertilizer use, and precipitation. This implies that their variance, covariance, and mean statistical characteristics hold steady throughout time, making it possible to incorporate them straight into additional modeling. On the other hand, variables like minimum temperature, tractors, agricultural productivity, and tube wells show non-stationary behavior at their levels but turn stationary after the first difference (I(1)), suggesting the existence of structural shifts or trends that need to be stabilized through differencing.

The analysis is affected in several ways by these findings. The dataset's heterogeneous temporal dynamics are implied by the mixed stationary levels. In contrast to economic variables like production and tractors, which are impacted by policy changes, technological advancements, and other structural factors, climatic variables like precipitation and maximum temperature are inherently stationary due to their reliance on stable natural systems.

To sum up, the outcomes of the unit root test offer a crucial basis for the economic modeling procedure. The study guarantees statistical correctness and robustness in examining the dynamic relationships between the chosen components and their effects on agricultural output by determining the proper transformation for each variable. The validity of the study findings and their policymaking implications are strengthened by this all-encompassing methodology.

Hausman's test

A statistical technique called the Hausman technique (Tables 6 and 7) is used to assess whether panel data analysis is better served by the Random Effects Model (REM) or the Fixed Effects Model (FEM). To determine whether there is a correlation between the random effects and the regressors, it analyses the coefficient estimates of the two models. With 8 degrees of freedom and a p-value of 0.9115, the Hausman test statistic in this instance is 3.336294. The null hypothesis, according to which the random effects are uncorrelated with the regressors, cannot be rejected if the p-value is higher than 0.05. Thus, the Random Effects Model would often be seen as reasonable in light of this outcome.

It is crucial to take note of the caution regarding zero variance in random effects, which suggests that the random effects model may not be appropriate. This calls into question the random effects model's underlying presumptions by indicating that the individual-specific effects are not changing substantially. Therefore, the Fixed Effects Model is favored in this analysis even though the Hausman test suggests that the random effects model may be appropriate. Given that random effects have zero variance, the fixed effects model makes more sense. This suggests that allowing for fixed variations between the cross-sections may better capture individual heterogeneity.

Hausman's test

A statistical technique called the Hausman technique (Tables 6 and 7) is used to assess whether panel data analysis is better served by the Random Effects Model (REM) or the Fixed Effects Model (FEM). To determine whether there is a correlation between the random effects and the regressors, it analyses the coefficient estimates of the two models. With 8 degrees of freedom and a p-value of 0.9115, the Hausman test statistic in this instance is 3.336294. The null hypothesis, according to which the random effects are uncorrelated with the regressors, cannot be rejected if the p-value is higher than 0.05. Thus, the Random Effects Model would often be seen as reasonable in light of this outcome.

It is crucial to take note of the caution regarding zero variance in random effects, which suggests that the random effects model may not be appropriate. This calls into question the random effects model's underlying presumptions by indicating that the individual-specific effects are not changing substantially. Therefore, the Fixed Effects Model is favored in this analysis even though the Hausman test suggests that the random effects model may be appropriate for the analysis. Given that random effects have zero variance, the fixed effects model makes more sense. This suggests that allowing for fixed variations between the cross-sections may better capture individual heterogeneity.

Table 3. Correlation coefficient analysis.

Correlation	PRODUCTION	AREA	FERTILIZER	TRACTORS	TUBEWELL	MIN_TEMP	MAX_TEMP	PRECIPITATION	WIND
PRODUCTION	1.000000								
AREA	0.468880	1.000000							
FERTILIZER	0.632703	0.663387	1.000000						
TRACTORS	0.724633	0.679929	0.653512	1.000000					
TUBEWELL	0.376820	0.404210	0.212570	0.656657	1.000000				
MIN_TEMP	0.216013	0.169151	0.290796	0.152088	-0.132846	1.000000			
MAX_TEMP	-0.340271	0.581644	0.750334	-0.546247	-0.553394	0.341553	1.000000		
PRECIPITATION	-0.440068	-0.558716	-0.646120	-0.384310	0.096598	-0.339397	-0.042719	1.000000	
WIND	0.052037	0.159990	0.424909	-0.036066	-0.098390	0.093429	0.003775	-0.294829	1.000000

Table 4. Unit root test results (Level).

Variable	ADF-Fisher Chi-square	PP-Fisher Chi-square	Stationary at Level?
Production	0.9846	0.8533	No
Area	0.0000	0.0000	Yes
Fertilizer	0.0289	0.0000	Yes
Tractors	0.8198	0.0027	No
Tubewell	0.2597	0.0077	No
Minimum Temp	0.1683	0.0000	No
Maximum Temp	0.0002	0.0000	Yes
Precipitation	0.0000	0.0000	Yes
Wind Speed	0.0454	0.0011	Yes

Table 5. Unit root test results (First difference).

Variable	ADF-Fisher Chi-square	PP-Fisher Chi-square	Stationary at First Difference?
Production	0.0000	0.0000	Yes
Tractors	0.0000	0.0000	Yes
Tubewell	0.0000	0.0000	Yes
Minimum Temp	0.0000	0.0000	Yes

Table 6. Hausman's test results.

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random effects	3.336294	8	0.9115

Table 7: Hausman's Test Statistics for Random and Fixed Effect Models

Variable	Fixed Coefficient	Random Coefficient	Variance of Difference
AREA	-0.013460	0.000673	0.000127
FERTILIZER	-0.002952	-0.000417	0.000444
D(TRACTORS)	0.000017	-0.000058	0.000000
D(TUBEWELL)	-0.000148	-0.000156	0.000000
D(MIN_TEMP)	-0.918668	-0.898685	0.018304
MAX_TEMP	0.919260	0.697293	0.077951
PRECIPITATION	-0.000170	0.000487	0.000005
WIND	0.283687	0.639443	2.076619

Coefficients Estimates from Fixed Effects Panel Regression Model

The results of the fixed effect model are represented in Table 8. The area shows a statistically significant positive effect (coefficient = 0.0135, p = 0.0480), meaning that an increase in the area under cultivation is linked to a marginal rise in the dependent variable. Consequently, results agree with those of Ahsan et al. (2020), who discovered that just a one percent increase in the cultivated area of cereal crops results in a about 0.56% increase in crop output. Previous empirical findings (Ahmed and Schmitz, 2011; Chandio et al., 2019; Ahsan et al., 2020) support this result. The results corroborate the previous studies of Qureshi et al. (2016) and Warsame (2021). Fertilizer has a positive and statistically significant effect (coefficient = 0.0429, p = 0.0368), indicating that adding more fertilizer causes the dependent variable to rise. The research's anticipated findings point to a significant correlation between fertilizer application and agricultural output. The findings of the study are supported by Chandio et al. (2018) investigation. According to Chandio et al. (2021a), Nepal produced more rice when fertilizers and better seedlings were used. In a similar vein, Ozdemir (2022) examined more recently how climate change and fertilizer use impacted agricultural output in several Asian countries. The findings demonstrated that agricultural productivity was significantly reduced by climate change, while it was significantly increased by fertilizer consumption. The results of this study are in line with earlier studies that looked at the effect of fertilizer usage on cereal output in the literature (Rehman et al., 2019; Chandio et al., 2021a; Chandio et al., 2021b; Rayamajhee et al., 2021). There is no discernible effect of the number of tractors (p = 0.9597) on the dependent variable (coefficient = 0.000017). While Hussain et al., (2018) discovered that agricultural machinery had a considerable impact on agriculture output, the data contradict their findings. There are no statistically significant differences between the minimum temperature (coefficient = -0.9187, p = 0.1364) and tubewell usage (coefficient = -0.000148, p = 0.3884). While, Abbas et al. (2022a) discovered that TMIN has a negative and significant coefficient, indicating that TMIN has a detrimental long-term effect on wheat productivity.

There is a statistically significant negative effect of precipitation (coefficient = -0.4402, p = 0.0298), indicating that more precipitation lowers the dependent variable. Although crops require water to grow, the negative effects of precipitation on agricultural productivity observed in this study—which corroborate earlier findings by Salim et al. (2020) and Huynh (2024)—can be explained by the possibility that excessive precipitation may also harm crop production or that torrential rains may cause floods, which are bad for agriculture. Despite a substantial standard error, wind (coefficient = -0.2837, p = 0.0416) has a statistically significant negative effect that highlights its meaningful impact. The results support those of Nana (2019), who found that cereal production decreases by 0.85% for every 10% rise in wind speed. The maximum temperature exhibits a statistically significant negative influence (coefficient = -0.7454, p = 0.0375), suggesting that greater maximum temperatures are linked to a decline in the dependent variable. The findings of this investigation are consistent with the (Bannayan et al., 2014, Sarker et al., 2014; Khan et al., 2019a; Khan et al., 2019b; Chandio et al., 2020b). Nelson et al. (2009) estimate that the effects of climate change could result in a 10%–15% drop in cereal production, which would increase expenses. Furthermore, Chandio et al. (2021a) demonstrated that in several Asian nations, such as Bangladesh, India, Indonesia, Pakistan, Sri Lanka, Thailand, and Vietnam, the temperature reduced rice productivity by 4%. Moreover, similar negative impacts of temperature on agricultural productivity have been discovered by Kumar et al. (2021), Ozdemir (2022), and Attiaoui and Boufateh (2019). This result, however, contradicts studies by Torvanger et al. (2004) and Kokic et al. (2005), which demonstrate that because of their cold climate, Australia and Norway benefit from higher temperatures in terms of agricultural productivity.

The dependent variable is significantly impacted by area, fertilizer, maximum temperature, wind, and precipitation, while tractors, tube wells, and minimum temperature have no discernible influence.

Model Evaluation and Diagnostic Statistics

The diagnostic statistics for the model validation are presented in Table 9. This R-squared is not very high, but it is typical in economic and social science research, where the dependent variable is influenced by a large number of unobservable factors. Although there are probably other factors or dynamics at work that have not been taken into consideration in this research, this number indicates that the model is only moderately good at explaining the link between the predictors and the outcome. The model is statistically significant overall, as indicated by the big F-statistic, which is a favorable indicator. However, the degree of model fit and the p-value determines how relevant this statistic is. At the 5% significance level, the model as a whole is statistically significant, according to the p-value of 0.0359. This indicates that the independent variables together account for a sizable amount of the variance in the dependent variable, allowing the null hypothesis—which holds that the model has no explanatory power—to be rejected. With a Durbin-Watson score of 2.588, the residuals appear to have no discernible autocorrelation, indicating that the model's mistakes are unrelated to one another. This is a favorable outcome because it shows that the model's error terms behave properly and validate the correctness of the regression results.

Table 8. Fixed effects model results.

Variable	Coefficient	Std. Error	p-value
C	-19.88384	20.38970	0.3304
AREA	0.013460	0.312456	0.0480
FERTILIZER	0.042952	0.091660	0.0368
D(TRACTORS)	0.000017	0.000336	0.9597
D(TUBEWELL)	-0.000148	0.000171	0.3884
D(MIN_TEMP)	-0.918668	0.614960	0.1364
MAX_TEMP	-0.745446	1.595343	0.0375
PRECIPITATION	-0.440170	0.184478	0.0298
WIND	-0.283687	5.241582	0.0416

Table 9. Model statistics.

Statistic	Value
R-squared	0.326891
F-statistic	65.55337
Prob(F-statistic)	0.035932
Durbin-Watson Statistic	2.588314

CONCLUSIONS AND RECOMMENDATIONS

The current study looked into how Pakistani agriculture productivity was affected by climatic and non-climatic variance. This empirical analysis used data from 1991 to 2021. In this work, the stationary issue was investigated utilizing the P-P, and ADF tests. Additionally, fixed effects panel data model methodology is utilized to find out the impact of climatic and non-climatic variables on agricultural productivity. This study includes the climatic variables such as average maximum and minimum temperature, precipitation, wind, and other non-climatic factors are cultivated area, tractor, tube well, and fertilizer use. These results underscore the significant effects of area, fertilizer, maximum temperature, precipitation, and wind on the dependent variable, while other factors like tractors, tube wells, and minimum temperature do not show significant impacts. The area has a statistically significant positive effect, indicating that an increase in the area under cultivation is associated with a slight increase in the dependent variable. Fertilizer shows a positive and statistically significant effect, suggesting that more fertilizer leads to an increase in the dependent variable. The number of tractors does not significantly impact the dependent variable. Tube well usage and minimum temperature do not exhibit statistically significant effects.

Precipitation has a statistically significant negative effect, suggesting that increased precipitation decreases the dependent variable. This study's analysis of the deleterious effects of precipitation on agricultural productivity revealed that, even while crops require water to thrive, excessive precipitation can also harm crop yield. Additionally, heavy rainfall can result in flooding, which is bad for agriculture. The wind has a detrimental impact that is statistically significant. Higher maximum temperatures are linked to a decline in the dependent variable, according to the statistically significant negative effect of maximum temperature.

Given that agriculture is the foundation of Pakistan's economy, the government and policymakers should set up awareness campaigns about climate change adoption to ensure agricultural productivity. Furthermore, Pakistan experiences abrupt and severe environmental changes as a result of the fast-changing climate, which lowers agriculture productivity levels. Strong action is therefore required to save the agricultural industry.

It is also advised that improved crop types that are resistant to temperature changes and drought be developed and put into practice in order to mitigate the harmful effects of climate change. Additionally, in order to help farmers adapt to the effects of climate change, agricultural extension officers should focus more on teaching them about techniques like mulching, plant rotations, shifting planting dates, and plant diversification. Additionally, meteorological departments should establish direct phone contact with farmers and promptly inform them of proactive measures.

REFERENCES

Abbas, A., Ullah, S., Ullah, W., Waseem, M., Dou, X., Zhao, C., Karim, A., Zhu, J., Hagan, D.F.T., Bhatti, A.S., 2022b. Evaluation and projection of precipitation in Pakistan using the Coupled Model Intercomparison Project Phase 6 model simulations. Int. J. Climatol. 6665–6684.

Abbas, F., Ahmad, A., Safeeq, M., Ali, S., Saleem, F., Hammad, H.M., Farhad, W., 2014. Changes in precipitation extremes over arid to semiarid and subhumid Punjab, Pakistan. Theor. Appl. Climatol. 116, 671–680.

Abbas, S., 2020. Climate change and cotton production: an empirical investigation of Pakistan. Environ. Sci. Pollut. Res. 27, 29580–29588. https://doi.org/10.1007/s11356-020-09222-0

Abbas, S., Kousar, S., Khan, M.S., 2022a. The role of climate change in food security; empirical evidence over Punjab regions, Pakistan. Environ. Sci. Pollut. Res. 29, 53718–53736.

Ahmad, I., Ahmad, B., Boote, K., Hoogenboom, G., 2020. Adaptation strategies for maize production under climate change for semi-arid environments. Eur. J. Agron. 115, 126040.

Ahmed, I., ur Rahman, M.H., Ahmed, S., Hussain, J., Ullah, A., Judge, J., 2018. Assessing the impact of climate variability on maize using simulation modeling under semi-arid environment of Punjab, Pakistan. Environ. Sci. Pollut. Res. 25, 28413–28430.

Ahmed, M., Schmitz, M., 2011. Economic assessment of the impact of climate change on the agriculture of Pakistan. Bus. Econ. Horizons 4, 1–12.

Ahsan, F., Chandio, A.A., Fang, W., 2020. Climate change impacts on cereal crops production in Pakistan: Evidence from cointegration analysis. Int. J. Clim. Chang. Strateg. Manag. 12, 257–269.

Alboghdady, M., El-Hendawy, S.E., 2016. Economic impacts of climate change and variability on agricultural production in the Middle East and North Africa region. Int. J. Clim. Chang. Strateg. Manag. 8, 463–472.

Ali, S., Zubair, M., Hussain, S., 2021. The combined effect of climatic factors and technical advancement on yield of sugarcane by using ARDL approach: evidence from Pakistan. Environ. Sci. Pollut. Res. 28, 39787–39804.

Aryal, J.P., Sapkota, T.B., Khurana, R., Khatri-Chhetri, A., Rahut, D.B., Jat, M.L., 2020. Climate change and agriculture in South Asia: Adaptation options in smallholder production systems. Environ. Dev. Sustain. 22, 5045–5075.

Attiaoui, I., Boufateh, T., 2019. Impacts of climate change on cereal farming in tunisia: A panel ARDL–PMG approach. Environ. Sci. Pollut. Res. 26, 13334–13345. https://doi.org/10.1007/s11356-019-04867-y.

Baig, I. A., Chandio, A. A., Salam, M. A., 2021. Does climate change asymmetrically affect rice productivity in India? New insight from NARDL cointegration approach. https://doi.org/10.21203/rs.3.rs-524765/v1.

Bannayan, M., Mansoori, H., Rezaei, E.E., 2014. Estimating climate change, CO 2 and technology development effects on wheat yield in northeast Iran. Int. J. Biometeorol. 58, 395–405.

Below, T., Artner, A., Siebert, R., Sieber, S., 2010. Micro-level practices to adapt to climate change for African small-scale farmers. A Rev. Sel. Lit. Environ. Prod. Technol. Div. 953.

Bhatla, R., Ghosh, S., Verma, S., Mall, R.K., Gharde, G.R., 2019. Variability of monsoon over homogeneous regions of India using regional climate model and impact on crop production. Agric. Res. 8, 331–346.

Chandio, A.A., Jiang, Y., Ahmad, F., Adhikari, S., Ain, Q.U., 2021a. Assessing the impacts of climatic and technological factors on rice production: Empirical evidence from Nepal. Technol. Soc. 66, 101607.

Chandio, A.A., Jiang, Y., Akram, W., Adeel, S., Irfan, M., Jan, I., 2021b. Addressing the effect of climate change in the framework of financial and technological development on cereal production in Pakistan. J. Clean. Prod. 288, 125637.

Chandio, A.A., Jiang, Y., Gessesse, A.T., Dunya, R., 2019. The nexus of agricultural credit, farm size and technical efficiency in Sindh, Pakistan: A stochastic production frontier approach. J. Saudi Soc. Agric. Sci. 18, 348–354.

Chandio, A.A., Jiang, Y., Rehman, A., Rauf, A., 2020a. Short and long-run impacts of climate change on agriculture: an empirical evidence from China. Int. J. Clim. Chang. Strateg. Manag. 12, 201–221. https://doi.org/10.1108/IJCCSM-05-2019-0026

Chandio, A.A., Jiang, Y., Wei, F., Guangshun, X., 2018. Effects of agricultural credit on wheat productivity of small farms in Sindh, Pakistan: are short-term loans better? Agric. Financ. Rev. 78, 592–610.

Chandio, A.A., Ozturk, I., Akram, W., Ahmad, F., Mirani, A.A., 2020b. Empirical analysis of climate change factors affecting cereal yield: evidence from Turkey. Environ. Sci. Pollut. Res. 27, 11944–11957.

Chandio, A.A., Zhang, H., Akram, W., Sethi, N., Ahmad, F., 2024. Climate change and crop production nexus: assessing the role of technological development for sustainable agriculture in Vietnam. Int. J. Clim. Chang. Strateg. Manag. 16, 177-200.

Chang, C., 2002. The potential impact of climate change on Taiwan's agriculture. Agric. Econ. 27, 51–64.

Chavas, D.R., Izaurralde, R.C., Thomson, A.M., Gao, X., 2009. Long-term climate change impacts on agricultural productivity in eastern China. Agric. For. Meteorol. 149, 1118–1128.

Coulibaly, T., Islam, M., Managi, S., 2020. The impacts of climate change and natural disasters on agriculture in African countries. Econ. Disasters Clim. Chang. 4, 347–364.

Dahri, S.H., Shaikh, I.A., Talpur, M.A., Mangrio, M.A., Dahri, Z.H., Hoogenboom, G., Knox, J.W., 2024. Modelling the impacts of climate change on the sustainability of rainfed and irrigated maize in Pakistan. Agric. Water Manag. 296, 108794.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. J. Am. Stat. Assoc. 74, 427–431.

Edokpayi, A.A., Garba, M.K., Ikuenobe, C.E., Edegbe, G.N., 2015. Panel Model Analysis of Impact of Climate Change on Crop Yields in Nigeria: A Fixed Effects Approach. Ilorin J. Sci. 2, 144–162.

Getachew, F., Bayabil, H.K., Hoogenboom, G., Teshome, F.T., Zewdu, E., 2021. Irrigation and shifting planting date as climate change adaptation strategies for sorghum. Agric. Water Manag. 255, 106988.

GOP, 2022. Agricultural Statistics Yearbook 2021-22. Ministry of National Food Security and Research, Islamabad, Pakistan.

Gul, A., Chandio, A.A., Siyal, S.A., Rehman, A., Xiumin, W., 2022. How climate change is impacting the major yield crops of Pakistan? an exploration from long-and short-run estimation. Environ. Sci. Pollut. Res. 29, 26660–26674.

Hafiza, B.S., Ishaque, W., Osman, R., Aziz, M., Ata-Ul-Karim, S.T., 2022. Simulation of wheat yield using CERES-Wheat under rainfed and supplemental irrigation conditions in a semi-arid environment. Agric. Water Manag. 264, 107510.

Haile, M.G., Wossen, T., Tesfaye, K., von Braun, J., 2017. Impact of climate change, weather extremes, and price risk on global food supply. Econ. Disasters Clim. Chang. 1, 55–75.

Hanif, U., Syed, S.H., Ahmad, R., Malik, K.A., Nasir, M., 2010. Economic impact of climate change on the agricultural sector of Punjab [with comments]. Pak. Dev. Rev. 771–798.

Hussain, J., Khaliq, T., Ahmad, A., Akhter, J., Asseng, S., 2018. Wheat responses to climate change and its adaptations: a focus on arid and semi-arid environment. Int. J. Environ. Res. 12, 117–126.

Hussain, S.S., Mudasser, M., 2007. Prospects for wheat production under changing climate in mountain areas of Pakistan–An econometric analysis. Agric. Syst. 94, 494–501.

Huynh, C.M., 2024. Climate change and agricultural productivity in Asian and Pacific countries: how does research and development matter? J. Econ. Stud. 51, 712–729.

Jan, I., Ashfaq, M., Chandio, A.A., 2021. Impacts of climate change on yield of cereal crops in northern climatic region of Pakistan. Environ. Sci. Pollut. Res. 28, 60235–60245.

Janjua, P.Z., Samad, G., Khan, N., 2014. Climate change and wheat production in Pakistan: An autoregressive distributed lag approach. NJAS - Wageningen J. Life Sci. 68, 13–19.

Khan, Asim, Ali, S., Shah, S.A., Khan, Aftab, Ullah, R., 2019b. Impact of climate change on maize productivity in Khyber Pakhtunkhwa, Pakistan. Sarhad J. Agric. 35, 594–601.

Khan, M.F., Nakano, Y., Kurosaki, T., 2019a. Impact of contract farming on land productivity and income of maize and potato growers in Pakistan. Food Policy 85, 28–39.

Klutse, N.A.B., Quagraine, K.A., Nkrumah, F., Quagraine, K.T., Berkoh-Oforiwaa, R., Dzrobi, J.F., Sylla, M.B., 2021. The climatic analysis of summer monsoon extreme precipitation events over West Africa in CMIP6 simulations. Earth Syst. Environ. 5, 25–41.

Kokic, P., Heaney, A., Pechey, L., Crimp, S., Fisher, B.S., 2005. Climate change: predicting the impacts on agriculture: a case study. Aust. Commod. Forecast. Issues 12, 161–170.

Kumar, R., Sharma, A., Srivastava, J.K., Siddiqui, M.H., Uddin, M.S., Aleya, L., 2021. Hydroxychloroquine in COVID-19: therapeutic promises, current status, and environmental implications. Environ. Sci. Pollut. Res. 28, 40431–40444.

Lobell, D.B., Field, C.B., 2007. Global scale climate–crop yield relationships and the impacts of recent warming. Environ. Res. Lett. 2, 14002.

Ludwig, F., Asseng, S., 2006. Climate change impacts on wheat production in a Mediterranean environment in Western Australia. Agric. Syst. 90, 159–179.

Luo, Q., Williams, M.A.J., Bellotti, W., Bryan, B., 2003. Quantitative and visual assessments of climate change impacts on South Australian wheat production. Agric. Syst. 77, 173–186.

Mendelsohn, R., Dinar, A., 1999. Climate change, agriculture, and developing countries: does adaptation matter? World Bank Res. Obs. 14, 277–293.

Mohorji, A.M., Şen, Z., Almazroui, M., 2017. Trend analyses revision and global monthly temperature innovative multi-duration analysis. Earth Syst. Environ. 1, 1–13.

Naheed, G., Rasul, G., 2010. Projections of crop water requirement in Pakistan under global warming. Pakistan J. Meteorol. 7, 45–51.

Nana, T.J., 2019. Impact of climate change on cereal production in Burkina Faso. J. Agric. Environ. Sci 8, 14–24.

Nath, H.K., Mandal, R., 2018. Heterogeneous climatic impacts on agricultural production: evidence from rice yield in Assam, India. Asian J. Agric. Dev. 15, 23–42.

Nath, P.K., Behera, B., 2011. A critical review of impact of and adaptation to climate change in developed and developing economies. Environ. Dev. Sustain. 13, 141–162.

Nelson, G.C., Rosegrant, M.W., Koo, J., Robertson, R., Sulser, T., Zhu, T., Ringler, C., Msangi, S., Palazzo, A., Batka, M., 2009. Climate change: Impact on agriculture and costs of adaptation. Intl Food Policy Res Inst.

Osman, R., Ata-Ul-Karim, S.T., Tahir, M.N., Ishaque, W., Xu, M., 2022. Multi-model ensembles for assessing the impact of future climate change on rainfed wheat productivity under various cultivars and nitrogen levels. Eur. J. Agron. 139, 126554.

Ozdemir, D., 2022. The impact of climate change on agricultural productivity in Asian countries: a heterogeneous panel data approach. Environ. Sci. Pollut. Res. 29, 8205–8217.

PBS, 2020 Pakistan Bureau of Statistics, Government of Pakistan. http://www.pbs.gov.pk. Accessed 28 September 2020.

Phillips, P., 1988. Testing for unit roots in time series regression. Biometrika 71, 599–607.

Praveen, B., Sharma, P., 2020. Climate change and its impacts on Indian agriculture: An econometric analysis. J. Public Aff. 20, e1972.

Qureshi, M.I., Awan, U., Arshad, Z., Rasli, A.M., Zaman, K., Khan, F., 2016. Dynamic linkages among energy consumption, air pollution, greenhouse gas emissions and agricultural production in Pakistan: sustainable agriculture key to policy success. Nat. Hazards 84, 367–381.

Rayamajhee, V., Guo, W., Bohara, A.K., 2021. The impact of climate change on rice production in Nepal. Econ. Disasters Clim. Chang. 5, 111–134.

Rehman, A., Chandio, A.A., Hussain, I., Jingdong, L., 2019. Fertilizer consumption, water availability and credit distribution: Major factors affecting agricultural productivity in Pakistan. J. Saudi Soc. Agric. Sci. 18, 269–274.

Salim, R., Hassan, K., Rahman, S., 2020. Impact of R&D expenditures, rainfall and temperature variations in agricultural productivity: empirical evidence from Bangladesh. Appl. Econ. 52, 2977–2990.

Sarker, M.A.R., Alam, K., Gow, J., 2014. Assessing the effects of climate change on rice yields: An econometric investigation using Bangladeshi panel data. Econ. Anal. Policy 44, 405–416.

Shashikumara, P., Gajghate, R., Bhatt Devate, N., Harikrishna, Mamrutha, H.M., Gopalareddy, K., Singh, G.P., 2022. Heat stress in wheat: Adaptation strategies, in: Thermotolerance in Crop Plants. Springer, pp. 1–21.

Suryabhagavan, K. V, 2017. GIS-based climate variability and drought characterization in Ethiopia over three decades. Weather Clim. Extrem. 15, 11–23.

Swaminathan, M.S., Kesavan, P.C., 2012. Agricultural research in an era of climate change. Agric. Res. 1, 3–11.

Torvanger, A., Twena, M., Vevatne, J., 2004. Climate policy beyond 2012: A survey of long-term targets and future frameworks. CICERO report. https://pub.cicero.oslo.no/cicero-xmlui/handle/11250/192022.

Tubiello, F.N., Rosenzweig, C., Goldberg, R.A., Jagtap, S., Jones, J.W., 2002. Effects of climate change on US crop production: simulation results using two different GCM scenarios. Part I: wheat, potato, maize, and citrus. Clim. Res. 20, 259–270.

Tubiello, F.N., Rosenzweig, C., Volk, T., 1995. Interactions of CO2, temperature and management practices: simulations with a modified version of CERES-Wheat. Agric. Syst. 49, 135–152.

Warsame, A.A., 2021. Climate change and crop production nexus in Somalia: an empirical evidence from ARDL technique. Environ. Sci. Pollut. Res. 28, 19838–19850. https://doi.org/10.1007/s11356-020-11739-3

You, L., Rosegrant, M.W., Wood, S., Sun, D., 2009. Impact of growing season temperature on wheat productivity in China. Agric. For. Meteorol. 149, 1009–1014.

Zakaria, A., Alhassan, S.I., Kuwornu, J.K.M., Azumah, S.B., Derkyi, M.A.A., 2020. Factors influencing the adoption of climate-smart agricultural technologies among rice farmers in northern Ghana. Earth Syst. Environ. 4, 257–271.