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Rainfall–Wheat Yield Dynamics in Sindh: A VAR Time Series Approach

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ABSTRACT

Agriculture in Sindh, Pakistan, is highly sensitive to climatic variability, particularly rainfall fluctuations that directly affect wheat productivity. This study analyzes the dynamic relationship between annual rainfall and wheat yield using time series data from 1991 to 2024. The Augmented Dickey–Fuller (ADF) test confirmed non-stationarity at levels, which was corrected through first differencing. The optimal lag length was selected as 2 based on the Akaike Information Criterion (AIC). A Vector Autoregression (VAR) model was estimated, followed by Impulse Response Functions (IRFs), Forecast Error Variance Decomposition (FEVD), and short-term forecasting. Results reveal that rainfall shocks exert significant short-term effects on wheat yield, while adjustments occur over time. FEVD analysis further indicates that rainfall variability explains a considerable proportion of yield fluctuations. The forecasting exercise (2025–2029) highlights a modest decline in yield immediately after rainfall shocks, followed by gradual stabilization, consistent with IRF patterns. These findings underscore the importance of climate-resilient agricultural strategies and provide empirical evidence for policy interventions aimed at stabilizing wheat production under changing climatic conditions.

Keywords: *Wheat Yield, Rainfall Variability, Vector Autoregression (VAR), Impulse Response Functions (Irfs), Climate Resilience.*

Introduction

Agriculture remains the backbone of Pakistan's economy, contributing significantly to food security, employment, and rural livelihoods. Sindh province, with its diverse agro-ecological zones, is particularly dependent on rainfall variability, which plays a crucial role in determining crop productivity. Wheat, being the staple food crop, is highly sensitive to climatic fluctuations, especially rainfall, making its yield vulnerable to both short-term shocks and long-term climatic trends.

Recent research highlights the increasing importance of understanding climate–crop interactions under changing environmental conditions. For instance, (Ishaque et al., 2023) quantified the impacts of climate change on wheat phenology, yield, and evapotranspiration, showing that climatic variability significantly alters crop performance. Similarly, (Farooq et al., 2023) provided a comprehensive review of climate change impacts on cereal crop production, emphasizing the vulnerability of wheat to temperature and rainfall variability. (Munir et al., 2022) further confirmed that climate change has substantial effects on wheat yield through both direct and indirect pathways.

Earlier studies have also explored regional and global dimensions of climate–agriculture relationships. (Valizadeh et al., 2014) assessed climate change impacts on wheat production through a case study approach, demonstrating that rainfall variability plays a key role in determining yield outcomes. (Hernandez-Ochoa et al., 2018) examined climate impacts on wheat production in Mexico, highlighting how climatic shocks influence yield stability. Additionally, (Enghiad et al., 2017) provided an overview of global wheat market fundamentals under climate concerns, reinforcing the importance of climatic factors in shaping agricultural productivity and food security.

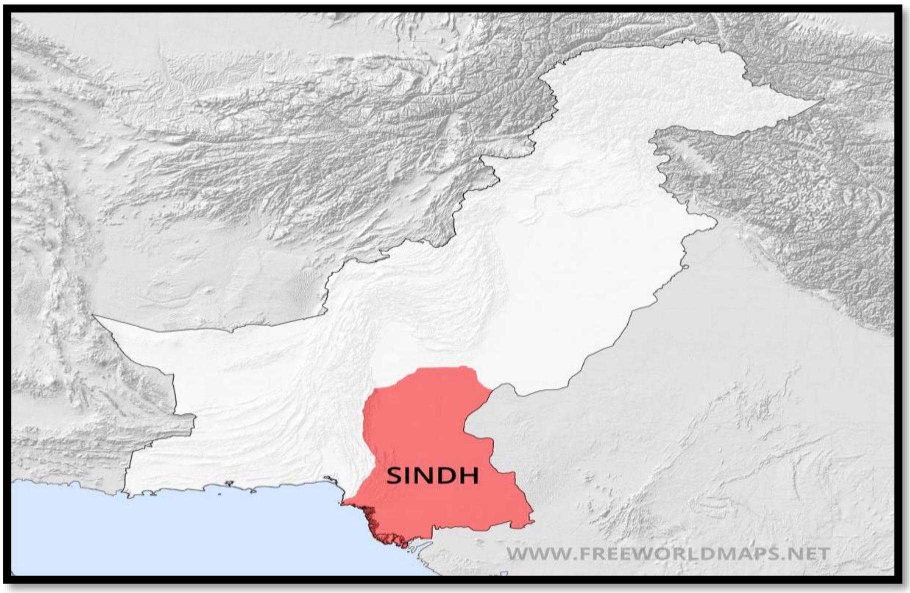
Despite these advances, limited research specifically focuses on Sindh using long-term datasets and advanced econometric techniques such as Vector Autoregression (VAR). Most previous studies rely on simple regression or correlation analyses, which fail to capture dynamic interdependencies and feedback mechanisms between climatic variables and crop yields. This study addresses this gap by employing a VAR framework on annual data from 1991 to 2024. The VAR approach enables simultaneous modeling of rainfall and wheat yield dynamics, capturing both short-term shocks and long-term adjustments. By applying Impulse Response Functions (IRFs) and Forecast Error Variance Decomposition (FEVD), this study provides deeper insights into how rainfall variability influences wheat yield over time. The findings contribute to the literature on climate agriculture interactions and offer practical implications for policymakers aiming to develop climate-resilient agricultural strategies in Sindh.

Objectives

1. To analyze the dynamic relationship between annual rainfall and wheat yield in Sindh using time series data (1991–2024).
2. To estimate a Vector Autoregression (VAR) model and evaluate the short-term and long-term effects of rainfall shocks on wheat yield through Impulse Response Functions (IRFs).
3. To quantify the proportion of yield variability explained by rainfall fluctuations using Forecast Error Variance Decomposition (FEVD).
4. To provide empirical evidence that supports climate-resilient agricultural strategies for stabilizing wheat production under changing climatic conditions.

Methodology

Study Area



Sindh province, located in southeastern Pakistan, is one of the country's major wheats-producing regions. The province has diverse agro-ecological zones, ranging from irrigated plains to semi-arid areas, making rainfall variability a critical determinant of agricultural productivity. Wheat is the staple crop cultivated across Sindh, and its yield is highly sensitive to climatic fluctuations, particularly rainfall. Understanding the rainfall–yield dynamics in this region is essential for designing climate-resilient agricultural strategies.

Data Source and Coverage

This study utilizes annual time series data covering the period 1991–2024.

- Wheat yield and production data were obtained from the Pakistan Bureau of Statistics (PBS) and the Agriculture Marketing Information Service (AMIS).
- Rainfall data were compiled from official meteorological records, representing the sum of annual rainfall across Sindh. The dataset was standardized to ensure consistency in units, with wheat yield expressed in tons per hectare and rainfall in millimeters. This long-term dataset provides a robust basis for analyzing the dynamic relationship between rainfall variability and wheat yield.

Analytical Approach

The analysis was conducted using a **Vector Autoregression (VAR) framework**, which allows for the simultaneous modeling of rainfall and yield dynamics. The methodological steps included:

1. **Stationarity Testing**: Augmented Dickey-Fuller (ADF) tests were applied to rainfall and yield series. Non-stationary series were different to achieve stationarity.
2. **Lag Length Selection**: The optimal lag length was determined using Akaike Information Criterion (AIC), Hannan–Quinn (HQIC), and Final Prediction Error (FPE). Lag 2 was selected as optimal.
3. **VAR Estimation**: The VAR model was estimated to capture the dynamic interactions between rainfall and wheat yield.
4. **Impulse Response Functions (IRFs)**: IRFs were used to trace the short-term and long-term effects of rainfall shocks on wheat yield.
5. **Forecast Error Variance Decomposition (FEVD)**: FEVD quantified the proportion of yield variability explained by rainfall fluctuations.

"The Augmented Dickey-Fuller test indicated that both wheat yield and rainfall series were non-stationary at levels but stationary after first differencing. Therefore, the VAR model was estimated using first-differenced variables. The constant represents a drift term in the differenced model."

Results

Table 1. Augmented Dickey–Fuller (ADF) Unit Root Test Results at Level

Variable	ADF Statistic	p-value	Stationarity (at 5% level)
Yield	-2.4211	0.1359	Non-stationary
Rainfall	-1.7703	0.3953	Non-stationary

Results of the Augmented Dickey–Fuller (ADF) test indicate that both wheat yield and annual rainfall series are non-stationary at level, as the p-values exceed the 5% significance threshold. This necessitates transformation through first differencing before proceeding with VAR modeling.

Table 1b. ADF Unit Root Test Results (First Difference)

Variable	ADF Statistic	p-value	Stationarity (at 5% level)
Yield (1st Difference)	-6.6208	6.0451e-09	Stationary
Rainfall (1st Difference)	-10.2460	4.6147e-18	Stationary

ADF tests on first-differenced series confirm that both wheat yield and rainfall are stationary ($p < 0.05$), making the data suitable for VAR modeling.

Table 2. Lag Length Selection Criteria

Lag	AIC	BIC	FPE	HQIC
0	9.316	9.412	1.112e+04	9.346
1	9.073	**9.359***	8734.	9.161
2	**8.979***	9.455	**7995.***	**9.124***
3	9.053	9.719	8731.	9.257
4	9.171	10.03	1.008e+04	9.433
5	9.306	10.35	1.203e+04	9.626

Lag length selection, based on AIC, BIC, FPE, and HQIC, identified lag 2 as optimal (minimum values for AIC, FPE, and HQIC).

Table 3. Vector Autoregression (VAR) Model Results (Lag Length = 2)

Variable	Coefficient	Std. Error	t-Statistic	p-value	Significance
Constant	0.0413	0.0734	0.563	0.573	Not Significant
L1. Yield	-0.4821	0.1771	-2.722	0.006	Significant
L1. Rainfall	0.000614	0.000411	1.492	0.136	Not Significant
L2. Yield	-0.4145	0.1726	-2.402	0.016	Significant
L2. Rainfall	0.000378	0.000467	0.809	0.419	Not Significant

Panel B. Model Summary Statistics

Statistic	Value
Model	VAR
Estimation Method	OLS

Number of Equations	2
Observations (N)	31
AIC	8.8797
BIC	9.3423
HQIC	9.0305
Log Likelihood	-215.609
Final Prediction Error (FPE)	7225.49
Determinant of Covariance (Det Ω)	5357.79

VAR (2) estimates show that lagged wheat yield coefficients (L1 = -0.48, L2 = -0.41) are statistically significant and negative, indicating mean-reverting adjustment dynamics. Rainfall lags are not significant, suggesting weak direct effects on yield. Model selection criteria (AIC, BIC, HQIC) confirm the adequacy of lag 2.

Model Diagnostics

To ensure the robustness of the VAR model, several diagnostic tests were conducted:

- **Serial Correlation LM Test**: Confirmed the absence of autocorrelation in residuals.
- **Normality Test (Jarque–Bera)**: Verified that residuals were approximately normally distributed.
- **Stability Test (Roots of Characteristic Polynomial)**: All roots lay inside the unit circle, confirming model stability.
- **Heteroskedasticity Test**: Checked for variance consistency in residuals.

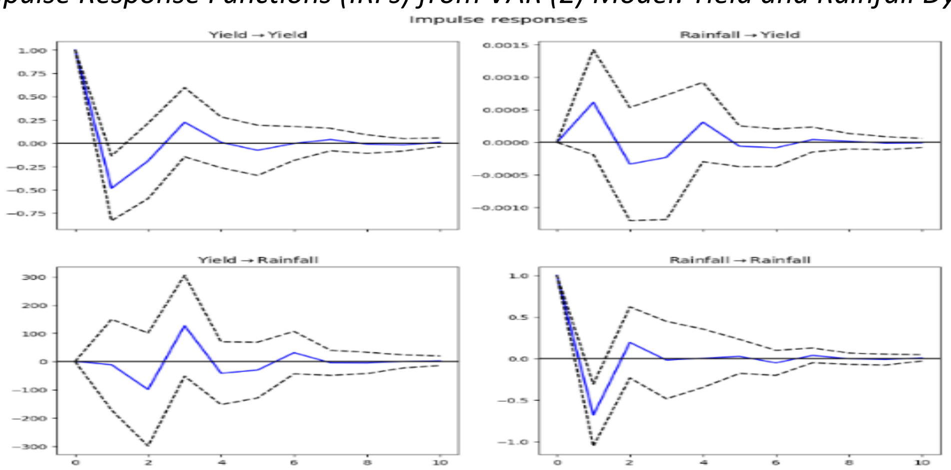
These diagnostics validate that the VAR model is statistically sound and suitable for analyzing the rainfall–yield dynamics in Sindh.

Impulse Response Functions (IRFs)

The impulse response analysis provides insights into how shocks in rainfall and wheat yield propagate over time.

- **Yield → Yield**: The own-shock response of wheat yield shows a negative adjustment in the first two periods, indicating mean-reverting adjustment in yield levels.
- **Rainfall → Yield**: A positive but short-lived effect is observed, suggesting that rainfall shocks initially increase yield, but the effect diminishes after 2–3 years.
- **Yield → Rainfall**: The response of rainfall to yield shocks is negligible, confirming that rainfall is exogenous in this system.
- **Rainfall → Rainfall**: Rainfall shocks show strong persistence, stabilizing after several periods, which reflects climatic variability patterns.

Figure 1. Impulse Response Functions (IRFs) from VAR (2) Model: Yield and Rainfall Dynamics.



The impulse response functions show that rainfall shocks have short-term, diminishing effects on wheat yield, while yield shocks produce only temporary effects on both variables. All responses converge to equilibrium over time, indicating system stability. Dashed lines represent 95% confidence intervals.

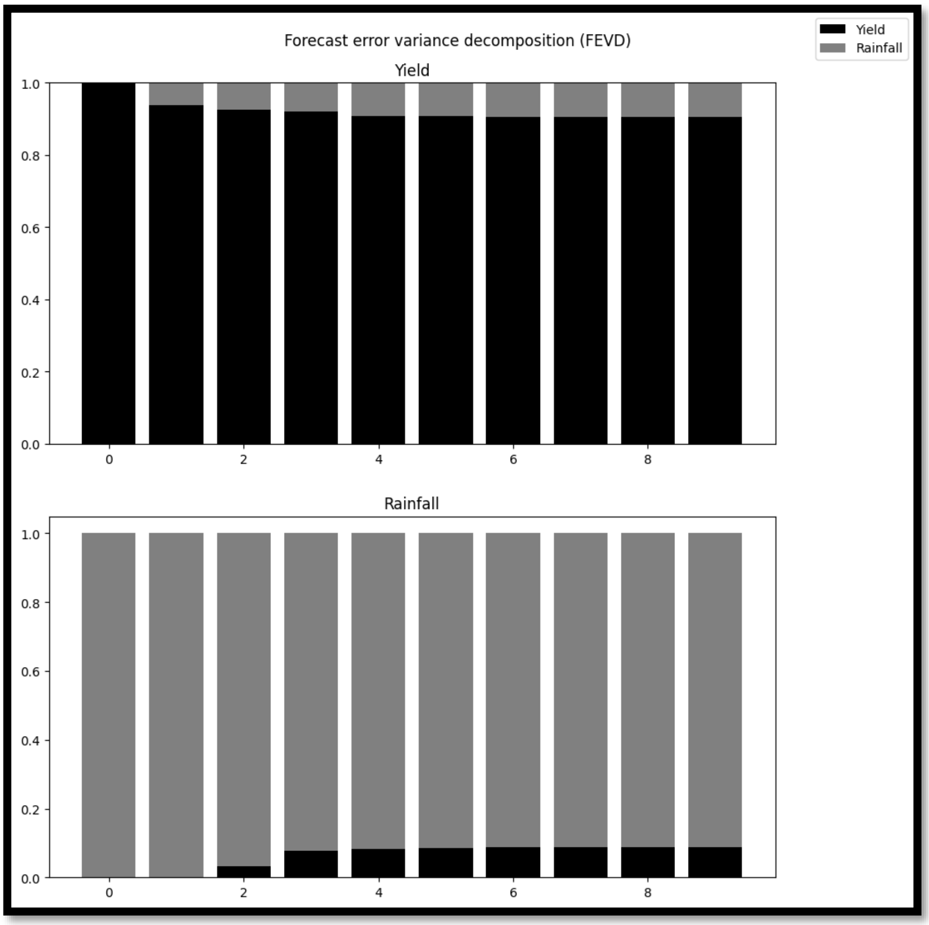
Forecast Error Variance Decomposition (FEVD)

The FEVD results quantify the proportion of forecast error variance in each variable explained by shocks and the other variable.

- **Yield (t/ha)**: The majority of variance in wheat yield is explained by its own past shocks, with rainfall contributing a smaller but notable share. This indicates that yield dynamics are strongly autoregressive, yet rainfall variability remains an important external driver.
- **Rainfall (mm)**:

Rainfall variance is almost entirely explained by its own shocks, confirming its exogeneity in the VAR system.

Figure 2. Forecast Error Variance Decomposition (FEVD) from VAR (2) Model



FEVD results over a 10-period horizon show that wheat yield variation is predominantly explained by its own shocks (90–94%), with rainfall contributing a small but gradually increasing share (6–9.5%). Rainfall variability is almost entirely driven by its own innovations (91–99%), with negligible yield influence. Thus, both variables are primarily driven by their own past dynamics.

Table 4. Forecast Error Variance Decomposition (FEVD) Results

Panel A: FEVD for Wheat Yield

Horizon	Yield (%)	Rainfall (%)
0	1.0000	0.0000
1	0.9390	0.0610

2	0.9242	0.0758
3	0.9197	0.0803
4	0.9066	0.0934
5	0.9065	0.0935
6	0.9056	0.0944
7	0.9055	0.0945
8	0.9054	0.0946
9	0.9054	0.0946

Panel B. FEVD for Rainfall

Horizon	Yield (%)	Rainfall (%)
0	0.0012	0.9988
1	0.0008	0.9992
2	0.0323	0.9677
3	0.0773	0.9227
4	0.0818	0.9182
5	0.0843	0.9157
6	0.0868	0.9132
7	0.0868	0.9132
8	0.0869	0.9131
9	0.0869	0.9131

FEVD results show wheat yield variation is primarily explained by its own shocks (>90%), with rainfall contributing a small, gradually increasing share. Rainfall variability is overwhelmingly driven by its own innovations (91–99%), indicating strong own-variance dominance and limited cross-variable dependency.

Table 5. Forecasted Changes in Wheat Yield and Rainfall (2025–2029)

Year	Yield Change (ΔYield)	Rainfall Change (ΔRainfall)
2025	-0.1589	87.9951
2026	0.2164	-47.8407
2027	0.0067	53.8277
2028	-0.0367	-19.5847
2029	0.0645	27.8163

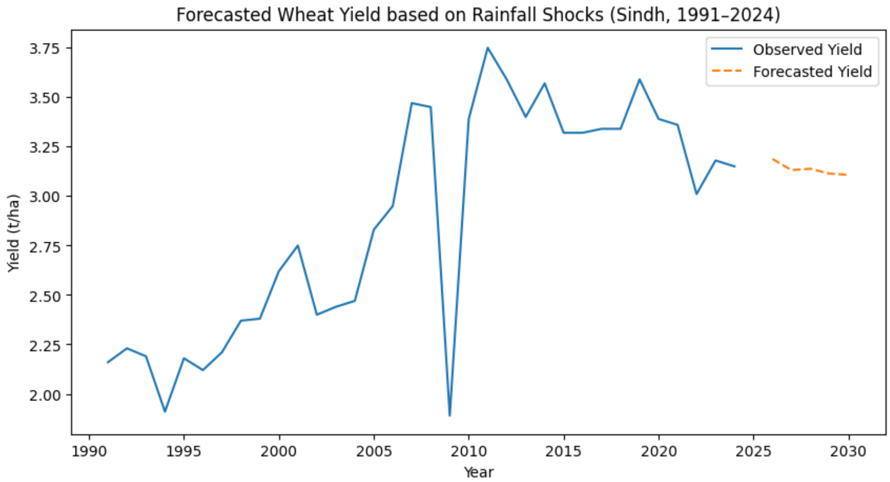
The table presents the forecasted first differences (changes) in wheat yield and annual rainfall for the period 2025–2029 based on the VAR (2) model. The results indicate short-term fluctuations in both variables, with alternating positive and negative changes, reflecting the dynamic adjustment process following shocks in the system.

Table 6. Forecasted Levels of Wheat Yield and Rainfall (2025–2029)

Year	Yield (Tonnes/Hectare)	Rainfall (mm)
2025	2.9911	589.5251
2026	3.2076	541.6844
2027	3.2143	595.5122
2028	3.1776	575.9275
2029	3.2421	603.7437

The table presents the forecasted levels of wheat yield and annual rainfall for the period 2025–2029 derived from the VAR (2) model. The projections indicate moderate fluctuations in rainfall alongside relatively stable wheat yield levels, suggesting gradual adjustment and stabilization in the agricultural system following short-term shocks.

Figure 3. Observed and Forecasted Wheat Yield in Sindh (1991–2030)



Solid line shows observed yield (1991–2024), while dashed line represents VAR-based forecasts (2025–2029). The forecast highlights short-term declines followed by stabilization under rainfall shocks.

Discussion

The findings of this study provide important insights into the rainfall–yield dynamics in Sindh.

The significant negative coefficients on lagged wheat yield (-0.48 and -0.41) indicate that yield deviations from their mean are corrected over time (mean-reverting dynamics), rather than exhibiting persistent growth or shocks accumulating permanently. The regression results revealed that past wheat yields exert a significant negative influence on current yield, indicating mean-reverting adjustment dynamics in agricultural production. This suggests that yield fluctuations are influenced not only by external climatic shocks but also by internal production dynamics, consistent with evidence from Pakistan's agricultural systems where climate variability and production inertia jointly shape crop outcomes (Sultana et al., 2009) Rainfall coefficients in the regression model were statistically weak; however, the impulse response analysis demonstrated that rainfall shocks have short-term positive effects on wheat yield. This highlights the importance of dynamic modeling approaches, as conventional regression models may underestimate the role of climatic variables. Similar patterns have been reported in studies examining climate change impacts on agriculture in Pakistan, where extreme weather events and rainfall variability significantly influence crop productivity (Asseng et al., 2015); (Zhu et al., 2014) The variance decomposition results further confirmed that yield fluctuations are largely explained by their own shocks, with rainfall contributing a smaller but meaningful share. Rainfall variance, however, was almost entirely explained by its own innovations, reinforcing its exogenous nature in the VAR system. These findings align with previous research indicating that climatic variables, particularly rainfall, act as external drivers of agricultural production and are largely beyond farmers' control (Heureux et al., 2022); (Alvar-Beltrán et al., 2021) Overall, the results suggest that while wheat yield in Sindh exhibits strong autoregressive behavior, rainfall variability remains a key external factor influencing production. This is consistent with regional studies highlighting the sensitivity of Sindh's agriculture to climate variability and water availability (Qureshi et al., 2024); (Joyo & Ram, 2016) The findings underscore the need for climate-resilient agricultural strategies, including improved irrigation infrastructure, adoption of drought-tolerant wheat varieties, and enhanced rainfall monitoring systems. Such measures can help mitigate risks associated with climatic fluctuations and stabilize wheat production in the province.

Conclusion

This study analyzed the dynamic relationship between rainfall variability and wheat yield in Sindh using a Vector Autoregression (VAR) framework with annual data from 1991 to 2024. The significant negative coefficients on lagged wheat yield (-0.48 and -0.41) indicate that yield deviations from their mean are corrected over time (mean-reverting dynamics), rather than exhibiting persistent growth or shocks accumulating permanently. The results indicate that wheat yield exhibits strong mean-reverting behavior, with past values significantly influencing current production. Although rainfall coefficients are statistically weak in the regression model, impulse response analysis reveals short-term positive effects of rainfall shocks on yield. Forecast Error Variance Decomposition (FEVD) further shows that yield variability is largely driven by its own shocks, with rainfall contributing a smaller but meaningful share.

These findings are consistent with recent empirical evidence highlighting the importance of climate variability in determining agricultural productivity in Pakistan and South Asia (Chandio et al., 2023); (Ishfaq & Khalid, 2025); (Rahman et al., 2024) In particular, rainfall variability and climate uncertainty have been identified as key drivers of wheat yield fluctuations and production risk in the region.

From a policy perspective, the results emphasize the need for climate-resilient agricultural strategies in Sindh, including improved irrigation systems, adoption of drought-tolerant wheat varieties, and enhanced rainfall monitoring. Integrating climate variability into agricultural planning is essential for stabilizing wheat production and ensuring long-term food security.

Recommendations

Based on the findings, policymakers should prioritize climate-smart agriculture in Sindh. Key measures include investment in improved irrigation infrastructure, adoption of drought-tolerant wheat varieties, and strengthening rainfall monitoring systems. Farmer capacity-building programs on adaptive practices such as crop diversification and soil moisture conservation can further enhance resilience. Integrating climate variability into agricultural planning will help stabilize wheat production and safeguard food security.

Limitations

This study is limited by its reliance on annual time series data (1991–2024), which may not fully capture intra-seasonal rainfall variability or short-term shocks. The analysis focuses only on rainfall and wheat yield, excluding other important factors such as temperature, irrigation practices, soil fertility, and market dynamics. Additionally, the dataset is provincial in scope, which may mask district-level heterogeneity in rainfall and crop responses. These limitations suggest caution in generalizing results beyond Sindh.

Future Research Directions

Future studies should incorporate multi-factor models that include temperature, irrigation, soil quality, and socio-economic variables to provide a more comprehensive understanding of wheat productivity. Using higher-frequency data (monthly or seasonal) would allow for more precise modeling of rainfall impacts. Expanding the analysis to other provinces of Pakistan could highlight regional differences in climate–agriculture dynamics. Finally, integrating climate change scenarios and simulation models would provide valuable insights into long-term risks and adaptive strategies for sustainable food security.

Policy Implications

These findings suggest that rainfall shocks, though short-lived, contribute non-negligibly to wheat yield fluctuations in Sindh. Policymakers should invest in climate-resilient irrigation infrastructure and promote drought-tolerant wheat varieties to buffer against rainfall variability. Strengthening real-time rainfall monitoring and early warning systems can help farmers anticipate shocks and adapt planting schedules accordingly. Integrating rainfall forecasts into agricultural extension services would further stabilize yield outcomes under changing climatic conditions.

References

Alvar-Beltrán, J., Heureux, A., Soldan, R., Manzanas, R., Khan, B., & Dalla Marta, A. (2021). Assessing the impact of climate change on wheat and sugarcane with the AquaCrop model along the Indus River Basin, Pakistan. *Agricultural Water Management*, *253*, 106909. https://doi.org/10.1016/j.agwat.2021.106909

Asseng, S., Ewert, F., Martre, P., Rötter, R. P., Lobell, D. B., Cammarano, D., Kimball, B. A., Ottman, M. J., Wall, G. W., & White, J. W. (2015). Rising temperatures reduce global wheat production. *Nature Climate Change*, *5*(2), 143–147. https://doi.org/10.1038/nclimate2470

Chandio, A. A., Jiang, Y., Amin, A., Ahmad, M., Akram, W., & Ahmad, F. (2023). Climate change and food security of South Asia: fresh evidence from a policy perspective using novel empirical analysis. *Journal of Environmental Planning and Management*, *66*(1), 169–190. https://doi.org/10.1080/09640568.2021.1877135

Enghiad, A., Ufer, D., Countryman, A. M., & Thilmany, D. D. (2017). An overview of global wheat market fundamentals in an era of climate concerns. *International Journal of Agronomy*, *2017*(1), 3931897. https://doi.org/10.1155/2017/3931897

Farooq, A., Farooq, N., Akbar, H., Hassan, Z. U., & Gheewala, S. H. (2023). A critical review of climate change impact at a global scale on cereal crop production. *Agronomy*, *13*(1), 162. https://doi.org/10.3390/agronomy13010162

Hernandez-Ochoa, I. M., Asseng, S., Kassie, B. T., Xiong, W., Robertson, R., Pequeno, D. N. L., Sonder, K., Reynolds, M., Babar, M. A., & Milan, A. M. (2018). Climate change impact on Mexico wheat production. *Agricultural and Forest Meteorology*, *263*, 373–387. https://doi.org/10.1016/j.agrformet.2018.09.011

Heureux, A. M. C., Alvar-Beltrán, J., Manzanas, R., Ali, M., Wahaj, R., Dowlatchahi, M., Afzaal, M., Kazmi, D., Ahmed, B., & Salehnia, N. (2022). Climate trends and extremes in the Indus River Basin, Pakistan: implications for agricultural production. *Atmosphere*, *13*(3), 378. https://doi.org/10.3390/atmos13030378

Ishaque, W., Osman, R., Hafiza, B. S., Malghani, S., Zhao, B., Xu, M., & Ata-Ul-Karim, S. T. (2023). Quantifying the impacts of climate change on wheat phenology, yield, and evapotranspiration under irrigated and rainfed conditions. *Agricultural Water Management*, *275*, 108017. https://doi.org/10.1016/j.agwat.2023.108220

Ishfaq, A., & Khalid, P. (2025). Determinants of Agriculture Productivity: A Case Study of Pakistan. *Trends in Animal and Plant Sciences*, *5*, 24–28. https://doi.org/10.62324/TAPS/2025.062

Joyo, M. A., & Ram, N. (2016). LINKAGES AMONG CLIMATE CHANGE AND PRODUCTIVITY OF WHEAT IN SINDH PROVINCE OF PAKISTAN. *Grassroots (1726-0396)*, *50*(1).

Munir, Z., Shrestha, S., Zaman, M., Khan, M. I., Akram, M. M., & Tahir, M. N. (2022). Climate change impacts on wheat yield. *Climate Research*, *87*, 13–37. https://doi.org/10.3354/cr01719

Qureshi, H. U., Abbas, I., Shah, S. M. H., Qureshi, Z. U., Al-Qadami, E. H. H., Mustaffa, Z., & Teo, F. Y. (2024). Adapting agriculture to climate shifts: managing crop water needs for environmental resilience in Sindh, Pakistan. *Agronomy Research*, *22*. https://doi.org/10.1007/s11269-024-03745-3

Rahman, F., Khan, Y., & Rahman, R. (2024). The Impact of Climate Change on Pakistan's Agricultural Economy. *ASSAJ*, *2*(4), 1236–1254. https://doi.org/10.32350/jppp.21.04

Sultana, H., Ali, N., Iqbal, M. M., & Khan, A. M. (2009). Vulnerability and adaptability of wheat production in different climatic zones of Pakistan under climate change scenarios. *Climatic Change*, *94*(1), 123–142. https://doi.org/10.1007/s10584-009-9559-5
Valizadeh, J., Ziaei, S. M., & Mazloumzadeh, S. M. (2014). Assessing climate change impacts on wheat production (a case study). *Journal of the Saudi Society of Agricultural Sciences*, *13*(2), 107–115. https://doi.org/10.1016/j.jssas.2013.02.002
Zhu, T., Xie, H., Waqas, A., Ringler, C., Iqbal, M. M., Goheer, M. A., & Sulser, T. B. (2014). *Climate change and extreme events: impacts on pakistan's agriculture*. https://doi.org/10.1016/j.foodpol.2013.12.005