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Climate Variability, Crop Yields, and Staple-Food Price Volatility in Pakistan: Provincial Panel Evidence

Sidra Rafique[1], Shahzadi Mahpara[2], Amanullah Tunio[3], Paras[4], Fatima Athar[5]
[1] Master in Public Health (MSPH) from Health Services Academy (HSA), Islamabad. Bachelors in Doctor of Nutrition and Dietetics (DND) from University of Veterinary and Animal Sciences (UVAS), Lahore.
Email: rrsidra8574@gmail.com
[2] Associate Professor, Department of Plant Breeding and Genetics, Ghazi University, Dera Ghazi Khan.
Email: smahpara@gudgk.edu.pk
[3] Assistant Professor, Department of Basic Engineering, Sindh Agriculture University, Tandojam, Pakistan.
Email: amanullahtunio786@gmail.com
[4] BSc, MSc, MPhil Botany Lecturer, Government Girls Degree College, Larkana.
Email: Bughioparas@gmail.com
[5] Pakistan Institute of Development Economics (PIDE).
Email: fatimaathar92@gmail.com

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Corresponding author:
Sidra Rafique
Email:
rrsidra8574@gmail.com

ABSTRACT

Climate variability influences agricultural productivity and staple-food markets; however, comparable provincial evidence from Pakistan is limited. This retrospective ecological panel analysis included Punjab, Sindh, Khyber Pakhtunkhwa, and Balochistan. ERA5-Land-based annual temperature and precipitation data spanned 2019 to 2024. Official provincial wheat yields were available for harvest years 2019 to 2024 (24 province-year observations), and rice yields for 2019 to 2023 (20 observations). January retail prices of wheat flour and broken basmati rice were collected for 2021 to 2025 from Lahore, Karachi, Peshawar, and Quetta, serving as urban market proxies for the provinces. Yield–price panels comprised 16 wheat observations (2021 to 2024) and 12 rice observations (2021 to 2023). Two-way fixed-effects models with HC3 robust standard errors assessed climate–yield and yield–price associations. Price fluctuations were defined as absolute January-to-January logarithmic changes, rather than within-year volatility or province-wide average prices. Wheat yields increased by 26.4% in Balochistan, 21.4% in Punjab, and 5.7% in Khyber Pakhtunkhwa, but declined by 7.3% in Sindh. Balochistan's rice yield decreased sharply in 2022 before recovering. Annual food-price movements varied by city and commodity. Neither climate–yield nor yield–price coefficients reached statistical significance; yield–price p-values were .899 for wheat flour and .938 for rice. Regional productivity and price movements varied substantially, but the small panels did not establish a reliable climate–yield–price relationship. Longer observation periods and higher-frequency price data are required to support robust agricultural risk assessment and food-market policy decisions.

Introduction

Climate variability is an increasingly significant issue in agricultural economics, especially in developing economies where agricultural production, rural livelihoods, and food-market stability are closely linked. Variations in temperature and precipitation influence agricultural output, production costs, commodity availability, and the stability of food supplies. Economically, these environmental disturbances constitute potential supply-side shocks that may affect agricultural productivity and introduce uncertainty into domestic food markets. Schmidhuber and Tubiello (2007) emphasized that climate change impacts food security

through multiple economic and agricultural pathways, including food availability, accessibility, and market stability. Ray et al. (2015) similarly estimated that climatic variability accounted for approximately one-third of observed global crop-yield variability, underscoring the economic significance of environmental fluctuations for agricultural production.

The relationship between climate variability and agricultural productivity is fundamental to understanding agricultural supply responses and commodity-market performance. Temperature and precipitation affect crop development, irrigation requirements, land productivity, and the efficiency of agricultural inputs. Alterations in these conditions can influence the quantity of agricultural output available for domestic consumption, storage, and trade. Lobell et al. (2011) demonstrated that historical climate trends adversely affected global wheat and maize production compared to a scenario without observed climatic changes. Lesk et al. (2016) also identified significant reductions in cereal production associated with extreme drought and heat events. These findings indicate that agricultural supply is sensitive to climatic disturbances, although the magnitude of the response depends on crop characteristics, agricultural technology, and regional production conditions.

Agricultural productivity responses matter given that environmental conditions vary across regions. Variations in irrigation infrastructure, farming practices, soil quality, and access to agricultural inputs can shape the economic consequences of similar climatic disturbances. Challinor et al. (2014) showed that agricultural adaptation could partially offset adverse climate-related yield effects, although its effectiveness varied across crops and geographical contexts. These findings suggest that analyses relying solely on national agricultural indicators may obscure important regional differences. Provincial panel-data analysis offers a means to examine such heterogeneity while accounting for persistent geographical characteristics and common annual influences.

Pakistan provides a pertinent context for examining these relationships due to its agricultural economy's diverse agroecological environments and regional production systems. Punjab and Sindh encompass major irrigated agricultural areas, whereas Khyber Pakhtunkhwa and Balochistan include mountainous, rain-fed, and arid agricultural environments. As a result, differences in precipitation, temperature, irrigation availability, and production infrastructure may contribute to variations in agricultural productivity. Abid et al. (2015) found that farmers in Punjab recognized climatic changes and adopted measures such as adjusting planting dates and crop varieties, although adaptation was constrained by financial limitations, insufficient information, and water shortages. Subsequently, Abid et al. (2016) reported that agricultural adaptation was positively associated with wheat productivity and crop income among surveyed farmers in Pakistan. These findings underscore the economic significance of agricultural adaptation and productive-resource availability.

The relationship between climate variability and agricultural performance has significant implications for rural household welfare and regional economic development. Variations in crop yields can affect farm income, production decisions, employment opportunities, and household purchasing power. Ali and Erenstein (2017) demonstrated that climate adaptation practices among Pakistani farmers were associated with improved food-security and poverty outcomes. These findings indicate that the economic consequences of climate variability extend beyond physical agricultural production and interact with household resources and adaptation capacity. However, farm-level evidence does not necessarily establish the direction or magnitude of climate-related effects across Pakistan's provinces, where agricultural structures and environmental conditions vary substantially.

The 2022 floods in Pakistan further illustrated the economic vulnerability of agricultural production to extreme environmental events. Exceptionally intense monsoon rainfall disrupted agricultural land, crop production, transportation, and rural livelihoods. Qamer et al. (2023) estimated that approximately 2.8 million hectares of agricultural land in Sindh were affected, resulting in substantial potential losses in major crops, including rice. Such disturbances can influence agricultural supply, farm income, and market expectations. However, the relationships between climatic disturbances and subsequent agricultural outcomes require empirical assessment, as annual production also depends on cultivated area, irrigation management, agricultural inputs, and other economic factors.

In addition to agricultural productivity, climate-related production disturbances can affect domestic food prices through supply-and-demand adjustments. Reductions in agricultural output may exert upward pressure on commodity prices when demand remains relatively stable. However, the transmission of production shocks to retail markets depends on factors such as commodity stocks, interregional trade, transportation costs, government procurement, market integration, and international prices. Headey and Fan (2008) demonstrated that major food-price increases result from interactions among agricultural supply, energy markets, international trade, and policy responses. Tadesse et al. (2014) and Tunio et al. (2026) similarly identified supply-and-demand fundamentals, energy-market developments, and financial factors as important influences on international food-price spikes and volatility. These studies indicate that agricultural productivity and retail-price instability should be analyzed as interconnected economic issues, rather than assuming a direct or immediate relationship.

Food-price movements are particularly significant in developing economies because changes in essential commodity prices affect household expenditure, real purchasing power, and economic welfare. Wheat flour and rice are key staple commodities in Pakistan, making their prices important indicators of domestic food-market conditions. Bellemare (2015) highlighted the importance of distinguishing food-price levels from price volatility when assessing economic and social consequences. This distinction is also important for measurement: annual changes in commodity prices reflecccapture-interval price movements, whereas conventional volatility estimates typically require more frequent observations. Consequently, the frequency and construction of price indicators must be considered when interpreting the relationship between agricultural output and market instability.

Despite extensive international research on climatic influences and agricultural productivity, important empirical questions persist regarding provincial agricultural performance and staple-food price fluctuations in Pakistan. Existing studies offer evidence on agricultural adaptation, climatic vulnerability, and food-market dynamics, yet these relationships are often examined separately or at varying geographical scales. An integrated provincial assessment can enhance understanding of whether annual temperature and precipitation differences are associated with wheat and rice yields, and whether variations in agricultural productivity correspond to subsequent movements in staple-food retail prices. Such analysis is particularly valuable for distinguishing geographically persistent production differences from year-specific agricultural and market conditions (Magsi et al. 2026).

This study examined climate variability, crop yields, and staple-food price fluctuations across Punjab, Sindh, Khyber Pakhtunkhwa, and Balochistan using publicly available secondary data. Wheat yields were analyzed for 2019–2024, and rice yields for 2019–2023. Annual temperature and precipitation data were integrated with provincial agricultural statistics, and retail wheat-flour and broken basmati rice prices from Lahore, Karachi, Peshawar, and Quetta were used to assess subsequent annual price movements. Separate two-way fixed-effects regression models were applied to investigate climate–yield and yield–price relationships. The study provides exploratory provincial evidence to agricultural and environmental economics by integrating climatic, agricultural, and commodity-market indicators within a unified empirical framework. Given the limited panel size and the use of annual absolute logarithmic price changes as a proxy for price fluctuations, the analysis identifies statistical associations rather than a causal climate–yield–price transmission mechanism.

Literature review

The economic relationship between climate variability and agricultural productivity is grounded in agricultural production theory and the concept of supply-side disturbances. Agricultural output is determined by productive inputs such as land, labor, capital, irrigation, and technology, in addition to environmental conditions that affect input effectiveness. Temperature and precipitation are key environmental determinants that can alter crop yields and the marginal productivity of agricultural resources. Adverse climatic conditions may constrain agricultural supply, increase production costs, and introduce uncertainty regarding future commodity availability. The economic consequences of these disturbances depend on the intensity and timing of exposure, crop characteristics, and producers' capacity to adjust production decisions.

Schlenker and Roberts (2009) presented influential empirical evidence on nonlinear temperature–yield relationships using United States county-level agricultural data. Their findings showed that crop productivity increased with temperature up to crop-specific thresholds, after which further heat exposure led to significant yield reductions. These results challenged the assumption of a linear relationship between agricultural productivity and temperature changes. From an economic perspective, nonlinear production responses indicate that marginal climatic effects vary across agricultural regions with different baseline temperatures. Therefore, identical temperature increases can produce different productivity outcomes depending on local environmental conditions.

Ortiz-Bobea et al. (2021) expanded the analysis to global agricultural productivity by estimating the historical impact of anthropogenic climate change on agricultural total factor productivity. Their findings indicated that climate change reduced global agricultural productivity by about 21% compared to a counterfactual scenario without anthropogenic climate change since 1961. The productivity effects were especially pronounced in warmer regions, demonstrating that technological improvements do not necessarily offset climate-related economic losses. These results underscore the importance of incorporating climatic information into agricultural productivity analysis, while acknowledging that production outcomes also depend on technological advancement, input utilization, and adaptation.

The theoretical literature indicates that climatic disturbances can alter agricultural output by affecting production efficiency and imposing environmental constraints. However, the direction and magnitude of these relationships are not uniform across different geographical regions or agricultural commodities.

Pakistan's agricultural economy functions within diverse climatic and agroecological environments, resulting in substantial variation in agricultural exposure and production conditions. Variations in temperature, rainfall, irrigation infrastructure, soil

characteristics, and productive resources influence crop performance across provinces. Comprehensive understanding of these relationships requires empirical assessment of climatic factors in conjunction with agricultural conditions.

Ali et al. (2017) investigated the influence of climatic variables on major crop yields in Pakistan using data from 1989 to 2015. The study incorporated maximum and minimum temperatures, rainfall, relative humidity, and sunshine, and utilized feasible generalized least squares as well as heteroskedasticity- and autocorrelation-consistent estimation techniques. The results showed that maximum temperature negatively affected wheat production, while minimum temperature was positively associated with several crop outcomes. Rainfall effects varied across crops, indicating that climatic responses depend on crop-specific production characteristics. The analysis provided empirical evidence of climate-sensitive agricultural productivity and highlighted the limitations of geographically aggregated information when agricultural environments differ substantially.

Mahmood et al. (2019) analyzed wheat-yield responses to climatic and socioeconomic factors in Pakistan's rain-fed agricultural regions. Utilizing farm-level observations and historical climate data, the researchers applied a stochastic production-function framework to assess both average yields and yield variability. The findings showed that temperature anomalies were linked to lower average yields, while cumulative precipitation was positively associated with mean yield and yield variability. Access to agricultural input markets and other production characteristics also influenced outcomes. The study demonstrated that climatic disturbances affect not only expected agricultural output but also production uncertainty, with implications for farm income, investment decisions, and risk management.

Shah et al. (2024) provided localized evidence by examining the relationships between climatic trends and wheat productivity in Bahawalnagar district, Punjab, from 1991 to 2022. The analysis identified changing temperature and precipitation patterns, with estimated effects on wheat production varying across climatic and agricultural indicators. Fertilizer use and humidity were positively associated with productivity in the reported models. These findings underscore the importance of agricultural inputs and local environmental conditions in interpreting climate–yield relationships. However, the study's geographical concentration limits its applicability to provinces with different agricultural production systems.

These studies demonstrate that agricultural productivity in Pakistan is sensitive to interactions among climatic conditions, agricultural inputs, and socioeconomic factors. They also highlight the necessity of geographically disaggregated analysis to distinguish regional production differences from aggregate agricultural trends.

Regional heterogeneity is a critical consideration in agricultural economics, as climatic exposure, access to productive resources, and agricultural management practices vary across geographical locations. As a result, regional productivity differences may reflect structural characteristics as well as annual climatic fluctuations.

Raza et al. (2019) examined climatic influences on wheat production in four districts of southern Punjab using panel data from 1998 to 2014. Their fixed-effects analysis included seasonal temperature and rainfall indicators, as well as agricultural inputs and infrastructure-related variables. The findings showed that temperature effects varied across months of the wheat-growing season, with higher April temperatures negatively impacting productivity. The researchers also identified nonlinear relationships between precipitation and wheat production during specific months. These results suggest that climatic exposure during specific crop-development periods matters more economically than annual averages. The use of fixed-effects estimation further highlights the importance of accounting for persistent regional differences in agricultural productivity analysis.

Zahid and Shah (2024) analyzed the relationship between climate change and farm-level technical efficiency in Punjab using a stochastic production frontier model. Their analysis included 537 farm-household panel observations across various cropping systems and agroecological environments. The findings indicated that temperature changes and precipitation fluctuations negatively affected agricultural production and technical efficiency. An estimated mean technical efficiency of approximately 0.82 suggests opportunities to improve productivity through enhanced agricultural management and input use. The study highlights the link between climatic exposure and agricultural production efficiency, suggesting that adaptation capacity may shape regional responses to environmental disturbances.

Alvar-Beltrán et al. (2021) assessed the implications of projected climate change for wheat and sugarcane production along Pakistan's Indus River Basin using the AquaCrop modeling framework. Their analysis evaluated alternative climate scenarios and irrigation-management practices across locations in Punjab and Sindh. The results indicated that agricultural responses depended on both climatic conditions and irrigation strategies, with variations between crops and geographical settings. These findings underscore the economic significance of water-resource management in climate-sensitive agriculture. However, the study's crop-simulation approach focused on projected production outcomes rather than observed historical econometric relationships.

Collectively, regional evidence indicates that agricultural responses to climate variability are influenced by irrigation infrastructure, farming practices, production efficiency, and local agroecological environments. These factors justify controlling for persistent provincial differences in empirical agricultural models. However, province fixed effects cannot capture all changes in agricultural technology, input prices, or water availability over time.

The relationship between agricultural productivity and food prices is shaped by the interaction of commodity supply and demand. Under otherwise stable market conditions, adverse production shocks reduce available agricultural supply and exert upward pressure on prices. Conversely, productivity improvements increase supply and reduce price pressure. However, retail food prices do not always respond proportionally or immediately to changes in local crop yields. Storage arrangements, market integration, transportation costs, international commodity prices, and government interventions can all influence the transmission of agricultural disturbances to consumers.

Brown and Kshirsagar (2015) analyzed the influence of domestic weather disturbances and international commodity-price shocks on local food prices across 554 markets in 51 developing countries. Using monthly data from 2008 to 2012, their analysis identified relationships between weather disturbances and local food affordability in about one-fifth of the examined market-price series. The study demonstrated that domestic environmental shocks can influence local food-market conditions independently of international commodity-price developments. However, the observed relationships varied across markets, reflecting differences in market structure, production systems, and exposure to external economic disturbances.

Kotz et al. (2024) examined the effects of climatic conditions on consumer-price inflation using over 27,000 monthly observations from countries worldwide. Their fixed-effects analysis showed that higher temperatures were associated with persistent increases in food and headline inflation, with effects varying across seasons and climatic regions. The researchers also identified additional influences from temperature variability and extreme precipitation. These findings extend the economic implications of climate variability beyond agricultural production to consumer-price dynamics and macroeconomic stability.

However, the relationships identified in international inflation analyses should not be directly equated with individual commodity-price movements. Changes in wheat-flour and rice prices may depend on product-specific supply conditions, market regulations, and regional distribution arrangements. Therefore, analyzing agricultural yields and commodity-price movements separately provides a means to identify observable relationships without assuming complete or immediate price transmission.

Food-price instability is a significant issue in agricultural and development economics, as unexpected commodity-price movements can affect household expenditure, agricultural marketing decisions, farm profitability, and consumer welfare. The degree of integration among regional and international commodity markets is particularly relevant for understanding how supply disturbances influence domestic retail prices.

Ceballos et al. (2017) investigated international-to-domestic grain-price transmission across 27 developing countries, covering 41 food products. Their analysis examined both price-level adjustments and volatility transmission using multivariate conditional heteroskedasticity models. The findings indicated that international commodity-price volatility was transmitted to several domestic markets, particularly for wheat and rice. Volatility transmission varied across countries and was more prevalent in economies with more dependent international grain trade. These results demonstrate that domestic commodity-price instability may reflect external market conditions rather than solely local agricultural production changes.

Sahito (2017) provided evidence specific to Pakistan by investigating wheat-market integration using monthly wholesale-price data from five regional markets between January 1988 and April 2011. The study employed cointegration analysis, vector error-correction modeling, and threshold vector error-correction techniques to examine price-adjustment processes and the impact of transaction costs. The findings revealed considerable differences in regional market adjustments, with Lahore exhibiting relatively strong responses under certain market conditions. The analysis suggests that transportation and transaction costs may influence the speed and magnitude of wheat-price transmission across Pakistani markets.

These findings have direct implications for provincial agricultural and retail-price analysis. Regional crop productivity can influence commodity availability, but the effects on urban retail prices may be moderated by interprovincial trade, public commodity stocks, transportation infrastructure, and national market conditions. As a result, the relationship between crop yields and retail food prices may be weaker or less immediate than predicted by a simple agricultural supply model.

A key methodological issue is the distinction between food-price changes and food-price volatility. Conventional volatility estimation typically requires repeated observations of price returns over short intervals, often using monthly or higher-frequency data. In contrast, an absolute annual logarithmic price change measures the magnitude of price movement between two observations one

year apart. While useful for describing annual commodity-price fluctuations, it does not capture within-year conditional volatility. This distinction is crucial when comparing results from annual provincial datasets with studies using monthly time-series or GARCH-type approaches.

The reviewed literature identifies three key relationships in agricultural and environmental economics. First, climatic conditions influence agricultural productivity, with the magnitude and direction of these effects varying by crop characteristics, regional production conditions, and timing of environmental exposure. Second, agricultural responses to climatic disturbances depend on irrigation infrastructure, agricultural management, technical efficiency, and access to productive resources. Third, food-price movements reflect interactions among domestic agricultural supply, international commodity markets, market integration, and institutional conditions.

Despite these contributions, significant limitations persist in the empirical evidence relevant to Pakistan's provincial agricultural and food-market systems. Much of the Pakistan-specific literature focuses on individual districts, farming systems, or agricultural commodities. While these studies provide valuable insights into local production conditions, they offer limited evidence of comparable relationships across Punjab, Sindh, Khyber Pakhtunkhwa, and Balochistan.

Furthermore, agricultural productivity and commodity-price fluctuations are often analyzed using separate empirical frameworks. As a result, existing research provides limited directly comparable evidence on how provincial variations in wheat and rice yields correspond to subsequent retail-price movements across major Pakistani markets. Differences in data frequency, commodity definitions, and geographic coverage further complicate integration and food-price information.

Another limitation involves the distinction between climatic variability and extreme-weather exposure. Annual temperature and precipitation measurements can identify broad geographical and temporal patterns, but they do not fully capture growing-season heat stress, short-duration flooding, or drought intensity. Econometric models based on annual climate indicators should therefore be interpreted as assessments of aggregate climatic associations rather than comprehensive representations of agricultural exposure.This study contributes to the literature by integrating publicly available provincial agricultural statistics, annual climate indicators, and selected retail food-price observations within an exploratory panel-data framework.k.

The empirical approach is structured around two related economic relationships. The first examines associations between annual temperature, precipitation, and provincial wheat and rice yields. The second evaluates whether differences in provincial crop productivity are associated with the magnitude of subsequent annual retail wheat-flour and rice-price changes.

The conceptual framework recognizes a potential sequence in which climatic conditions influence agricultural productivity, and agricultural supply changes may contribute to commodity-price movements. However, food prices are also affected by market integration, trade, storage, and economic policy. Therefore, the two empirical relationships are estimated separately rather than interpreted as a formally identified causal transmission pathway.

Province and province-year fixed effects are employed to account for persistent geographical differences and common annual influences. Wheat and rice are analyzed separately due to differences in their agricultural production systems and market characteristics. The analysis covers wheat yields for 2019–2024, rice yields for 2019–2023, and matched annual food-price fluctuations from selected provincial capitals. contribution lies in providing a comparative provincial assessment of climate-sensitive agricultural productivity and staple-food price movements. The limited number of provinces, short observation periods, and annual aggregation constrain statistical inference, but the framework establishes a basis for identifying regional economic patterns and clarifying priorities for more comprehensive agricultural and food-market research.

Methodology

Research design

A retrospective ecological panel analysis assessed associations among annual climate indicators, provincial crop yields, and annual retail food-price fluctuations in Punjab, Sindh, Khyber Pakhtunkhwa, and Balochistan. The analytical unit was the province-year. Separate models were developed for wheat and rice due to differences in reporting periods, production systems, and retail products. The analyses included descriptive comparisons, climate–yield regressions, yield–price regressions, and a rice-yield sensitivity analysis. The study estimated observational associations without establishing a causal climate–yield–price transmission pathway.

Data sources and geographic coverage

Provincial wheat and rice yields, measured in kilograms per hectare (kg/ha), were obtained from the Ministry of National Food Security and Research publication Agricultural Statistics of Pakistan 2023–24. Yield was defined as output per unit of cultivated area, not as total crop production. Therefore, changes in yield were not interpreted as equivalent changes in the quantity supplied to markets.

Annual mean temperature (°C) and annual precipitation (mm) were sourced from the ERA5-Land-based provincial series published by Climategate. The provider aggregated distinct inhabited grid targets instead of calculating agricultural-area-weighted provincial means, so these series served as regional climate proxies. Annual precipitation was retained as the source indicator and did not measure flood exposure, irrigation supply, or rainfall during crop-specific growth stages.

January retail prices for 2021–2025 were obtained from the Pakistan Bureau of Statistics monthly essential-item price annexes. Lahore, Karachi, Peshawar, and Quetta were selected as urban markets corresponding to Punjab, Sindh, Khyber Pakhtunkhwa, and Balochistan, respectively. Wheat-flour prices were recorded in nominal Pakistani rupees per 20-kg bag, and broken basmati rice prices in rupees per kilogram. These data represented city-specific retail indicators rather than province-wide average prices. Aggregate provincial rice yields were matched to a single retail rice product; the model did not isolate basmati-specific supply.

Panel construction and temporal alignment

Agricultural and climate records were matched by province and assigned to the harvest year. According to the manuscript's crop-year convention, wheat was assigned to the ending calendar year of the agricultural reporting period, while rice was assigned to its starting calendar year. For example, an agricultural period labelled 2023–24 corresponded to wheat harvest year 2024 and rice harvest year 2023. Calendar-year climate indicators were matched to these assigned years. This alignment did not reconstruct growing-season exposure, as wheat spans calendar years and annual climate summaries include months outside the relevant production season.

The wheat climate–yield panel included data from 2019 to 2024 (4 provinces × 6 years = 24 observations), and the rice panel included data from 2019 to 2023 (4 × 5 = 20 observations). The wheat yield–price panel covered interval-start years 2021–2024 (16 observations), and the rice yield–price panel covered 2021–2023 (12 observations). All four principal panels were balanced within their respective periods. Complete records were used without statistical imputation. Additional rice-price observations for 2024 were included in descriptive price summaries but not in the rice yield–price regression, as the rice-yield series ended in 2023.

For each price interval labelled t, the January price in year t was compared with the January price in year t + 1 and matched to the yield assigned to year t. For example, the 2022 interval compared January 2022 with January 2023 and was paired with the 2022 harvest-year yield. Since this interval began before the harvest, the price analysis did not follow a strictly post-harvest or lagged-yield design.

Variable construction and descriptive analysis

Climate conditions were summarized by province using the mean, minimum, and maximum annual values for 2019–2024. Crop yields were presented in kg/ha, and changes between the first and final observed years were calculated as 100 × (Y_final / Y_initial − 1). These were descriptive comparisons; no formal tests of between-province differences were reported.

Let P_{it} denote the January nominal price of a given commodity in the city matched to province i in year t. Signed percentage price changes and absolute logarithmic price changes were calculated separately:

$$C_{it} = 100 \times (P_{i,t+1} / P_{it} - 1) \quad (1)$$

$$F_{it} = 100 \times |ln(P_{i,t+1} / P_{it})| \quad (2)$$

C_{it} retained the direction of price movement and was used in the matched descriptive table. F_{it} measured its magnitude, in log-percentage points, and was the outcome in the price regressions. Annual summaries of F_{it} were arithmetic means across the four cities with equal city weights. F_{it} was neither a signed inflation rate nor an estimate of within-year price volatility. A large value could reflect a price increase or a price decrease. The analysis used nominal prices without deflation.

Climate and crop yield models

Separate two-way fixed-effects ordinary least-squares regressions related the natural logarithm of crop yield to annual temperature and precipitation:

$$ln(Y_{it}) = \alpha_i + \lambda_t + \beta_1 T_{it} + \beta_2 (R_{it} / 100) + \varepsilon_{it} \quad (3)$$

Y_{it} denotes crop yield, T_{it} annual mean temperature, and R_{it} annual precipitation. Province fixed effects (α_i) accounted for time-invariant provincial characteristics, and year fixed effects (λ_t) accounted for common annual influences. These were separate province and year effects, not province-by-year interaction effects. Coefficients were identified from predictor variation remaining after adjustment for both sets of effects. The model imposed common climate slopes across provinces.

β_1 represented the log-yield difference associated with a 1°C higher annual temperature, conditional on precipitation and the fixed effects. β_2 represented the corresponding difference per 100 mm of precipitation. For a one-unit predictor change, the exact model-implied percentage difference was 100 × [exp(β) − 1]; 100β was only an approximation for small coefficients. The specification contained no nonlinear climate terms, seasonal exposure indicators, or time-varying agricultural input controls. Coefficients were therefore interpreted as conditional associations rather than crop response functions or estimates of long-term climate-change effects.

Crop yield and retail price models

Separate regressions paired wheat yields with wheat-flour price fluctuations and aggregate rice yields with broken basmati rice price fluctuations:

$$F_{it} = \mu_i + \tau_t + \theta (Y_{it} / 100) + u_{it} \quad (4)$$

μ_i and τ_t denote province-linked market and interval-start-year fixed effects. Because each province was matched to one city, province and city identifiers represented the same grouping in these models. θ was the estimated difference in F_{it}, measured in log-percentage points, associated with a 100-kg/ha higher yield. It was not a price elasticity, an estimate of signed price inflation, or the percentage change in volatility. A negative coefficient indicated a smaller magnitude of annual price movement, without distinguishing increases from decreases.

The models excluded total production, crop area, commodity stocks, interprovincial trade, procurement policies, and transport costs. Year effects addressed common annual influences but did not account for province-specific changes in these omitted variables. The two model families were estimated independently and did not represent a mediation or simultaneous-equations analysis.

Estimation and Statistical Inference

Models were estimated with province and year indicators, employing reference categories to avoid redundant parameters. HC3 heteroskedasticity-consistent covariance estimates were applied. Confidence intervals and two-sided p-values were calculated using the student's t distribution with residual degrees of freedom, consistent with the reported results. For the full-rank specifications, residual degrees of freedom were 13 for the wheat climate model, 10 for the rice climate model, 8 for the wheat price model, and 5 for the rice price model. The nominal significance threshold was set at .05, and the analyses were exploratory.

HC3 adjusted for heteroskedasticity and observation leverage but did not address within-province serial correlation or cross-province residual dependence. Given the inclusion of four provinces and short time series, neither HC3 inference nor conventional cluster asymptotics ensured reliable finite-sample coverage. Estimates and confidence intervals were interpreted with these limitations in mind. Non-significant coefficients did not demonstrate equivalence or confirm the absence of an economically meaningful association.

The reported R^2 represented the overall fit of each complete model, including fixed effects. It did not reflect a within-province R^2 or the explanatory contribution of climatic predictors alone. Descriptive geographical differences were not considered statistically significant without a corresponding test.

Sensitivity Analysis

The rice climate–yield model was re-estimated after excluding Balochistan's 2022 yield of 813 kg/ha. This exclusion reduced the sample from 20 to 19 observations, resulting in an unbalanced panel and leaving 9 residual degrees of freedom. The outcome transformation, climatic predictors, fixed effects, and HC3 t-based inference were maintained. Changes in coefficient magnitude

and direction were examined to assess influence. The complete sample remained the primary analysis; exclusion did not confirm that the observation was erroneous or that a specific weather event caused the yield decline.

Data Transparency and Interpretive Limits

The analysis utilized aggregated secondary data and did not involve participant recruitment or identifiable individual records. Interpretation was constrained by the small panels, annual climate aggregation, urban-market price coverage, aggregate rice-to-product matching, and unmeasured time-varying determinants. The short study period supported exploratory interannual comparisons rather than attribution of long-term climatic trends.

Ethical and Data-Transparency Considerations

The study utilized publicly accessible secondary datasets consisting of aggregated provincial agricultural statistics, reanalysis-derived climatic observations, and published retail commodity prices.

Results

Descriptive Assessment of Provincial Climate Variability

The empirical analysis commenced with an examination of annual temperature and precipitation differences across Pakistan's four provinces from 2019 to 2024. These climatic indicators served as the foundation for evaluating geographical heterogeneity and their subsequent associations with agricultural productivity.

Table 1.;Descriptive statistics of provincial climatic conditions, 2019–2024

Province	Mean temperature (°C)	Temperature range (°C)	Mean rainfall (mm)	Rainfall range (mm)
Punjab	24.51	23.91–24.98	476.0	246.8–658.2
Sindh	27.11	26.92–27.49	280.3	112.9–586.9
Khyber Pakhtunkhwa	13.17	12.47–13.77	834.2	453.2–1,036.3
Balochistan	21.69	20.96–22.23	257.5	97.1–413.2

The results indicated significant geographical variation in climatic conditions. Sindh reported the highest mean annual temperature (27.11°C), followed by Punjab (24.51°C) and Balochistan (21.69°C). Khyber Pakhtunkhwa recorded the lowest mean temperature (13.17°C), consistent with the climatic characteristics of the regions included in the source's estimates.

Precipitation patterns also showed pronounced regional differences. Khyber Pakhtunkhwa received the highest mean annual rainfall (834.2 mm), while Balochistan experienced the lowest (257.5 mm). Punjab and Sindh reported intermediate rainfall levels of 476.0 mm and 280.3 mm, respectively.

Significant interannual fluctuations in rainfall were observed. In Sindh, annual rainfall increased from 117.6 mm in 2021 to 586.9 mm in 2022. Balochistan's rainfall rose from 97.1 mm to 413.2 mm during the same period.

These findings confirm considerable geographical heterogeneity in Pakistan's climatic conditions. However, the annual indicators do not differentiate between growing-season rainfall and precipitation outside agricultural production periods. Therefore, these differences reflect general climatic exposure rather than direct measures of crop-specific weather stress.

Provincial Variation in Wheat Productivity

Provincial wheat yield data from 2019 to 2024 were analyzed to assess changes in agricultural productivity and regional differences in production performance.

Table 2: Provincial wheat-yield trends, 2019–2024 (kg/ha)

Province	2019	2020	2021	2022	2023	2024	Change (%)
Punjab	2,829.0	2,977.9	3,098.1	3,053.8	3,275.0	3,434.2	+21.4
Sindh	3,589.7	3,392.8	3,362.3	3,009.8	3,182.1	3,326.8	−7.3

Khyber Pakhtunkhwa	1,846.0	1,554.2	1,787.3	1,791.7	1,920.3	1,950.4	+5.7
Balochistan	2,221.0	2,026.7	2,531.3	2,648.0	2,788.9	2,807.2	+26.4

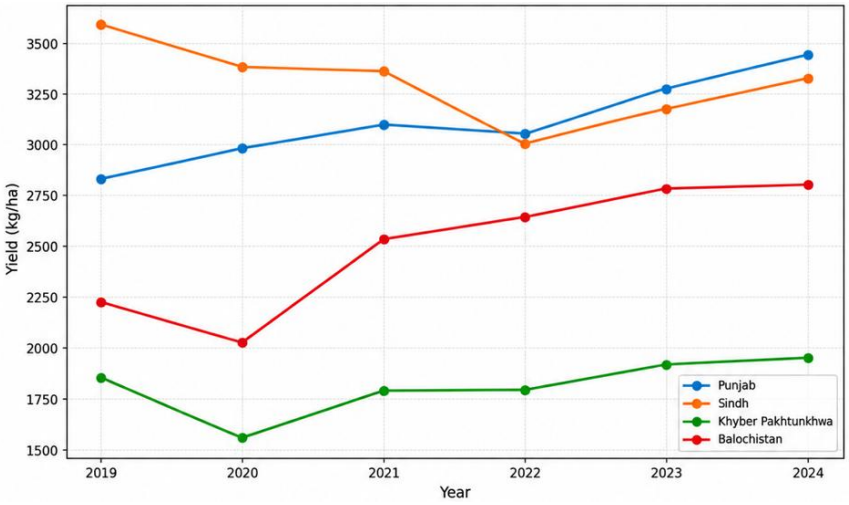


Figure 1: Provincial wheat and rice productivity trends

The descriptive findings revealed substantial interprovincial variation in wheat productivity. Punjab increased from 2,829.0 kg/ha in 2019 to 3,434.2 kg/ha in 2024, a cumulative improvement of 21.4%. Balochistan demonstrated the highest proportional increase (26.4%), although its absolute wheat yield in 2024 remained lower than that of Punjab and Sindh.

Khyber Pakhtunkhwa recorded a comparatively modest increase of 5.7%, reaching 1,950.4 kg/ha in 2024. Conversely, Sindh declined from 3,589.7 kg/ha in 2019 to 3,326.8 kg/ha in 2024, a reduction of 7.3%.

The yield trajectories varied across provinces. Punjab exhibited a generally upward trend despite a temporary decline in 2022. In contrast, Sindh underwent consecutive reductions through 2022, followed by partial recovery in subsequent years.

From an agricultural economics perspective, these differences reflect heterogeneous productivity performance across regional production systems. However, yield changes alone do not isolate the relative effects of climate variability, agricultural inputs, irrigation availability, or technological advancements.

Rice Productivity and Regional Production Instability

Rice productivity was analyzed using provincial data from 2019 to 2023. The findings offer further evidence of crop-specific variation in agricultural performance.

Table 3: Provincial rice-yield trends, 2019–2023 (kg/ha)

Province	2019	2020	2021	2022	2023
Punjab	2,042	2,214	2,262	2,316	2,349
Sindh	3,321	3,408	3,782	3,335	3,776
Khyber Pakhtunkhwa	2,442	2,442	2,452	2,422	2,550
Balochistan	3,259	3,252	3,251	813	3,241

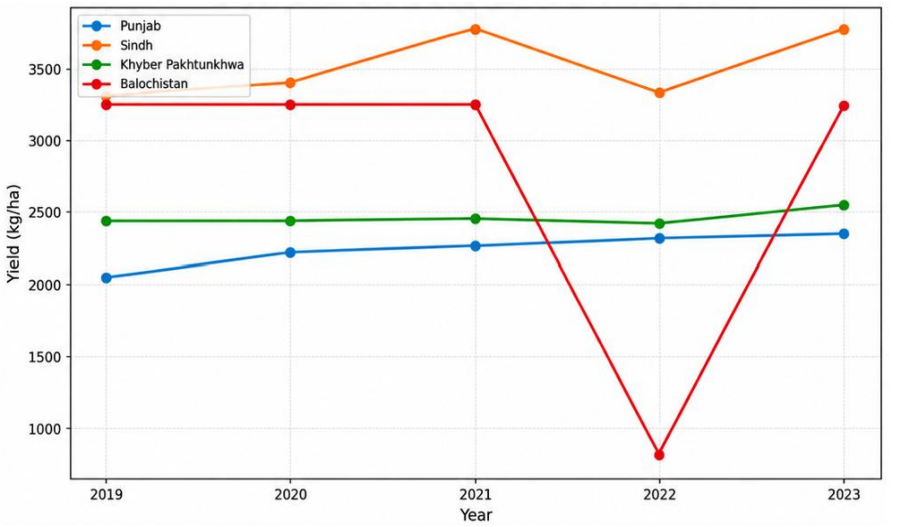


Figure 2: Provincial Rice-Yields trends 2019_2023

Rice yields varied significantly across provinces and years. Punjab showed a consistent upward trend, increasing from 2,042 kg/ha in 2019 to 2,349 kg/ha in 2023. Sindh maintained high productivity throughout the period, with yields of 3,782 kg/ha in 2021 and 3,776 kg/ha in 2023.

Khyber Pakhtunkhwa exhibited stable yields, ranging from 2,422 to 2,550 kg/ha. In contrast, Balochistan experienced a marked decline from 3,251 kg/ha in 2021 to 813 kg/ha in 2022, followed by a recovery to 3,241 kg/ha in 2023.

The Balochistan case is significant, as the unusually large decline may substantially affect estimated climate–yield relationships within a small provincial panel.

The 2022 decline occurred during a period of severe climatic disruption in Pakistan. However, the aggregated yield data do not clarify whether the reduction was due to flooding, damage to cultivated areas, irrigation constraints, or other production disturbances.

Overall, the rice-yield results reveal substantial differences in provincial productivity stability. These findings underscore the need for separate crop-specific analyses rather than aggregating wheat and rice into a single agricultural outcome.

Integration of Climate, Agricultural Productivity, and Commodity-Price Observations

The analysis subsequently incorporated provincial climatic data, wheat yields, and annual retail food-price changes for 2021–2024. Retail-price data were matched to selected provincial capitals to assess geographical differences in commodity-market trends.

Table 4: Matched provincial climate, wheat-yield, and annual food-price observations, 2021–2024

Province	Year	Rainfall (mm)	Temperature (°C)	Wheat yield (kg/ha)	Flour price change (%)	Rice price change (%)
Punjab	2021	326.6	24.86	3,098.1	+27.91	+28.00
Punjab	2022	556.6	24.98	3,053.8	+17.73	+69.14
Punjab	2023	246.8	24.46	3,275.0	+116.06	+40.60
Punjab	2024	479.7	24.85	3,434.2	−38.74	−20.68
Sindh	2021	117.6	27.26	3,362.3	−6.90	+17.62
Sindh	2022	586.9	26.95	3,009.8	+112.32	+62.95
Sindh	2023	112.9	27.06	3,182.1	+14.06	+40.64
Sindh	2024	269.0	27.49	3,326.8	−29.27	+0.94

Khyber Pakhtunkhwa	2021	752.7	13.53	1,787.3	+7.78	+42.34
Khyber Pakhtunkhwa	2022	833.4	13.77	1,791.7	+138.92	+32.89
Khyber Pakhtunkhwa	2023	453.2	13.21	1,920.3	+7.65	+53.72
Khyber Pakhtunkhwa	2024	951.1	13.51	1,950.4	−37.36	−17.02
Balochistan	2021	97.1	22.23	2,531.3	+45.41	0.00
Balochistan	2022	413.2	21.81	2,648.0	+84.22	+52.37
Balochistan	2023	112.9	21.91	2,788.9	+8.59	+65.74
Balochistan	2024	287.0	22.01	2,807.2	−33.27	0.00

The matched observations revealed significant geographical variation in agricultural conditions and commodity-price adjustments. Wheat-flour prices rose markedly in several markets during the earlier comparison periods.

Between January 2022 and January 2023, wheat-flour prices increased substantially in Peshawar (138.92%) and Karachi (112.32%). In the following period, Lahore experienced a wheat-flour price increase of 116.06% between January 2023 and January 2024.

The final comparison period indicated a widespread reversal in wheat-flour prices. From January 2024 to January 2025, wheat-flour prices declined by 38.74% in Lahore, 37.36% in Peshawar, 33.27% in Quetta, and 29.27% in Karachi.

Rice-price changes exhibited greater heterogeneity across markets. In the final observation interval, rice prices declined in Lahore and Peshawar, increased slightly in Karachi, and remained unchanged in the reported Quetta series.

The results indicated that agricultural productivity and retail-price movements did not display consistently proportional changes across provinces. However, descriptive comparisons alone could not determine whether these differences were attributable to market integration, agricultural supply conditions, commodity stocks, or other economic factors.

Magnitude of Annual Staple-Food Price Fluctuations

The magnitude of annual commodity-price movements was assessed using absolute logarithmic price changes. This measure captured both positive and negative price movements without permitting increases and decreases to offset each other.

Table 5: Average magnitude of annual staple-food price fluctuations across selected provincial capitals

Year	Wheat-flour price fluctuation	Broken basmati rice price fluctuation
2021	19.17	19.05
2022	59.95	42.98
2023	26.45	40.43
2024	42.72	10.69

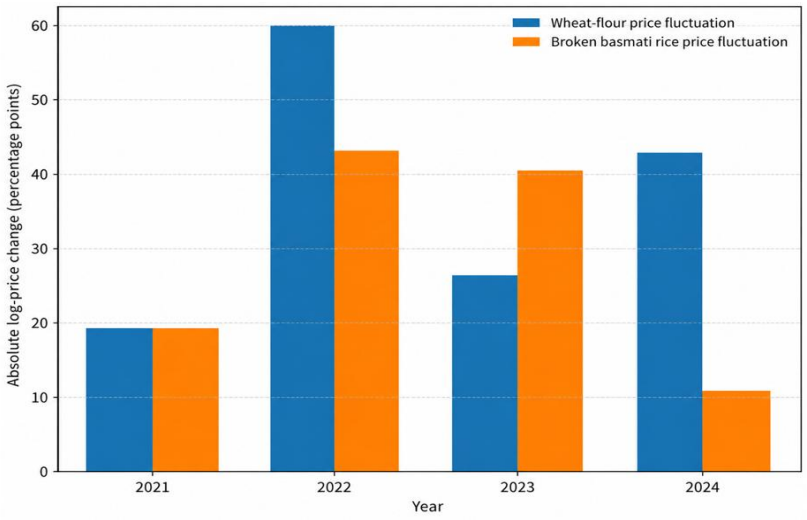


Figure 3: Average magnitude of annual wheat-flour selected provincial capitals, 2021–2024

Wheat-flour prices experienced the highest average annual fluctuation in 2022, reaching 59.95 log-percentage points. The indicator declined to 26.45 in 2023 and then increased to 42.72 in 2024.

Broken basmati rice displayed a distinct pattern. The average price-fluctuation measure was 42.98 in 2022 and 40.43 in 2023, followed by a substantial decline to 10.69 in 2024.

The divergence between wheat-flour and rice price fluctuations highlights commodity-specific differences in annual retail market adjustments. Notably, the substantial magnitude of wheat-flour price movements in 2024 resulted from significant price reductions rather than renewed price increases.

These observations indicate that the magnitude of retail price changes varies across commodities and years. However, they do not provide estimates of conditional price variance or short-term commodity market volatility.

Fixed-Effects Estimates of Climate–Yield Relationships

Two-way fixed-effects regressions were employed to examine conditional associations between annual climatic conditions and provincial crop yields. Separate models were estimated for wheat and rice, with province and harvest-year fixed effects included in each specification.

Table 6. Two-way fixed-effects regression estimates for wheat and rice productivity

Variable	Wheat model β (95% CI)	p-value	Rice model β (95% CI)	p-value
Mean temperature (per 1°C)	0.196 (−0.104 to 0.495)	.182	0.231 (−1.284 to 1.745)	.741
Annual rainfall (per 100 mm)	0.011 (−0.053 to 0.075)	.712	0.009 (−0.307 to 0.325)	.951
Province fixed effects	Included	—	Included	—
Year fixed effects	Included	—	Included	—
Observations	24	—	20	—
R^2	0.956	—	0.488	—

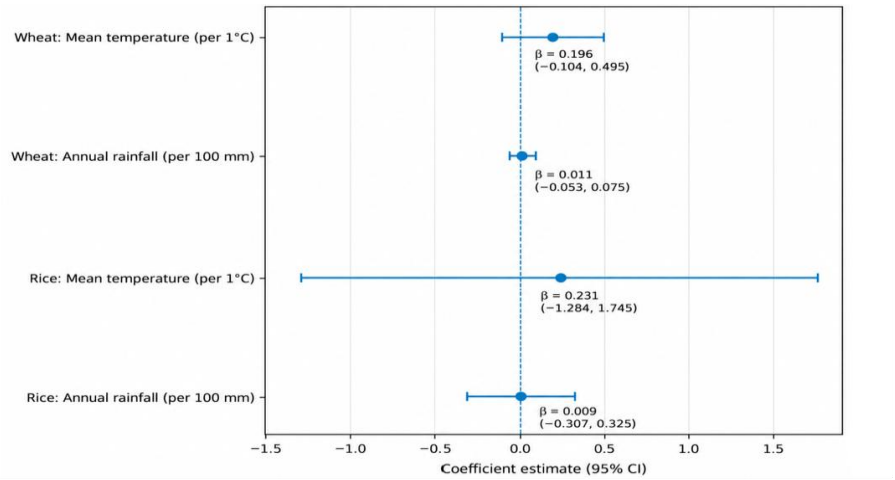


Figure 4: Two-way fixed-effects regression coefficients and 95% confidence intervals for the associations of temperature and rainfall with provincial wheat and rice yields. The vertical dashed line indicates the null effect (β = 0).

The wheat-yield model yielded a positive temperature coefficient of 0.196. However, this relationship was not statistically significant (p = .182), and the confidence interval included zero (−0.104 to 0.495). The rainfall coefficient was 0.011 per 100-mm increase, with a 95% confidence interval of −0.053 to 0.075 (p = .712).

These results did not provide sufficiently precise evidence for either a positive or negative relationship between annual climatic conditions and wheat productivity after controlling for province and year fixed effects.

The rice-yield model produced a temperature coefficient of 0.231 (95% CI −1.284 to 1.745; p = .741). The estimated rainfall coefficient was 0.009 (95% CI −0.307 to 0.325; p = .951). Both coefficients were statistically non-significant and associated with wide confidence intervals.

The wheat model recorded an R^2 of 0.956, compared with 0.488 for the rice model. However, the high explanatory fit in the wheat specification also reflected the inclusion of province and year fixed effects and could not be attributed solely to climatic predictors.

The estimated coefficients therefore provided no statistically conclusive evidence of annual climate–yield associations in the available panels. These results do not establish that temperature and precipitation are economically irrelevant to agricultural productivity. Instead, the limited number of observations and the use of aggregated climatic indicators constrained the precision of the estimated relationships.

Agricultural Productivity and Subsequent Food-Price Fluctuations

The second set of regressions assessed whether provincial crop yields were associated with the magnitude of subsequent annual retail-price movements. Wheat yields were matched to wheat-flour price changes, and rice yields were matched to broken basmati rice price changes.

Table 7: Two-way fixed-effects estimates of crop-yield and annual food-price fluctuation relationships

Parameter	Wheat-flour price model	Rice-price model
Crop-yield coefficient (per 100 kg/ha)	−1.384	−0.338
HC3 robust standard error	10.586	4.138
95% confidence interval	−25.795 to 23.027	−10.976 to 10.300
p-value	.899	.938
Province fixed effects	Included	Included

Year fixed effects	Included	Included
Observations	16	12
R^2	0.375	0.574

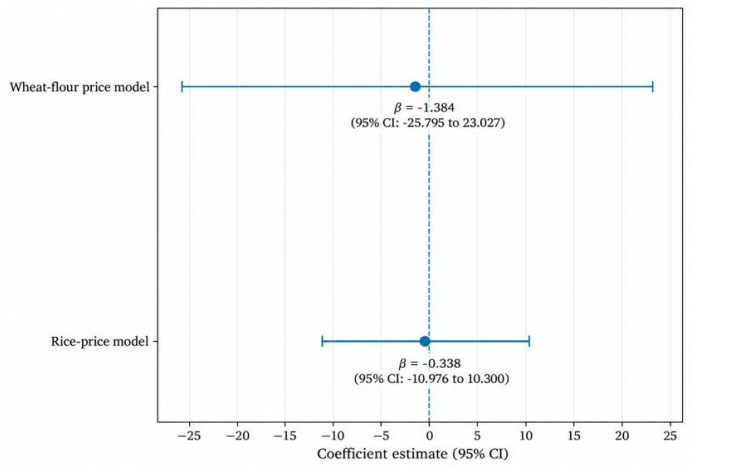


Figure 5: Two-way fixed-effects estimates of the associations between provincial crop yields and subsequent annual food-price fluctuations.

The wheat-flour price model yielded a negative estimated crop-yield coefficient (β = −1.384), indicating a negative association between wheat productivity and the magnitude of subsequent annual price movements. However, this coefficient was not statistically significant (p = .899), with a confidence interval ranging from −25.795 to 23.027.

The rice-price model also produced a negative, statistically non-significant coefficient (β = −0.338; 95% CI −10.976 to 10.300; p = .938).

The models recorded R^2 values of 0.375 and 0.574, respectively, reflecting the explanatory fit of the complete specifications, which included province and year fixed effects.

The results did not establish statistically reliable relationships between provincial crop productivity and subsequent annual food-price fluctuations. The wide confidence intervals indicated that the models lacked sufficient precision to distinguish small associations from potentially meaningful effects.

These findings further highlighted the limitations of relying solely on provincial agricultural productivity to explain retail-market movements, especially when commodity stocks, transport costs, procurement arrangements, and international market conditions were not directly incorporated into the empirical specifications.

Sensitivity Analysis and Coefficient Stability

A sensitivity analysis was conducted for the rice-yield model to assess the influence of Balochistan's unusually low rice-yield observation in 2022.

The primary model included all 20 province-year observations, while the restricted model excluded the Balochistan 2022 observation, reducing the sample to 19.

After exclusion, the estimated temperature coefficient shifted from +0.231 to −0.072 (p = .488). Similarly, the estimated rainfall coefficient changed from +0.009 to −0.019 (p = .424).

Neither variable was statistically significant in the restricted specification. However, the change in coefficient direction indicated sensitivity to the influential observation.

This result demonstrated the instability of the climate–rice-yield estimates in a small provincial panel. The observed changes did not establish that the Balochistan rice-yield decline resulted from a specific weather event, nor did they provide evidence of a stable inverse climate–productivity relationship.

The sensitivity findings therefore reinforced the need for cautious interpretation of the principal regression estimates.

Empirical Findings

The descriptive and econometric analyses yielded three principal findings.

First, substantial regional differences were observed in climatic conditions and agricultural productivity. Wheat yields increased across three provinces during 2019–2024, while Sindh experienced an overall decline. Rice yields exhibited greater instability, particularly in Balochistan during 2022.

Second, staple-food retail prices experienced considerable annual changes, with the magnitude and direction of movements differing across commodities, cities, and observation periods. Wheat-flour prices exhibited pronounced increases followed by substantial declines, whereas rice-price movements displayed a more heterogeneous geographical pattern.

Third, the fixed-effects estimates did not identify statistically significant relationships between annual climatic conditions and crop yields, nor between crop productivity and subsequent annual food-price fluctuations. The sensitivity analysis further demonstrated that the rice-yield estimates were influenced by an exceptional province-year observation.

Overall, the empirical findings established substantial provincial heterogeneity in agricultural and commodity-market outcomes. However, the available data did not support a statistically reliable estimate of a climate–yield–food-price transmission mechanism. These results should therefore be interpreted as exploratory economic evidence, with particular consideration given to the short panel periods, limited geographical units, annual climate aggregation, and selected urban retail-price observations.

Discussion

This study investigated the relationships among climate variability, agricultural productivity, and staple-food price fluctuations across the four provinces of Pakistan. The results indicated substantial geographical variation in temperature, precipitation, wheat and rice yields, and retail commodity-price movements. Wheat productivity increased in Punjab, Khyber Pakhtunkhwa, and Balochistan from 2019 to 2024, while Sindh experienced an overall decline. Rice productivity was more unstable, especially in Balochistan during 2022. Nevertheless, the two-way fixed-effects models did not reveal statistically significant associations between annual climatic conditions and crop yields or between crop productivity and subsequent annual food-price fluctuations. These findings suggest that the provincial panel demonstrates regional heterogeneity but does not establish a robust climate–agriculture–price transmission mechanism.

The observed geographical differences align with economic research highlighting the heterogeneous effects of climatic conditions across production environments. Dell et al. (2014) demonstrated that weather-related economic outcomes depend on geographical characteristics, baseline climatic conditions, and sectoral structures. Their review also underscored the value of panel-data approaches for analyzing economic responses to weather variation. The present findings similarly indicate that climatic exposure and agricultural performance vary considerably among Pakistan's provinces. However, variations in provincial productivity cannot be attributed solely to climatic conditions, as agricultural technology, irrigation availability, input utilization, and other time-varying production determinants were not fully incorporated into the empirical models.

The observed improvements in wheat yields in Punjab and Balochistan may be attributable to changes in production practices, agricultural inputs, environmental conditions, or other unobserved factors. Burke and Emerick (2016) showed that agricultural adaptation can mitigate climate-related productivity losses, although long-term adaptation in their United States study offset only a limited portion of the adverse effects of extreme heat. This evidence suggests that technological and managerial adaptation may affect agricultural performance but should not be assumed to eliminate climatic risks. Therefore, the provincial differences identified in Pakistan warrant further investigation using detailed data on irrigation systems, agricultural inputs, and farming practices.

The fixed-effects regression estimates did not yield statistically conclusive evidence that annual temperature or rainfall was associated with wheat or rice productivity. In the wheat-yield model, the estimated temperature coefficient was positive ($\beta = 0.196$), but not statistically significant ($p = .182$). The rainfall coefficient was also not statistically significant ($\beta = 0.011$; $p = .712$).

Comparable results were observed for rice, with temperature and rainfall coefficients of 0.231 (p = .741) and 0.009 (p = .951), respectively.

These estimates should not be interpreted as evidence of beneficial climatic effects on agricultural productivity. The confidence intervals encompassed both negative and positive values, indicating considerable uncertainty about the direction and magnitude of these relationships.

Deryng et al. (2014) demonstrated that extreme heat can negatively impact agricultural production, especially during critical crop-development stages. Their findings underscore a key limitation of annual climate indicators, which may obscure short-term climatic disturbances during planting, flowering, or grain development. Similarly, Deschênes and Greenstone (2007) highlighted the importance of econometric specification and weather variation in estimating agricultural responses to climatic conditions. Their research emphasized that estimated economic effects are sensitive to methodological choices and the specific outcomes analyzed.

In this study, province and year fixed effects controlled for persistent regional characteristics and common annual influences. However, the short observation period, limited number of provinces, and reliance on annual climatic averages constrained statistical precision. Therefore, the lack of statistically significant coefficients does not imply that climate variability lacks economic consequences for Pakistan's agricultural sector.

The significant reduction in Balochistan's rice yield during 2022 was among the most notable findings. Rice productivity decreased from 3,251 kg/ha in 2021 to 813 kg/ha in 2022, then recovered to 3,241 kg/ha in 2023. This substantial variation highlights the potential importance of exceptional province-year observations in analyses of agricultural productivity.

This reduction coincided with severe flooding and agricultural disruption in Pakistan. Abubakar et al. (2024) documented extensive agricultural damage from the 2022 floods using satellite-based data. Their research identified significant impacts on agricultural land and cropping activities, especially in Sindh. While these findings offer relevant contextual evidence of climate-related agricultural disruption, they do not establish the specific cause of the rice-yield decline observed in Balochistan.

The sensitivity analysis indicated that this exceptional observation affected the rice regression. Excluding Balochistan's 2022 rice yield altered the estimated temperature coefficient from +0.231 to −0.072 and the rainfall coefficient from +0.009 to −0.019. Neither estimate reached statistical significance.

From an econometric perspective, these changes in coefficients suggest limited stability in the estimated climate–rice-yield relationships. The findings underscore the need to consider influential observations and the economic consequences of extreme agricultural disturbances when assessing production risks.

The food-price analysis identified significant annual changes in wheat-flour and broken basmati rice prices across Lahore, Karachi, Peshawar, and Quetta. Wheat-flour prices increased substantially during several observation intervals, followed by notable reductions between January 2024 and January 2025. Rice-price movements were more heterogeneous across cities and years.

The largest average annual wheat-flour price fluctuation occurred in 2022, reaching 59.95 log-percentage points. Broken basmati rice also experienced its highest average fluctuation in 2022, at 42.98 log-percentage points. These results demonstrate commodity-specific differences in annual retail-price movements.

From an agricultural economics perspective, the relationship between crop productivity and retail prices depends on interactions among commodity supply, demand, inventories, and market adjustment mechanisms. Roberts and Schlenker (2013) demonstrated that agricultural commodity prices are influenced by supply and demand elasticities and the availability of stored commodities. Their research established that agricultural production shocks can affect market prices through changes in inventories and expectations about future supply.

The present findings support the need to consider these mechanisms when interpreting food-price movements. However, this study did not directly measure commodity stocks, market expectations, or supply and demand elasticities. As a result, the observed price changes cannot be attributed to specific market mechanisms.

Gilbert and Morgan (2010) emphasized the importance of distinguishing food-price levels from price volatility and demonstrated that agricultural commodity-price variability depends on broader market conditions. This distinction matters because the present analysis used absolute annual logarithmic price changes rather than conventional monthly price-volatility measures. Therefore, the findings indicate differences in the magnitude of annual price movements but do not provide estimates of within-year market volatility.

The fixed-effects estimates indicated negative but statistically non-significant relationships between agricultural productivity and subsequent annual price fluctuations. The estimated wheat-yield coefficient was −1.384 (p = .899), and the rice-yield coefficient was −0.338 (p = .938). Both estimates had wide confidence intervals, reflecting considerable uncertainty. Improvements in provincial agricultural productivity were associated with reduced retail-price fluctuations. However, they did not rule out an economically meaningful relationship.

The limited explanatory power may stem from short observation periods and the omission of key market determinants. Food prices are influenced by various economic factors, including transportation costs, trade arrangements, commodity inventories, procurement policies, and general inflation. Consequently, changes in provincial crop productivity may have limited immediate correspondence with price movements in selected urban markets.

Hertel et al. (2010) demonstrated that climate-induced changes in agricultural productivity can affect commodity prices, national economic welfare, and poverty outcomes through interconnected market mechanisms. Their findings highlighted that economic consequences depend on household characteristics, market participation, and the broader structure of agricultural economies.

In Pakistan, regional crop production and consumer markets are also interconnected, but this analysis did not explicitly estimate interprovincial commodity flows or market integration. Therefore, the estimated yield–price relationships should be interpreted as exploratory statistical associations rather than as measures of agricultural supply transmission or commodity-price elasticity.

The empirical findings have implications for agricultural risk management, commodity-market monitoring, and regional economic policy in Pakistan. Although the regression estimates were statistically inconclusive, the descriptive evidence revealed substantial geographical differences in agricultural productivity and significant fluctuations in staple-food retail prices.

First, the observed provincial differences highlight the importance of geographically differentiated agricultural planning. Agricultural policies designed around national averages may overlook regional differences in climatic conditions and constraints. Improved access to crop-specific weather information, irrigation infrastructure, and agricultural extension services could support more informed production decisions.

Second, the pronounced rice-yield reduction in Balochistan in 2022 highlights the importance of monitoring major agricultural production disruptions. Strengthening crop-loss assessment systems, agricultural risk information, and disaster-response planning could enhance the information available to producers and policymakers.

Third, the substantial annual fluctuations in wheat-flour and rice prices underscore the importance of transparent commodity-market monitoring. Regular publication of regional wholesale and retail prices, commodity stocks, and interregional supply information could improve the evidence base for assessing market instability and planning food-security interventions.

Wheeler and von Braun (2013) emphasized that climatic changes influence food security through agricultural production, market access, and the stability of food systems. Their findings support the importance of jointly considering agricultural productivity and food-market conditions when developing climate-responsive economic policies.

However, this study did not evaluate specific agricultural or market interventions. Therefore, these recommendations represent policy priorities informed by the broader literature and descriptive findings, rather than interventions whose effectiveness was established by the reported regressions.

The principal methodological contribution of this study was the integration of provincial climate, agricultural productivity, and staple-food price observations within a unified empirical framework. The application of two-way fixed-effects models enabled the analysis to account for persistent provincial differences and common annual influences.

Nevertheless, several limitations restrict the economic interpretation of the results.

The climate–yield models included only 24 wheat and 20 rice province-year observations, while the corresponding price models comprised 16 and 12 observations, respectively. These limited samples reduced statistical power and the precision of coefficient estimates.

Cameron et al. (2008) demonstrated that conventional statistical inference can be unreliable when regression errors exhibit within-group dependence and the number of clusters is small. With only four provinces, this concern was particularly relevant to the present analysis. Although HC3 robust standard errors were employed, they did not fully address serial correlation or the challenges associated with inference from very few geographical units.

Additional limitations included the aggregation of climate data to annual values, the use of selected urban retail markets, and the exclusion of several relevant economic variables. These factors prevented the models from isolating the separate contributions of climatic disturbances, agricultural inputs, government policies, and market conditions.

Future research should utilize longer provincial or district-level panels that incorporate growing-season temperature, extreme rainfall, irrigation availability, input prices, cultivated area, and agricultural technology. Higher-frequency commodity-price observations would also enable more rigorous estimation of price volatility and regional market transmission.

Such improvements would enable future research to evaluate more detailed economic mechanisms and distinguish agricultural supply shocks from broader commodity-market disturbances.

The findings demonstrated significant provincial heterogeneity in climatic conditions, agricultural productivity, and staple-food price movements in Pakistan. Wheat yields followed distinct regional trajectories, rice productivity showed pronounced instability in Balochistan during 2022, and retail food prices underwent substantial annual adjustments. The fixed-effects estimates did not yield statistically conclusive evidence of relationships between annual climatic indicators and crop yields or between crop productivity and subsequent annual food-price fluctuations.

The results therefore provide exploratory evidence for agricultural and environmental economics but do not establish a causal climate–yield–price relationship. The principal implication is the importance of integrating agricultural, climatic, and commodity-market information while acknowledging the limitations of small provincial panels and aggregated observations.

Enhanced agricultural data systems, regionally targeted adaptation strategies, and transparent food-market information can provide a stronger foundation for climate-responsive economic policy and future empirical research in Pakistan.

Conclusion

This study investigated the relationships among climate variability, agricultural productivity, and staple-food price fluctuations across Pakistan's four provinces using a longitudinal panel-data framework. The results indicated pronounced regional differences in temperature, precipitation, wheat and rice yields, and retail commodity-price movements. Wheat productivity increased in Punjab, Khyber Pakhtunkhwa, and Balochistan from 2019 to 2024, whereas Sindh experienced an overall decline. Rice yields demonstrated greater instability, especially in Balochistan during 2022.

The two-way fixed-effects regression models did not detect statistically significant associations between annual climatic conditions and crop yields. Likewise, the relationships between agricultural productivity and subsequent staple-food price fluctuations remained statistically inconclusive. These findings indicate limitations in statistical precision rather than providing evidence that climate variability and agricultural supply lack economic consequences.

Overall, this study offers exploratory provincial evidence underscoring the significance of regional agricultural conditions and commodity-market dynamics for Pakistan's agricultural economy.

The findings underscore the need to strengthen climate-responsive agricultural planning, irrigation infrastructure, and agricultural risk management. Provincial governments are advised to prioritize enhanced climate-monitoring systems, efficient water-resource utilization, and agricultural extension services to support productivity and resilience.

Furthermore, transparent commodity-market information, improved storage infrastructure, and systematic monitoring of regional food prices could facilitate more informed agricultural and food-security policies. Enhanced coordination between agricultural institutions and market authorities may also strengthen responses to production disruptions and price instability.

Future research should incorporate longer provincial panels, growing-season climatic indicators, agricultural input costs, and higher-frequency food-price observations to generate more precise econometric evidence. These enhancements would reinforce the empirical foundation for agricultural investment, commodity-market stabilization, and sustainable economic development in Pakistan.

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