



Disentangling Climate and Non-Climate Determinants of Cereal Productivity: Evidence from India's Arid and Semi-Arid Regions

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Abstract: Assessing the impact of annual climate variability on cereal crop yields is crucial for addressing food security challenges in countries with arid and semi-arid regions. Using district/state panel data for India (1998-2021), this study estimates fixed-effects, fully modified OLS (FMOLS), and dynamic OLS (DOLS) models and applies Pedroni and Kao tests to establish long-run relationships between climate, agricultural inputs, and yields of wheat, rice, and millets (bajra, jowar, and other small millets). Cointegration results indicate a stable long-run association among variables. Across crops, cultivated area is a strong, positive correlate of productivity. For wheat, higher mean maximum temperature and greater rainfall (when excessive) reduce yields, while agricultural credit supports productivity; mean minimum temperature shows limited effects. For rice, area remains strongly positive, temperature effects are generally negative but imprecisely estimated, and aridity substantially depresses yields. For millets, maximum (and in some models minimum) temperature lowers yields, whereas rainfall, fertiliser, and agricultural credit are yield-enhancing. Taken together, the results show that models omitting input and financial controls risk overstating climate impacts; including credit and fertiliser management meaningfully attenuates climate-only effects. Policy implications include targeting heat-risk management and stress-tolerant varieties where temperature pressures are acute, improving water management in rainfall-sensitive systems, strengthening access to well-structured agricultural credit, and promoting fertiliser stewardship and place-specific crop strategies to bolster resilience and sustain cereal production under a changing climate.

Key words: Climate change, aridity index, arid and semi-arid regions, crop yield, food security, India.

Climate change poses significant challenges to agriculture, particularly in developing nations, where reliance on agriculture for livelihoods, limited resources, and technological constraints amplify vulnerabilities (Ahsan *et al.*, 2020; FAO, 2012). Fluctuations in temperature, precipitation, and the occurrence

of extreme weather events have adversely affected agricultural output, particularly in Southeast Asia and tropical nations, which face significant food security threats (Chandio *et al.*, 2020; Trinh *et al.*, 2021). Although rich countries may experience certain benefits from climate change due to technical progress, the agricultural sectors in developing nations are particularly vulnerable to climate-related disturbances (Abbas, 2022; IPCC, 2022).

Agriculture in arid and semi-arid regions faces significant challenges from climate variability, which directly threatens food security in these vulnerable areas (IPCC, 2022). India, with its vast agricultural landscape, includes arid zones covering 15.8% of the country's geographical area and semi-arid zones encompassing 37% (Kalsi, 2007). These regions, spanning 13 states, are critical for the cultivation of staple cereal crops such as wheat, rice, and millets (including bajra, jowar, and other small millets). These dryland districts face persistent exposure to heat and rainfall variability, making them a priority setting for estimating crop-specific climate effects that directly inform food-security and adaptation policy (Anh *et al.*, 2023; Chandio *et al.*, 2020).

This study examines the impact of annual climate fluctuations on the yields of major cereal crops in arid and semi-arid regions of India from 1998 to 2021. This research utilises the Aridity Index (AI) established by UNEP to classify locations according to climate aridity, facilitating a targeted examination of agricultural results in these areas. Climatic variations, notably increasing maximum temperatures and erratic precipitation patterns, directly influence agricultural growth cycles and indirectly intensify issues such as pest infestations, weed proliferation, and soil degradation (Adams *et al.*, 1998; Agovino *et al.*, 2019). Climate change, by its significant impact on agricultural productivity, is inextricably connected to all Sustainable Development Goals (SDGs). Its effects are particularly significant for essential Sustainable Development Goals, including the eradication of poverty (SDG 1), the elimination of hunger (SDG 2), the promotion of good health and well-being (SDG 3), and the development of gender equality (SDG 5) (FAO, 2012). These variables collectively threaten the yield of key food crops, with significant

consequences for food and nutritional security (Godfray *et al.*, 2010).

This research, unlike prior studies, includes essential variables such as fertiliser application and agricultural financing, which are crucial in alleviating the negative effects of climate variability (Rehman *et al.*, 2019). The application of fertilisers can mitigate crop susceptibility to fluctuations in temperature and precipitation, whereas agricultural financing enables farmers to implement adaptive technologies and practices (Grigorieva *et al.*, 2023). Disregarding these elements, as often observed in analogous studies, jeopardises the accuracy of assessing the adverse impacts of climate variability on agricultural production.

This study quantifies the impact of annual climate variability on cereal productivity in India's arid and semi-arid districts from 1998 to 2021, while explicitly accounting for key non-climatic factors that influence climate responses. This analysis focuses on wheat, rice, and millets (bajra, jowar, and small millets), which are central to food and nutritional security and differ substantially in climate sensitivity and adaptation potential across India's dry regions. This study utilises the fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS), and fixed effect models.

Study Area Description

This study first classifies the regions based on the aridity index. After selecting the arid and semi-arid districts, the study examines the impact of climatic factors on major crops while controlling for fertilizer use and agricultural credit.

Aridity index: Firstly, the study calculated the aridity index for India using the datasets provided by TerraClimate. TerraClimate datasets are monthly and time-varying from 1958 to the current year at a 0.5-degree spatial resolution. It provides datasets on potential evapotranspiration and precipitation on a yearly basis from 1958-2022 (Abatzoglou *et al.*, 2018). The potential evapotranspiration used in this study is derived from the TerraClimate dataset, which applies the ASCE Penman-Monteith method. This method is widely accepted for estimating evapotranspiration based on key climatic variables, including solar radiation, temperature, humidity, and wind

Table 1. List of districts (grouped by States) selected for study

State	Arid districts	Semi-arid districts
Rajasthan	Barmer, Bikaner, Churu, Ganganagar, Hanumangarh, Jaisalmer, Jalore, Jhunjhunu, Jodhpur, Karauli, Nagaur, Sikar	Ajmer, Alwar, Banswara, Baran, Bharatpur, Bundi, Chittorgarh, Dausa, Dholpur, Dungarpur, Jaipur, Kota, Pali, Pratapgarh, Rajsamand, Sawai Madhopur, sirohi, Tonk, Udaipur
Gujarat	Kutch	Ahmedabad, Amreli, Banas Kantha, Bharuch, Bhavnagar, Botad, Dawarka, Gandhinagar, Gir Somnath, Jamnagar, Junagadh, Mehsana, Morbi, Panch Mahal, Rajkot, Sabar Kantha, Surendranagar
Haryana	Sirsa	Ambala, Bhiwani, Charkhi-Dadri, Faridabad, Fatehabad, Gurgaon, Hisar, Jhajjar, Jind, Kaithal, Karnal, Kurukshetra, Mahendragarh, Panipat, Rewari, Rohtak, Sonapat
Punjab	Firozpur, Fazika	Amritsar, Barnala, Bathinda, Fatehgarh Sahib, Jalandhar, Kapurthala, Ludhiana, Mansa, Moga, Muktsar Sahib, Patiala, Sangrur, Taran-Taran
Karnataka	-	Bagalkote, Bangalore, Belgaum, Bellary, Bijapur, Chamarajanagar, Chikmagalur, chikkaballapur, Chitradurga, Davangere, Dharwad, Gadag, Gulbarga, Hassan, Haveri, Kodagu, Kolar, Koppal, Mandya, Mysore, Raichur, Ramanagara, Shimoga, Tumkur, yadagir
Maharashtra	-	Ahmednagar, Akola, Amravati, Aurangabad, Beed, Buldhana, Dhule, Jalgaon, Jalna, Kolhapur, Nashik, Nandubur, Osmanabad, Parbhani, Pune, Sangli, Satara, Solapur, Washim
Andhra Pradesh	-	Anantapur, Chittoor, Guntur, Kurnool, Nellore, Prakasam, YSR (Kadapa)
Madhya Pradesh	-	Alirajpur, Barwani, Burhanpur, Dhar, Jhabua, Khargone, Khandwa
Tamil Nadu	-	Coimbatore, Dindiguli, Erode, Karur, Madurai, Namakkal, Ramanathapuram, Salem, Theni, Tiruchirappalli, Tiruppur, Virudhunagar
Uttar Pradesh	-	Agra, Aligarh, Bagpat, Banda, Etah, Etawah, Firozabad, Gautam Budhha Nagar, Kanpur, Mahoba, manpuri

speed. The ASCE Penman-Monteith equation ensures a standardized approach for calculating potential evapotranspiration and is considered the most accurate model for assessing water demand in different climatic conditions. By using this method, the study ensures a robust estimation of potential evapotranspiration, which forms a crucial component of the aridity index calculation used in this study. This study calculated the aridity index using the FAO-UNEP's methodology of calculation of the aridity index (UNEP, 1992).

$AI = \text{Precipitation} / \text{Potential Evapotranspiration}$

By using this method, this study identified the arid and semi-arid regions of India for our study. The identified districts are presented in Table 1.

Figure 1 illustrates the percentage share of cereal, wheat, and rice production in the states during 2021-22. Uttar Pradesh dominates in overall cereal production, contributing the largest share, particularly in wheat

and rice. Punjab and Madhya Pradesh also play significant roles, with Punjab being a major wheat producer and Madhya Pradesh contributing substantially to both wheat and cereal production. Rajasthan, with its arid climate, has a notable share of cereal production, emphasizing its focus on climate-resilient crops. States like Andhra Pradesh and Telangana exhibit substantial rice production shares due to their favourable semi-arid conditions and irrigation infrastructure. Karnataka, Tamil Nadu, and Maharashtra have a more balanced contribution to cereal production, supported by their diverse cropping systems.

This spatial variability in production highlights the diversity in cropping patterns across arid and semi-arid regions. While northern states like Punjab and Uttar Pradesh focus heavily on wheat and rice, southern states emphasize rice and coarse cereals like millets. Understanding this regional diversity is crucial for tailoring climate adaptation strategies and ensuring sustainable agricultural

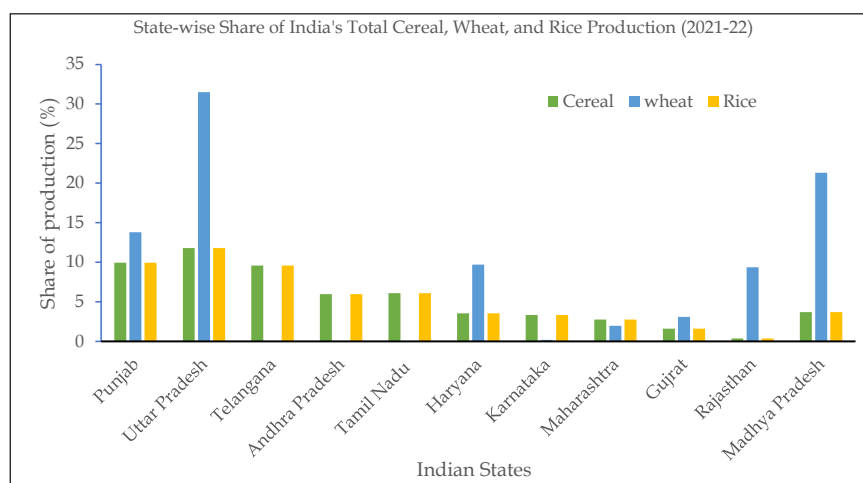


Fig. 1. Percentage share of production (cereals, wheat, and rice) in study area states; Source: compiled based on data from RBI (RBI: Reserve Bank of India, Handbook of Statistics on Indian States, 2021-22).

development in the face of climate variability (Sahoo *et al.*, 2024). The selected states provide a comprehensive representation of India's cereal production landscape, making them ideal for studying the impacts of climate variability on agricultural yields.

Impact of Climatic Factors on Agricultural Production

Climate change is seriously impacting many aspects of agricultural production. However, the impact may vary by region and crops. Various studies highlighted the impact of climatic factors on agricultural production (Chandio *et al.*, 2022; Deressa *et al.*, 2009; Gornall *et al.*, 2010; Kumar *et al.*, 2024; Prasanna, 2014) cereal production, and yield using the country-level time series data of 1965–2015. With the autoregressive distributed lag (ARDL, but there is a significant divergence in results. One study by (Baig *et al.*, 2023) highlights the impact of climatological factors such as precipitation patterns and carbon emissions; the results suggest that these factors considerably contribute to the increase in wheat production in India. Chandio *et al.* (2020) mentioned the agriculture sector are globally impacted by climate change. This study aims to examine and explore the impact of global climate change on agricultural output in China over the period of 1982–2014.

Design/methodology/approach: Different unit root tests including augmented Dickey–Fuller, Phillips–Perron and Kwiatkowski, Phillips, Schmidt and Shin are used to check the order of integration among the study variables.

The autoregressive distributed lag (ARDL) investigated the impact of meteorological factors on agricultural output. The study reveals that temperature and rainfall have a significant negative impact on agricultural output in the long run. Another study by (Chung *et al.*, 2015) Central Highland of Vietnam. The Ordinary Least Square method was applied to establish the relationships between climatic factors and rice yields in two different growing seasons. The climatic factors are average maximum temperature (avemaxT examines the impact of climatic factors on rice yield in Vietnam in the Winter-Spring and Summer-Autumn seasons. The results suggest that average rainfall positively contributes to rice yield, average maximum temperature negatively contributes to rice yield in both seasons, and minimum temperature has a positive impact on rice yield in WS seasons.

Worldwide arid and semi-arid regions are disproportionately impacted by climate change. One study by (Gunawat *et al.*, 2022) suggests that wheat yield will decrease in the near and far future due to climate change in semi-arid regions. One study from Africa highlighted that rainfall positively contributes to cereal production. However, the impact of temperature was typically unfavorable (Pickson *et al.*, 2020). Another study from dry regions of the world (Eastern Africa), using the data from 1990–2018 and DOLS and FMOLS models, highlighted that average temperature negatively impacts cereal production in the short-run and long-run. Further, the results suggest that cultivated areas and rural populations negatively impact

Table 2. Variables description

Variables	Description	Source
Wheat yield	t ha ⁻¹ (tons hectare ⁻¹)	Ministry of Agriculture and Farmer's Welfare (MOA & FW)
Rice yield	t ha ⁻¹	
Millet yield	t ha ⁻¹	
Wheat cultivated area	Ha (hectare)	
Rice cultivated area	Ha	
Millet cultivated area	Ha	
Agricultural credit (AC)	SCBs credit: Agriculture (Rs. million)	CMIE Prowess
Fertilizer used in wheat production (Wferti)	Total Consumption (NPK) in tons	ICRISAT
Fertilizer used in rice production (Rferti)	Total Consumption (NPK) in tons	
Fertilizer used in millet production (Mferti)	Total Consumption (NPK) in tons	
Average maximum temperature (MaxT)	Degree Celsius	NASA Climate Portal
Average minimum temperature (MinT)	Degree Celsius	
Average precipitation (AP)	Mm	

cereal production in the concerned regions. Another study from the semi-arid state of India, Punjab, investigated the impact of seasonal climatic factors and the area under production for Wheat and Rice crops; using the FMOLS, DOLS, and PMG models, the study suggests that minimum temperatures positively impact the wheat and rice, while maximum temperatures have a negative impact. Moreover, rainfall has a significant adverse impact on wheat yield (Bhardwaj *et al.*, 2022).

Data and Variables

This study employed secondary data sources to examine and present the effects of climate change on arid and semi-arid regions of India. Longitudinal panel datasets at the district level for production and yield have been obtained from the Ministry of Agriculture and Farmer's Welfare (MOA & FW, GoI), while climatic data have been sourced from the NASA Climate Portal. Monthly series for maximum temperature, minimum temperature were aggregated to annual measures by computing yearly averages. The study used the four-year moving average for fertilizer used data as it is available till 2017 from ICRISAT. Moreover, some new districts were formed during the period of study (1998-2021), such districts are merged in the parental districts. This study focused on the principal cereal crops in India, specifically wheat, rice, and millets among the 22 primary crops cultivated in the country. It is essential to comprehend the effects of climate change on these crops individually to ascertain the extent to which climate influences climate-

resilient compared to non-resilient crops in arid and semi-arid parts of India, as climate change affects grain production and food security. This study examines arid and semi-arid districts in India. Table 2 provides a detailed account of the variables, encompassing their symbols, units, and data sources. Research reveals that minimum and maximum temperatures, along with precipitation, are the primary factors of crop yield. The analysis investigates the influence of mean minimum temperature, mean maximum temperature, and mean precipitation on principal cereal crops in arid and semi-arid regions of India.

Materials and Methods

Panel unit root test

To provide unbiased outcomes, it is crucial to verify the stationarity of the variables prior to assessing the influence of climate change on the primary crops of arid semi-arid regions of India. The estimate procedure used the original unit-root tests developed by cross-section augmented Dickey-Fuller (CADF) and Im, Pesaran, and Shin (IPS) (Blackburne and Frank, 2007). The assumptions behind these tests are that each cross-sectional data series in the investigation is statistically autonomous.

The equation representing the CADF is as follow:

$$\Delta y_{it} = \gamma_i y_{i,t-1} + \sum_{n=1}^{r_i} \Delta y_{i,t-1} + \rho_{m,i} \delta_{m,t} + \mu_{i,t} \quad \dots 1$$

In this context, y represents the variable being examined for a unit root. In this equation, Δ indicates the differentiated form of the variable, being less than zero indicates the absence of a unit root, contradicting the null hypothesis of > 0 . The equation for IPS is

$$\Delta y_{it} = (1 - r_i)\rho_i + r_i\Delta y_{i,t-1} + \mu_{i,t} \quad \dots 2$$

The null hypothesis (H0) posits that the panel series contains a unit root, i.e., that the series is non-stationary. The alternative hypothesis (H1) posits that the series is stationary; rejecting H0 therefore provides evidence against a unit root and in favor of stationarity.

Cointegration test

To examine the presence of long-term associations among variables, panel cointegration techniques have been employed as a critical step in the analysis. After confirming the stationarity of the panel data through unit root tests, the Pedroni residual cointegration test (Pedroni, 1999; Pedroni, 2004) was applied to assess whether the variables exhibit cointegration. The Pedroni test evaluates the null hypothesis (H_0) of no cointegration against the alternative hypothesis (H_1) that assumes all panels are cointegrated. This approach accounts for cross-sectional dependency and heterogeneity, making it well-suited for diverse panel datasets.

In addition to the Pedroni test, the Kao residual cointegration test (Kao, 1999) was utilized as an additional method to validate the presence of cointegration. The Kao test operates under the null hypothesis (H_0) of no cointegration and an alternative hypothesis (H_1) that assumes all panels demonstrate cointegration. By accommodating heterogeneity across panels, this method strengthens the robustness of the analysis. Employing both the Pedroni and Kao tests ensures comprehensive validation of long-term equilibrium relationships among the variables, enabling reliable subsequent modeling and interpretation of results. These methodological choices align with best practices in panel data econometrics, ensuring the robustness and reliability of the findings.

Models used in the study

Panel cointegration tests exclusively ascertain the long-term relationship among the variables. It cannot indicate the direction or signal for

the coefficients of the variables employed in the investigation. Various panel models are accessible: pooled ordinary least squares (POLS), generalised method of moments (GMM), fixed effects, random effects, pooled mean group (PMG), fully modified ordinary least squares (FMOLS), and dynamic ordinary least squares (DOLS), which can elucidate the direction of the coefficients of the variables examined in the study. examined the properties of OLS in the context of panel data and demonstrated that OLS exhibits inconsistent characteristics when applied to such data. Moreover, the study also employs the fixed effect model; these results using multiple models show the robustness of the study.

Fixed-effects panel model are estimated to identify within-district relationships between weather, management, and cereal yields. For district i in agricultural year t ,

$$\ln y_{it} = \alpha_i + \beta' X_{it} + \gamma' Z_{it} + u_{it} \quad \dots 3$$

and, to allow input-weather and finance-input complementarities,

$$\ln y_{it} = \alpha_i + \beta' X_{it} + \gamma' Z_{it} + u_{it} \quad \dots 4$$

Here is the is the yield of crop (wheat, rice, millets), expressed in natural logarithms. Yield data were originally recorded in tonnes per hectare ($t\ ha^{-1}$). For consistency across the estimation sample, yield was converted to hectograms per hectare ($hg\ ha^{-1}$) prior to regression analysis, where $1\ t\ ha^{-1} = 10,000\ t\ ha^{-1}$ exactly. Descriptive statistics (Table 3) are reported in the original unit of $t\ ha^{-1}$ for ease of interpretation, while all regression results are estimated using the natural log of yield (wheat, rice, millets) in $hg\ ha^{-1}$. Because, many district-year yield values in $t\ ha^{-1}$ are well below one, particularly for rice and in lower-productivity districts, which compresses the natural-log series close to zero and, in some cases, produces negative values. Rescaling to a larger unit avoids this compression while leaving the estimated elasticities unaffected, since a proportional rescaling of the dependent variable shifts only the regression intercept and not the slope coefficients. are district fixed effects that absorb time-invariant heterogeneity, soil texture, topography, long-run infrastructure, and cultural practices- thereby mitigating omitted-variable bias. collects the climate variables (growing-season mean maximum and minimum temperature

and average precipitation) contains non-climate controls, including crop-specific area of the crop, fertiliser used in that particular crop, and agricultural credit.

All continuous variables are log-transformed, so coefficients can be interpreted as elasticities or semi-elasticities. Models are estimated separately by crop using ordinary least squares on the within transformation, with heteroskedasticity-robust standard errors clustered by district to accommodate serial correlation within panels. This specification delivers mean-based, distribution-agnostic elasticities for each crop and provides a transparent baseline for interpreting the interaction effects of precipitation and credit with fertiliser in arid and semi-arid settings.

DOLS and FMOLS strategies are superior because of their greater performance in a limited sample, addressing autocorrelation and endogeneity concerns by incorporating lags. This study employs FMOLS, DOLS. The functional representations of DOLS, FMOLS tests are delineated in Equations 5 and 6.

The equation for FMOLS is the following:

$$\hat{\beta}_{FMOLS} = N^{-1} \sum_{i=1}^N \left[\left(\sum_{t=1}^T (Z_{i,t} - \bar{Z}_i)^2 \right)^{-1} \left(\sum_{t=1}^T (Z_{i,t} - \bar{Z}_i)^2 \bar{A} \bar{A}_{i,t} - \bar{T} \gamma_i \right) \right] \quad \dots 5$$

The DOLS equation:

$$y_{it} = X'_{it-1} \gamma + \sum_{i=-p}^p \phi_{ij} \Delta X_{it+j} + \omega_{it} \quad \dots 6$$

In all specifications, inference is conducted to account for temporal dependence by

clustering heteroskedasticity-robust standard errors by district, which allows for within-district serial correlation. Since climate shocks may be spatially correlated between adjacent districts (forming cross-sectional dependence), we also measure robustness by comparing outcomes between multiple estimators (FE, FMOLS, and DOLS) and by interpreting coefficients in a conservative way, where not all approaches yield the same significant result. In areas where cross-sectional dependence is strong, long-run estimates should be regarded as average relationships between arid and semi-arid districts, rather than local causal effects.

Results and Discussions

The results are reported in three steps in this section. Firstly, summarizing the distribution of yields, inputs, and climate variables in arid and semi-arid districts. Second, we provide unit-root and cointegration tests that would support long-run modeling. Third, we discuss the estimated yield elasticities of FE, FMOLS, and DOLS crop-by-crop, focusing on the magnitude of the coefficients and their implications for climate-risk management and input/credit policy in dryland systems.

The summary statistics of variables are reported in Table 3. Wheat yield has a broad range from 0.52 to 7.46 t ha⁻¹, with a high standard deviation (1.38), indicating significant variability across observations. Wheat area also shows considerable variability, ranging from 1 to 478000 hectares, with a mean of 94015.99 hectares. Fertilizer usage in wheat data is

Table 3. Descriptive statistics of variables used in the model

Variable	Obs	Mean	Std. Dev.	Min	Max
Wheat Area	2,876	94015.99	88780.48	1	478000
Wheat Yield	2,871	2.78	1.38	0.052	7.46
Wferti	2,297	21987.74	15873.9	266.7	95599.14
Rice Area	2,872	58218.91	77272.03	0.25	406100
Rice Yield	2,864	2.45	1.17	0.002	6.32
Rferti	2,297	33295.72	24037.62	403.86	144764.4
Millet Area	3,101	85050.81	125504.1	1	1021947
Millet Yield	3075	1.24	0.74	0.001	6.97
Mferti	2,297	4816.362	3477.14	58.42	20940.76
Agri_credit	3,119	13829.92	19001.79	16.5	227529
MmaxT	3,360	44.6753	2.978802	34.86	50.55
MminT	3,360	6.864235	4.508168	-1.64	20.63
AP	3,360	720.8875	420.4136	21.09	4503.52

Table 4. Correlation matrix for wheat

Variables	lnWheat_Yield	lnWheat_Area	lnAC	lnWferti	lnMaxT	lnMinT	lnAP
lnWheat_Yield	1.000						
lnWheat_Area	-0.138	1.000					
lnAC	0.224	-0.090	1.000				
lnWferti	0.261	0.221	0.409	1.000			
lnMaxT	0.053	0.793	-0.171	0.140	1.000		
lnMinT	-0.313	-0.523	-0.064	-0.167	-0.632	1.000	
lAP	-0.012	-0.343	0.246	0.022	-0.525	0.345	1.000

available for 2297 observations, with a mean of 21987.74 tons.

Rice yield averages 2.45 t ha⁻¹, ranging from 0.002 to 6.32 t ha⁻¹, reflecting diverse productivity levels. The area under rice cultivation shows considerable variation, with an average of 58218.91 ha and a maximum of 406100 ha. Fertilizer usage for rice averages 33295.72 tons, with notable differences across regions. Agricultural credit also varies widely, suggesting disparities in financial support. Climatic variables, including maximum temperature, minimum temperature, and annual average precipitation, exhibit broad ranges, emphasizing the diverse environmental conditions influencing rice production.

Millet yield averages 1.24 t ha⁻¹, with high variability (standard deviation:0.7361) and a maximum of 6.97 t ha⁻¹. The area under millet cultivation shows significant variability, with an average of 85050.81 hectares and a maximum of over 1021947 hectares, reflecting regional disparities. Fertilizer usage for millet averages 4,816.36 tons. Agricultural credit also displays large variability, with a mean of 13,829.92 Rs. million, highlighting disparities in financial support across regions. These statistics indicate considerable diversity in millet production inputs and outputs, emphasizing the importance of region-specific strategies to enhance productivity.

The correlation analysis (Table 4) highlights that wheat yield benefits from agricultural credit and fertilizer usage, but it is negatively impacted by higher minimum temperatures, suggesting climate sensitivity. While maximum temperature shows a weak positive correlation with yield, minimum temperature and precipitation constraints significantly influence cultivation patterns. The negligible effect of precipitation on yield points to the importance of irrigation. Additionally, the expansion of wheat area correlates with higher maximum temperatures, suggesting that farmers' adaptive strategies are at play. These findings underscore the importance of targeted interventions, such as improving access to credit and enhancing fertilizer use, to mitigate the climate impacts on wheat production. This positive raw correlation should not be read as a causal effect: in the multivariate long-run models reported in Table 9, the fertiliser coefficient for wheat turns negative and significant once cultivated area, temperature, precipitation, and agricultural credit are controlled for. This sign reversal is consistent with confounding, fertiliser use is correlated with unobserved factors such as irrigation access and credit availability that independently raise yields, rather than a genuine yield-reducing effect of fertiliser at the bivariate level; it is discussed further alongside the Table 9 results.

Table 5. Correlation matrix for rice

Variables	lnRice_Yield	lnRice_Area	lnAC	lnRferti	lnMaxT	lnMinT	lnAP
lnRice_Yield	1.000						
lnRice_Area	0.869	1.000					
lnAC	0.037	0.091	1.000				
lnRferti	0.436	0.504	0.378	1.000			
lnMaxT	-0.063	-0.078	-0.159	0.037	1.000		
lnMinT	-0.013	-0.024	-0.057	-0.040	-0.610	1.000	
lnAP	0.352	0.401	0.274	0.312	-0.453	0.301	1.000

Table 6. Correlation matrix for millet

Variables	lnMillet_Yield	lnMillet_Area	lnAC	lnMferti	lnMaxT	lnMinT	lnAP
lnMillet_Yield	1.000						
lnMillet_Area	0.795	1.000					
lnAC	0.056	-0.106	1.000				
lnMferti	-0.037	-0.264	0.378	1.000			
lnMaxT	-0.105	-0.001	-0.159	0.037	1.000		
lnMinT	0.219	0.221	-0.057	-0.040	-0.610	1.000	
lnAP	0.061	-0.144	0.274	0.312	-0.453	0.301	1.000

The correlation matrix shows that rice yield strongly correlates with the area under cultivation (lnRice_Area, 0.869) and moderately with fertilizer use (lnRferti, 0.436) and annual precipitation (lnAP, 0.352), highlighting their importance in productivity (presented in table 5). Agricultural credit has a weak influence, while maximum and minimum temperatures show negligible direct effects on yield. The strong negative correlation between lnMaxT and lnMinT (-0.610) reflects their inverse relationship. These findings highlight the importance of inputs such as land, fertilizer, and rainfall in rice production.

The correlation matrix shows (Table 6) that millet yield has a strong positive correlation with millet area (lnMillet_Area, 0.795) and a weak positive correlation with annual precipitation (lnAP, 0.061). Fertilizer usage and maximum temperature have weak negative correlations with millet yield, while minimum temperature has a moderate positive correlation (0.219). These relationships highlight the importance of

cultivation area and minimum temperature for millet yield, while other factors show limited direct influence.

The results of the CADF and IM-Pesaran unit root tests indicate that all variables wheat yield, wheat area, agricultural credit, fertilizer use, and climatic factors (maximum and minimum temperatures, and precipitation), are stationary at the 1% significance level under both intercept-only and intercept-with-trend conditions. This suggests that the data series do not contain unit roots, ensuring stable long-term relationships and reliability for econometric modelling. Results are similar for the rice and millet models: rice yield, rice area, rice fertilizer use, millet yield, millet area, and millet fertilizer use were all stationary at the 1% level under both specifications. The shared control variables such as agricultural credit and the climatic factors of maximum temperature, minimum temperature, and precipitation, were likewise consistently stationary across all three crop models, reinforcing the reliability of these

Table 7. Panel unit root tests

Variables	CADF		IM-Pesaran test	
	Intercept	Intercept and trend	Intercept	Intercept and trend
lnWheat_Yield	-21.7006***	-32.2403***	-1.5860***	-1.8344***
lnWheat_Area	-26.7310***	-27.5666***	-2.3538***	-2.7879***
lnWferti	-3.1286***	-3.9194***	-1.6724***	-2.1886***
lnRice_Yield	-28.7599***	-35.7821***	-2.4615***	-3.0052***
lnRice_Area	-13.2501***	-18.2536***	-1.9060***	-2.5634***
lnRferti	-3.1286***	-3.9194***	-2.3128***	-2.8336***
lnMillet_Yield	-29.6504***	-42.1575***	-2.8818***	-3.1366***
lnMillet_Area	-14.1766***	-23.0047***	-1.9598***	-2.6835***
lnAC	-8.6094***	-8.0803***	-1.8385***	-2.2362***
lnMferti	-3.1286***	-3.9194***	-1.6724***	-2.1886***
lnMaxT	-65.4560***	-55.8068***	-3.2584***	-3.3383***
lnMinT	-44.4603***	-40.8045***	-3.0134***	-3.2085***
lnAP	-37.9969***	-58.4465***	-2.8942***	-3.3513***

Table 8. Panel cointegration test for wheat, rice and millet

Tests	Wheat crop		Rice crop		Millet crop	
	Statistics	p-value	Statistics	p-value	Statistics	p-value
Pedroni cointegration test						
Modified Phillips-Perron t	4.8150	0.0000	1.3329	0.0913	0.5507	0.2909
Phillips-Perron t	-3.0185	0.0013	-12.6745	0.0000	-13.9387	0.0000
Augmented Dickey-Fuller t	-3.4527	0.0003	-12.9105	0.0000	-15.1251	0.0000
Kao test						
Augmented Dickey-Fuller t	-5.0413	0.0000	0.0030	0.4988	6.3110	0.0000
Unadjusted modified Dickey-Fuller t	-14.5391	0.0000	-31.1148	0.0000	-34.8047	0.0000
Unadjusted Dickey-Fuller t	-8.4662	0.0000	-20.2383	0.0000	-20.6216	0.0000

common inputs for the subsequent wheat, rice, and millet analyses.

The panel cointegration tests for the wheat crop, including the Pedroni and Kao tests, confirm a long-term equilibrium relationship among the variables. All test statistics, such as the Modified Phillips-Perron t (4.8150, p-value = 0.0000), Phillips-Perron t (-3.0185, p-value = 0.0013), and Augmented Dickey-Fuller t (-3.4527, p-value = 0.0003), strongly reject the null hypothesis of no cointegration. Similarly, the Kao test results, with significant negative values for the Augmented Dickey-Fuller t (-5.0413) and other variations, also confirm cointegration. These findings suggest that, despite short-term fluctuations, the variables maintain a stable and consistent long-term relationship, which is essential for analyzing the impact of climatic and input variables on wheat yields.

The cointegration tests for the rice crop reveal mixed results. The Pedroni test reveals significant cointegration for most statistics, including the Phillips-Perron t-statistic (-12.6745, p = 0.0000) and the Augmented Dickey-Fuller t-statistic (-12.9105, p = 0.0000), indicating a stable long-term relationship among the variables. However, the Modified Phillips-Perron t statistic (1.3329, p = 0.0913) is not significant, suggesting some inconsistency. The Kao test further supports cointegration, yielding highly significant results for the Unadjusted modified Dickey-Fuller t-statistic (-31.1148) and the Unadjusted Dickey-Fuller t-statistic (-20.2383). Despite the non-significant Augmented Dickey-Fuller t (p = 0.4988) under the Kao test, the overall evidence strongly suggests that rice yield and its explanatory variables share a long-term equilibrium relationship.

The cointegration tests for millet crop also support for the existence of a long-term equilibrium relationship between the variables. In the Pedroni test, the Phillips-Perron t (-13.9387, p = 0.0000) and Augmented Dickey-Fuller t (-15.1251, p = 0.0000) statistics reject the null hypothesis of no cointegration, though the Modified Phillips-Perron t (p = 0.2909) is not significant, so support across the Pedroni statistics is not unanimous. The Kao test shows that the Unadjusted Modified Dickey-Fuller t (-34.8047) and Unadjusted Dickey-Fuller t (-20.6216) are consistent with cointegration, while the Augmented Dickey-Fuller t (6.3110, p = 0.0000) has an unexpected positive sign for this statistic and should be re-verified against the underlying software output before being cited as confirmatory. Overall, most of the Pedroni and Kao statistics indicate that there is a long run relationship between the variables affecting millet yield, although the evidence is not unanimous across all sub-tests.

Wheat area is consistently positive and precisely estimated, with elasticities around 0.82-0.83 in the long-run models, implying that a 1% increase in wheat area is associated with ~0.82-0.83% higher long-run yield, likely reflecting better allocation to wheat-suitable land and scale-related management advantages. Maximum temperature depresses wheat yield materially and significantly in most estimators (e.g., DOLS: $\beta = -4.9427$, $p < 0.01$; FMOLS: $\beta = -4.8524$, $p < 0.01$; FE: $\beta = -2.2399$, $p < 0.05$), consistent with heat-stress losses. Minimum temperature is small and statistically indistinct from zero across models. Annual precipitation is negative and significant in several specifications, supporting the view that excessive precipitation can hinder wheat productivity (Zhai *et al.*, 2017; Meressa and

Table 9. Results for DOLS and FMOLS

Variables	DOLS		FMOLS		FE	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Wheat						
lnWheat_Area	0.8324*** (0.0221)	0.8189*** (0.0272)	0.8338*** (0.0191)	0.8216*** (0.0244)	1.1763*** (0.0351)	0.8110*** (0.0118)
lnMaxT	-4.9427*** (1.7189)	-4.5017 (1.9542)	-4.8524*** (1.2655)	-4.8783*** (1.4923)	-2.2399** (0.8652)	-4.0361*** (0.7696)
lnMinT	0.0644 (0.1079)	0.0271 (0.1202)	0.0688 (0.0797)	-0.0177 (0.0832)	.06211 (.0402)	0.0246 (0.0430)
lnAP	-0.2642** (0.1428)	-0.2156 (0.1620)	-0.2248** (0.1109)	-0.1244 (0.1251)	-0.0608 (0.0604)	-0.1147** (0.0567)
lnAC		0.0980** (0.0506)		0.0728* (0.0438)		0.0042 (0.0332)
lnWferti		-0.2665*** (0.0828)		-0.2453*** (0.0776)		-0.2371*** (0.0337)
Arid semi-arid Dummy		-0.1796 (0.2313)		-0.0853 (0.2094)		-0.0235 (0.2051)
R-square	0.8419	0.8382	0.8388	0.8321	0.7851	0.8491
Rice						
lnRice_Area	0.7407*** (0.0223)	0.7350*** (0.0200)	0.7367*** (0.0209)	0.7325*** (0.0276)	0.8251*** (0.0215)	0.7911*** (0.0126)
lnMaxT	-2.5905 (1.9439)	-1.4001 (2.5537)	-2.3532 (1.5791)	-0.6245 (1.9874)	-1.3002 (0.8701)	-0.5186 (0.9715)
lnMinT	-0.1320 (0.1548)	-0.1948 (0.2165)	-0.0797 (0.1142)	-0.1059 (0.1065)	0.0552 (0.0406)	0.0497 (0.0729)
lnAP	0.0238 (0.2171)	-0.5026* (0.2917)	0.0210 (0.0173)	-0.4053* (0.2217)	-0.0260 (0.0599)	-0.0275 (0.1016)
lnAC		-0.0526 (0.0896)		-0.0671 (0.0769)		-0.4433*** (0.0552)
lnRferti		-0.1122 (0.1545)		-0.1393 (0.1430)		0.1143** (0.0618)
Dummy		-2.0902*** (0.0493)		-2.0011*** (0.3727)		-2.0456*** (0.0456)
R-square	0.7287	0.7766	0.7248	0.7690	0.6212	0.7291
Millets						
lnMillet_Area	0.6046** (0.0235)	0.6404 (0.0258)	0.6226*** (0.0213)	0.6600*** (0.0230)	0.8201*** (0.0174)	0.6674*** (0.0104)
lnMaxT	-1.1595 (1.5660)	-2.6562 (1.8758)	-1.1123 (1.2727)	-2.4374** (1.4485)	-2.9311*** (0.7652)	-1.2840*** (0.7201)
lnMinT	-0.0791 (0.1316)	-0.0498 (0.1654)	-0.0534 (0.0956)	-0.1549 (0.1094)	-0.1833*** (0.0357)	-0.1197*** (0.0554)
lnAP	0.5941*** (0.1621)	-0.0716 (0.2012)	0.8293*** (0.1332)	0.0851** (0.1571)	0.5726*** (0.0526)	0.4403*** (0.0694)
lnAC		0.1699*** (0.0631)		0.1531*** (0.0550)		-0.0252 (0.0404)
lnMferti		0.2641** (0.1038)		0.2097** (0.0980)		0.4324*** (0.0417)
Dummy		-1.3335*** (0.0870)		-1.1895*** (0.2631)		
R square	0.6200	0.6996	0.6238	0.6951	0.6301	0.6851

Note: Indicators *, **, and *** denote the significance level at 10%, 5%, and 1% correspondingly

Bantie, 2024; Baris-Tuzemen and Lyhagen, 2024). Agricultural credit is yield-enhancing in long-run estimators, an increase in credit is associated with ~0.07-0.10% higher long-run wheat yield, likely by enabling timely input purchase and adaptive investments. The correlation matrix indicates a positive bivariate association between wheat yield and fertiliser use. However, in the regression analysis, the fertiliser coefficient turns negative in some specifications after accounting for cultivated area, temperature, precipitation, and agricultural credit. The arid/semi-arid dummy is not statistically different from zero, indicating that within this dryland sample, heat and rainfall dynamics matter more than the arid/semi-arid classification.

Since the models are estimated in double-log (log-log) form, each coefficient can be interpreted directly as an elasticity: a 1% change in a given regressor is associated with a percentage change in crop yield equal to the estimated coefficient, holding other factors constant. As shown in Table 9, these elasticities vary considerably across variables and crops, ranging in absolute magnitude from below 0.1 to nearly 5. In the case of wheat, the long-run estimators of the elasticity of maximum temperature are large and negative (around -4.0 to -4.9), which means that even small proportional increases in maximum temperatures in already-hot districts can cause economically significant losses in yield; this further supports the argument of heat-risk reduction (stress-tolerant varieties, modified sowing times, and protective irrigation where possible).

The log-log models all have a positive and estimated rice area with estimated elasticities of 0.73-0.82 between estimators, meaning that a one percent change in rice area leads to a 0.73-0.82 percent change in rice yield. This implies that the districts that increase rice production will end up dedicating their lands to areas where rice is comparatively better endowed with access to irrigation, management, and complementary infrastructure. Temperature coefficients are generally negative but imprecisely estimated, indicating limited direct temperature effects in these settings (Zhang *et al.*, 2010; Peng *et al.*, 2004). precipitation turns negative in some DOLS specifications, suggesting vulnerability to excess moisture. Rice has a strong yield penalty

in arid compared to semi-arid districts (large negative dummy coefficient) which implies that structural water constraints are the dominant factor; it justifies water-saving rice methods, diversification of crops where irrigation is not reliable, and investment in water management in the most constrained arid areas. Credit is not significant in the long-run estimators but turns adverse in FE, while fertiliser is positive only in FE, consistent with short-run input responsiveness.

Millet area is positively associated with yield in all estimators (e.g., DOLS: $\beta=0.6404$, FE: $\beta=0.8201$, FMOLS: $\beta=0.6226$), implying that a 1% expansion in millet area is associated with about a 0.62-0.82% increase in yield, likely reflecting better allocation of land to millet-suitable plots and stronger management intensity in millet-growing districts. Maximum temperature is consistently detrimental where precisely estimated (DOLS: $\beta= -2.6562$; FMOLS: $\beta= -2.4374$, $p<0.05$; FE: $\beta= -1.2840$, $p<0.01$), and minimum temperature turns significantly negative in FE, highlighting heat sensitivity (Chandio *et al.*, 2020). millets exhibit a strong positive precipitation elasticity (between 0.44 and 0.83 in major models), which is also characteristic of moisture-limiting environments, where rainfall availability is yield-promoting; resilience can be increased by policies that enhance soil moisture retention and access to drought-tolerant millet seed on time. Credit is positive and significant in long-run estimators (DOLS: $\beta=0.1699$, $p<0.01$; FMOLS: $\beta=0.1531$, $p<0.01$), implying that a 1% increase in credit is associated with ~0.15-0.17% higher yield in the long run., while fertiliser ($\ln Mferti$) is uniformly yield-enhancing ($\beta\approx 0.21$ -0.43, $p<0.05$ or better). The arid dummy is again large and negative (≈ -1.19 to -1.33 , $p<0.01$), implying arid districts have ~70-74% lower millet yields than semi-arid districts.

Notably, the use of fertiliser and agricultural credit alters the meaning of climate impacts. The negative sign of the fertiliser coefficients in long-run models for wheat is consistent with inefficiency, misuse, or diminishing marginal returns in dryland environments; this suggests that fertiliser stewardship and soil testing are preferable to blanket intensification. The yield of wheat and millet is positively related to credit in long-run estimators, indicating that liquidity can facilitate the use of adaptive inputs

and practices. Collectively, these findings suggest that climate impacts on cereal yields are substantially mediated by management and financial factors rather than operating through climatic alone; adaptation policy must therefore address climate exposure jointly with the input and credit environment (Zhai *et al.*, 2017; Meressa and Bantie, 2024; Baris-Tuzemen and Lyhagen, 2024).

Conclusion and Policy Suggestions

This study examines how climatic, agricultural, and financial factors influence wheat, rice, and millet yields in India's arid and semi-arid regions. Three key findings emerge. First, cultivated area is consistently and positively associated with yields across all three cereals, indicating persistent scale and management-intensity effects across estimators. Second, higher maximum temperatures are associated with lower yields across all three cereals, but the relationship is strongest and most precisely estimated for wheat and millet; for rice, the temperature coefficient is negative but not consistently significant across specifications (Table 9). This reinforces the need to accelerate breeding, diffusion, and farmer access to heat- and drought-tolerant varieties (Hasan *et al.*, 2019; Birthal *et al.*, 2014). Minimum temperatures effects are generally small and, in some models, adverse. Third, precipitation effects are crop-specific: excess precipitation is detrimental for wheat, consistent with evidence that waterlogging and disease pressure can undermine productivity (Zhai *et al.*, 2017; Meressa and Bantie, 2024; Baris-Tuzemen and Lyhagen, 2024), while millets generally benefit from moisture availability, and rice shows mixed responses with a pronounced penalty in arid settings (Zhang *et al.*, 2010; Peng *et al.*, 2004).

Combined, these data indicate the significance of climate-intelligent agronomy. It focuses on water management and water conservation (e.g., micro-irrigation and rainwater harvesting) in rainfall-sensitive systems (Barati *et al.*, 2022) and improved fertiliser stewardship to address inefficiencies (Pan and Zhang, 2018). Timely and properly organized agricultural credit can also be expanded to allow farmers to invest in irrigation, new technologies, and better management (Ekwere and Edem, 2014; Ozdemir, 2024). Regional heterogeneity

suggests that place-based strategies can generate gains, including promoting millets in semi-arid zones to strengthen resilience and food security (Kheya *et al.*, 2023; Kumar *et al.*, 2024). The directions are consistent with current national efforts. Such evaluations guide district-level contingency plans which prescribe climate-resistant crops, varieties, and management practices. This can be achieved through complementary investments in climate monitoring and early warning systems, which aim to minimize losses associated with weather shocks by enhancing the timeliness and accuracy of farm decisions (Masupha *et al.*, 2021). A coordinated portfolio of interventions offers a pragmatic path to strengthen cereal productivity under intensifying climate risks. Key elements include breeding and seed systems for stress tolerance, water-saving irrigation, nutrient-use efficiency, risk-aligned credit, and actionable climate services.

This study employs panel regressions with aggregate district level data, which can obscure plot-level heterogeneity in soils, management methods, and the quality of inputs. The main sources of inputs, such as cultivated area, fertiliser, and credit, can be endogenous to yields; yet, the estimators applied address these issues, although some residual bias might still exist. Moreover, annual climate summaries often fail to capture intra-seasonal processes and extremes (e.g., heatwaves and the timing/variance of rainfall). Spatial dependence, varietal adoption, irrigation reliability, or input quality are also not explicitly modeled or assumed to be log-linear, and the analysis is based on log-linear relationships. The findings are thus only relevant in arid and semi-arid regions and may not be applicable as a generalization to other agro-ecological systems. The future studies are recommended to integrate the high-frequency weather data and crop phenology, utilize the causal designs (e.g. instrumental variables or threshold-based designs), and integrate the spatial econometric techniques. This would be even enhanced by farm-level data on credit terms, varietal adoption, reliability of irrigation and quality of inputs to enhance inference and policy relevance.

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