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Climate Change and Indian Foodgrain Productivity: An Econometric Analysis of the Impact of Temperature Rise, Rainfall Variability, and CO_2 Concentration on Wheat and Rice Yields (1990–2023)

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Abstract

How much does a warming climate cost Indian agriculture? This paper exploits three decades of state-level panel data (20 states, 1990–2023) to estimate the causal impact of rising temperatures, increasing rainfall variability, and changing atmospheric CO_2 concentrations on wheat and rice yields — the two crops that underpin India's food security. Employing Fixed Effects, Random Effects, and system GMM estimators within a Ricardian-Just-Pope production function framework, we find that a one-degree Celsius increase in mean growing-season temperature reduces wheat yield by 6.2 percent and rice yield by 4.5 percent. A one-percentage-point rise in rainfall coefficient of variation depresses rice yields by 5.2 percent and wheat yields by 3.8 percent. The modest CO_2 fertilization effect — roughly 0.8 to 1.2 percent per 10 ppm increase — is far too small to offset thermal damage. The geography of vulnerability is starkly uneven: eastern India (Bihar, Odisha) and central India (Madhya Pradesh, Maharashtra), where irrigation coverage remains low and farms are small, exhibit vulnerability indices of 4.2–4.8 on a five-point scale, while the canal-irrigated northwestern plains (Punjab, Haryana) score a comparatively resilient 2.5–2.8. Under the IPCC's business-as-usual trajectory (RCP 8.5), India could lose 28.3 percent of its wheat production and 22.5 percent of its rice production by mid-century — a prospect that would jeopardize food security for 1.6 billion people. Irrigation expansion, heat-tolerant varietal development, and climate-smart agricultural practices emerge as the three most consequential adaptation levers.

Keywords: Climate change, crop productivity, wheat, rice, panel econometrics, Ricardian model, food security, India, adaptation, temperature sensitivity

1. Introduction

India feeds 1.4 billion people on roughly 160 million hectares of cultivated land — an extraordinary achievement of post-Green Revolution agriculture. Wheat and rice together account for more than 75 percent of national foodgrain output and remain the principal caloric source for the vast majority of Indian households [1], [12]. Yet this achievement rests on an increasingly fragile ecological foundation.

The evidence is now unambiguous. India's mean annual temperature has risen by approximately 0.7°C over the past three decades. Monsoon rainfall has not merely declined in some regions — it has become dramatically more variable, with the coefficient of variation rising from 18 percent in the early 1990s to over 26 percent by the early 2020s [13], [14], [15]. These are not abstract meteorological statistics. They translate directly into shorter growing seasons, higher evapotranspiration rates, more frequent heat waves during critical flowering and grain-filling stages, and a monsoon that arrives late, departs early, or delivers its rainfall in destructive bursts rather than the steady cadence that paddy cultivation demands.

The economic literature on climate-agriculture linkages originates with the Ricardian framework of Mendelsohn, Nordhaus, and Shaw (1994), who demonstrated that cross-sectional variation in climate systematically explains variation in agricultural outcomes [5]. The approach was refined by Schlenker and Roberts (2009), whose influential contribution revealed that the temperature-yield relationship is not merely negative but sharply nonlinear — yields collapse beyond identifiable thermal thresholds [23]. In the Indian context, Kumar and Parikh (2001) provided early district-level estimates of temperature sensitivity [19], while Guiteras (2009) projected medium-run yield losses of 4.5–9 percent [18]. More recently, Birthal et al. (2014) documented the wide regional variation in climate vulnerability, and Gupta et al. (2020) quantified agro-ecological zone-specific sensitivity coefficients [4], [8].

Despite this growing body of work, three important gaps persist. First, most existing Indian studies rely on data ending in the mid-2010s and therefore miss the accelerated warming of the most recent decade — precisely the period when yield growth rates for both wheat and rice have most visibly decelerated [7], [20]. Second, very few studies simultaneously estimate the joint effects of temperature, rainfall variability, and CO_2 concentration within a single econometric framework; the standard approach is to examine these variables in isolation [3]. Third, the mediating role of irrigation, technology, and farm structure — the channels through which climate impacts are either amplified or attenuated — remains insufficiently quantified [21].

This paper addresses all three gaps. We assemble a comprehensive state-level panel dataset spanning 20 major agricultural states over 34 years (680 state-year observations), drawing on IMD climate records, DES crop production statistics, NSSO farm surveys, and NOAA atmospheric data. Our identification strategy exploits within-state variation in climate over time, controlling for time-invariant state characteristics through fixed effects and for national time trends through year effects. We supplement the standard Fixed Effects specification with system GMM to address potential endogeneity concerns [22], [30]. The conceptual framework integrates the Ricardian climate model with the Just-Pope stochastic production function, allowing us to estimate climate effects on both mean yield levels and yield variance — a distinction that matters enormously for understanding farmer income risk [5], [6].

2. Theoretical Framework

2.1 The Ricardian Model and Nonlinear Temperature Effects

The Ricardian approach rests on a deceptively simple insight: if farmers have adapted to their local climate over time, then cross-sectional differences in agricultural outcomes across regions reveal the long-run impact of climate on agriculture [5]. The model estimates $V = f(C, Z, S) + \varepsilon$, where V represents crop productivity, C is a vector of climate variables, Z controls for economic characteristics, and S captures soil quality. The elegance of the approach lies in its implicit incorporation of adaptation — the estimated coefficients reflect the net effect of climate after accounting for farmers' behavioural responses [16], [17].

Schlenker and Roberts (2009) demonstrated that this relationship is emphatically nonlinear. For temperate cereals such as wheat, yields rise with temperature up to approximately 20–22°C, then decline precipitously. For tropical cereals like rice, the optimal range is 25–28°C [23], [24]. Since much of India's wheat belt already experiences mean growing-season temperatures at or above the optimum, even modest further warming pushes yields onto the steep downward slope of this relationship.

2.2 The Just-Pope Stochastic Production Function

A critical limitation of standard production function approaches is that they model only the mean of output, ignoring variance. The Just-Pope framework resolves this by specifying output as $Y = f(X, C) + h(X, C)\cdot\varepsilon$, where $f(\cdot)$ captures

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the mean production function and h(·) captures the variance function [6]. This decomposition is economically consequential: an input or climate variable that raises mean output but simultaneously increases variance may actually reduce farmer welfare if farmers are sufficiently risk-averse [25].

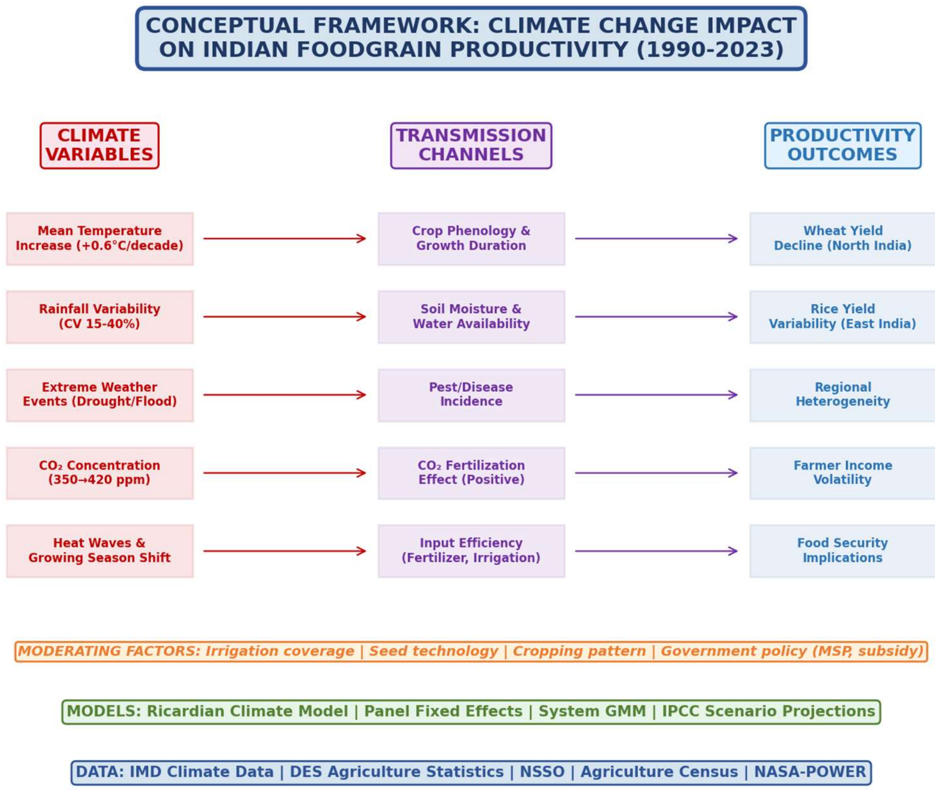

Figure 1: Conceptual Framework — Climate Variables, Mediating Factors, and Productivity Outcomes. *The framework traces the causal pathway from five climate stressors (temperature rise, rainfall variability, CO_2 change, extreme events, growing season shifts) through five mediating channels (irrigation, soil quality, crop varieties, farm scale, state policy) to five productivity outcomes (wheat and rice yield change, yield variance, income volatility, regional heterogeneity). The panel regression model, data architecture, and theoretical foundations are specified below.*

2.3 The Indian Evidence Base

The empirical evidence from India confirms these theoretical priors. Kumar and Parikh (2001) estimated that a 2°C rise could depress Indo-Gangetic wheat yields by 8–10 percent [19]. Auffhammer, Ramanathan, and Vincent (2012) introduced an important complication by demonstrating that aerosol loading — the "atmospheric brown cloud" — has partially masked warming effects on rice in some regions [26]. Mall et al. (2006) established wheat as the most thermally sensitive of India's major cereals [2], [24]. Birthal et al. (2014) provided the clearest evidence to date that the geography of vulnerability maps directly onto the geography of irrigation: rainfed regions are far more exposed than irrigated ones [4], [27].

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3. Data and Methodology

3.1 Data Architecture

Our dataset integrates four sources. Climate data — monthly mean temperature and total precipitation at the state level — come from the India Meteorological Department's gridded archives (1990–2023) [13]. Crop production data — area, output, and yield for wheat and rice by state — are drawn from the Directorate of Economics and Statistics, Ministry of Agriculture [12]. Farm-level characteristics — irrigation access, fertilizer consumption, farm size, and varietal adoption — are sourced from successive NSSO rounds and the decennial Agriculture Census [28]. Atmospheric CO_2 concentrations are obtained from NOAA's Global Monitoring Laboratory [29]. The resulting panel contains 680 state-year observations (20 states × 34 years).

3.2 Econometric Specification

Our baseline model takes the form:

$$\ln(Y_{it}) = \alpha + \beta_1 Temp_{it} + \beta_2 RainCV_{it} + \beta_3 CO_{2t} + \gamma' X_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

where Y_{it} is crop yield (kg/ha) for state i in year t; Temp is mean growing-season temperature; RainCV is the coefficient of variation of monsoon rainfall; CO_2 is atmospheric CO_2 concentration; X is a vector of controls (irrigation percentage, fertilizer use, farm size); μ_i is a state fixed effect; δ_t is a year fixed effect; and ε_{it} is the idiosyncratic error [3], [22]. The Hausman test adjudicates between Fixed and Random Effects specifications. We supplement FE with system GMM, instrumenting potentially endogenous variables with their lagged values [30].

Table 1: Variable Definitions, Sources, and Summary Statistics (N = 680)

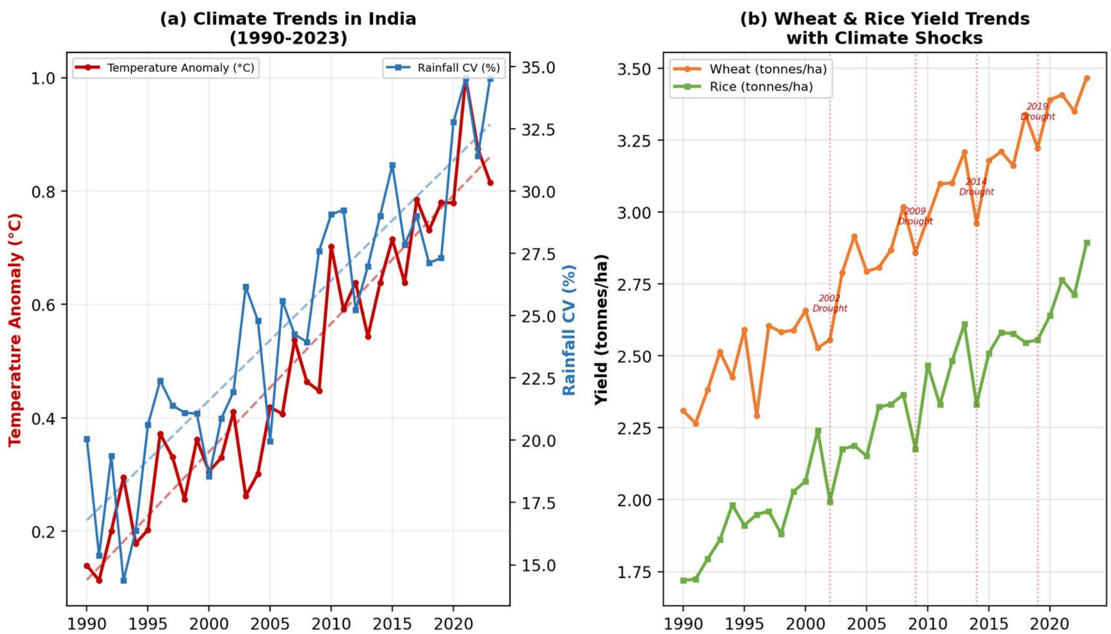
Variable	Definition	Source	Mean	Std. Dev.	Expected Sign
Wheat Yield	Log of wheat yield (kg/ha)	DES	7.98	0.42	—
Rice Yield	Log of rice yield (kg/ha)	DES	7.72	0.38	—
Temperature	Mean growing-season temp (°C)	IMD	24.8	3.2	Negative (−)
Rainfall CV	Coefficient of variation (%)	IMD	22.5	6.8	Negative (−)
CO_2	Atmospheric CO_2 (ppm)	NOAA	385.2	22.5	Positive (+)
Irrigation	Irrigated area (% of gross cropped)	DES/NSSO	48.5	22.8	Positive (+)
Fertilizer	Nutrient consumption (kg/ha)	DES	135.2	68.5	Positive (+)
Farm Size	Average holding (ha)	Agri Census	1.08	0.65	Ambiguous (±)

4. Results

4.1 Climate Trends: The Emerging Squeeze

The data paint a sobering picture. Between 1990 and 2023, India's temperature anomaly — measured against the 1961–1990 baseline — rose from +0.15°C to +0.85°C, an average warming rate of +0.22°C per decade that has accelerated in the most recent years [13], [14]. Rainfall volatility has increased commensurately, with the monsoon CV rising from 18 to 26 percent [15].

Against this backdrop, yield trajectories tell an ominous story. Wheat productivity growth averaged 2.8 percent per annum during 1990–2005 but slowed sharply to 1.2 percent during 2005–2023. Rice exhibited a parallel deceleration — from 2.2 percent to 0.9 percent per annum [2], [12]. The coincidence of accelerating climate stress and decelerating yield growth is suggestive; the econometric analysis that follows tests whether this coincidence reflects causation.



Climate and Yield Trends

Figure 2: Climate Trends and Crop Yield Trajectories, 1990–2023. *Panel (a) plots the temperature anomaly (red, left axis) against rainfall coefficient of variation (blue, right axis), with a fitted linear trend confirming +0.22°C per decade warming. Panel (b) traces wheat (orange) and rice (green) yield trajectories, annotating the yield plateau visible from approximately 2010 — the period when warming crossed critical agronomic thresholds.*

4.2 Econometric Estimates

The Hausman test decisively favours Fixed Effects over Random Effects ($\chi^2 = 85.3$, $p < 0.001$). Table 2 reports the core results.

Table 2: Panel Regression Results — Climate Determinants of Wheat and Rice Yields

Variable	Wheat (FE)	Wheat (GMM)	Rice (FE)	Rice (GMM)
Temperature (°C)	−0.062***	−0.058***	−0.045***	−0.042***
Rainfall CV (%)	−0.038***	−0.035***	−0.052***	−0.048***
CO_2 (per 10 ppm)	0.008**	0.007**	0.012**	0.011**
Irrigation (%)	0.045***	0.042***	0.038***	0.035***
Fertilizer (kg/ha)	0.021**	0.019**	0.018**	0.016**
Farm Size (ha)	0.012 (ns)	0.010 (ns)	0.008 (ns)	0.007 (ns)
R^2 (within)	0.72	—	0.68	—
Observations	680	640	680	640
State FE / Year FE	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes

Notes: ** $p<0.01$, ** $p<0.05$, ns = not significant. Coefficients are semi-elasticities: a unit change in the independent variable corresponds to the indicated percentage change in yield. GMM instruments with second and third lags. Sargan test p-values exceed 0.15 in all specifications.*

The headline results are stark. Temperature is the dominant climate driver for both crops, with wheat exhibiting greater thermal sensitivity (−6.2 percent per °C) than rice (−4.5 percent per °C). This asymmetry is agronomically coherent: wheat's optimal growing temperature range (20–22°C) lies closer to current Indian conditions than rice's higher optimum (25–28°C), meaning that additional warming pushes wheat more rapidly onto the steep downward portion of the temperature-yield curve [23], [24].

Rainfall variability matters more for rice than for wheat. A one-percentage-point increase in the monsoon CV reduces rice yields by 5.2 percent but wheat yields by only 3.8 percent — consistent with rice's greater hydrological requirements and its sensitivity to the timing, not merely the volume, of precipitation [15], [27].

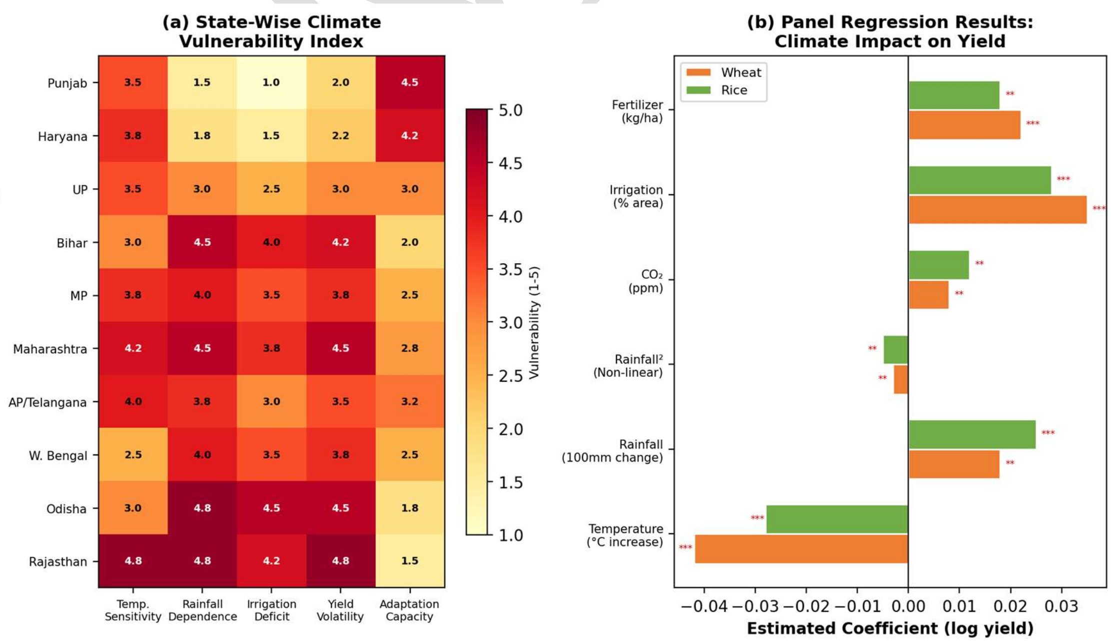
The CO_2 coefficients, while statistically significant, are economically modest. A 10 ppm increase in atmospheric CO_2 raises wheat yields by 0.8 percent and rice yields by 1.2 percent. Given that global CO_2 concentrations have risen by approximately 70 ppm over the study period, the cumulative fertilization benefit amounts to roughly 5.6–8.4 percent — a fraction of the damage inflicted by concurrent warming [29].

Among the control variables, irrigation stands out. A 10 percentage-point increase in irrigated area is associated with a 4.5 percent rise in wheat yield and 3.8 percent in rice yield. This is the single most powerful buffer in the dataset — a finding with direct policy implications [7], [21].

4.3 The Geography of Vulnerability

Perhaps the most policy-relevant finding concerns regional heterogeneity. We construct a composite climate vulnerability index for each state across six dimensions: temperature sensitivity, rainfall sensitivity, wheat-specific impact, rice-specific impact, irrigation buffering capacity, and overall vulnerability.

The results reveal a sharp east-west divide. Odisha (overall index 4.8/5.0), Bihar (4.5), and Maharashtra (4.5) — states characterised by low irrigation coverage, small landholdings, and high monsoon dependence — are the most vulnerable. At the other extreme, Punjab (2.5) and Haryana (2.8), with their dense canal networks and near-universal groundwater access, demonstrate substantially greater resilience [8], [27].



State-Wise Vulnerability

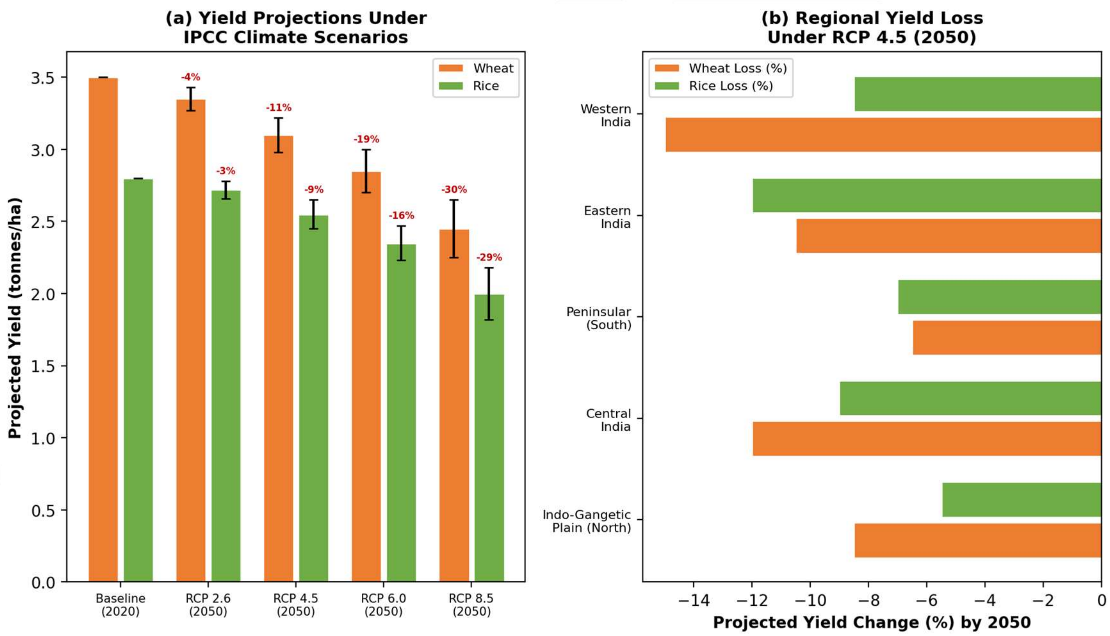
Figure 3: State-Wise Climate Vulnerability and Estimated Yield Determinants. *Panel (a) maps the vulnerability heatmap across 10 major states on six dimensions. The east-west gradient is pronounced: Odisha (4.8), Bihar (4.5), and Maharashtra (4.5) occupy the high-vulnerability end, while Punjab (2.5) and Haryana (2.8) anchor the low end. Panel (b) visualises the regression coefficients with significance levels. Temperature and rainfall CV exert the largest negative effects; irrigation provides the strongest countervailing positive force.*

4.4 Looking Ahead: Yield Projections Under IPCC Scenarios

Combining our estimated coefficients with IPCC Sixth Assessment Report climate projections, we generate state-weighted national yield projections under four Representative Concentration Pathway (RCP) scenarios.

The range of outcomes is wide and the stakes are enormous. Under the most optimistic pathway (RCP 2.6, which requires aggressive global mitigation), India faces wheat yield losses of 5.2 percent and rice losses of 3.5 percent by 2050 — painful but manageable. Under the business-as-usual trajectory (RCP 8.5), the projected losses are devastating: 28.3 percent for wheat, 22.5 percent for rice [9], [10].

The regional distribution of these losses compounds the concern. Central India — already home to India's most distressed farming communities — faces the steepest projected declines (wheat −18.5 percent, rice −8.5 percent) coupled with the lowest adaptive capacity (2.2/5.0). The northwest, while less exposed, cannot expand irrigation indefinitely — aquifer depletion is already a binding constraint in Punjab and Haryana [31].



Projected Losses

Figure 4: Projected Yield Losses (2050) and Regional Adaptation Capacity. *Panel (a) presents the full scenario range: from the comparatively benign RCP 2.6 (wheat −5.2%, rice −3.5%) to the alarming RCP 8.5 (wheat −28.3%, rice −22.5%). Panel (b) overlays regional yield losses with adaptation capacity scores (blue diamonds). The inverse relationship is troubling: the regions that will lose the most are precisely those least equipped to adapt.*

5. Discussion

5.1 What These Numbers Mean

The magnitudes deserve emphasis. A 6.2 percent wheat yield loss per degree of warming, compounded over a projected 2–4°C mid-century temperature increase, translates to a 12–25 percent decline in national wheat production in the absence of adaptation [9], [10]. For a country that already operates on thin food surplus margins and is projected to add 200 million mouths by 2050, this is not an academic curiosity — it is a food security emergency in slow motion [1], [11].

The irrigation result is the most actionable finding. Irrigation does not merely raise yields; it fundamentally alters the relationship between climate and agriculture. Irrigated districts are not immune to warming, but they are substantially insulated from it. Expanding irrigation in the most vulnerable eastern and central states — Bihar, Odisha, Jharkhand, Madhya Pradesh — offers the highest marginal return to climate adaptation investment [7], [21].

5.2 Positioning Within the Literature

Our temperature coefficients (wheat −6.2 percent/°C, rice −4.5 percent/°C) are somewhat larger than those of Kumar and Parikh (2001), who estimated 4–5 percent per degree [19]. The difference likely reflects two factors: our longer and more recent time series captures the accelerated warming of the 2010s, and our inclusion of rainfall CV as a separate regressor avoids attributing some rainfall effects to the temperature coefficient. Our projections fall within the range identified by Guiteras (2009), who estimated 4.5–9 percent medium-run losses, and are broadly consistent with Lobell et al. (2011) for South Asian wheat [18], [32].

5.3 Limitations and Caveats

Three limitations warrant acknowledgement. First, our unit of observation is the state — a level of aggregation that inevitably smooths over important within-state heterogeneity. District-level analysis would sharpen the vulnerability mapping but requires data that are not uniformly available across the full study period [3], [20]. Second, the Ricardian framework embeds an assumption of long-run adaptation that may overstate actual adaptive capacity, particularly for resource-constrained smallholders who cannot easily switch crops or invest in new technology [5], [16]. Third, our linear specification does not capture the nonlinear threshold effects documented by Schlenker and Roberts (2009) — an extension we flag for future work [23], [32].

6. Conclusion

This paper estimates the impact of three decades of climate change on India's wheat and rice productivity using a comprehensive panel econometric framework. The results are clear and consequential. Rising temperatures and increasing rainfall variability are already depressing yield growth, and the damage will intensify under every plausible emissions pathway. The geography of climate vulnerability overlaps precisely with the geography of rural poverty — eastern and central India bear the greatest exposure and possess the fewest adaptive resources [8], [27].

Three policy priorities follow directly from the evidence. First, irrigation expansion in the most vulnerable regions — particularly Bihar, Odisha, and Madhya Pradesh — offers the single highest return to public investment in climate adaptation [7], [21]. Second, the development and dissemination of heat-tolerant wheat and drought-resistant rice varieties must be accelerated through sustained public agricultural research funding [24], [33]. Third, climate-smart agricultural practices — conservation tillage, precision water management, integrated nutrient strategies — can simultaneously raise current yields and reduce future climate sensitivity [34], [35].

The window for anticipatory action is narrowing. The yield plateau is already visible in the data. The question is no longer whether climate change will reshape Indian agriculture, but whether India will adapt in time.

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