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Climate Change and Agricultural Productivity in Indian States: A Panel Data Analysis with Non-Linear Climate Effects (1990–2023)

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Abstract

Indian agriculture employs roughly 46 per cent of the workforce yet contributes only about 17 per cent of gross value added, leaving rural livelihoods sharply exposed to climatic shocks. According to the Intergovernmental Panel on Climate Change (IPCC, 2022), South Asia has already warmed by approximately 0.7°C since 1950 and is projected to warm by a further 1.5–4.5°C by the end of the twenty-first century. Whether and to what extent rising temperatures and shifting monsoon patterns have already reduced Indian agricultural productivity is a question of first-order policy importance. Drawing on an unbalanced panel of twenty major Indian states over 1990–2023, this paper estimates the effect of temperature and precipitation on agricultural value added per hectare using a fixed-effects framework that includes a quadratic specification in climate variables, state fixed effects, year fixed effects, and a battery of agronomic and policy controls. The empirical strategy follows the new climate-economy literature pioneered by Deschenes and Greenstone (2007) and Schlenker and Roberts (2009), extended through panel cointegration tests à la Pedroni (2004) to address non-stationarity concerns. Findings indicate a statistically significant inverted-U relationship between growing-season temperature and productivity, with an estimated growing-season optimum of approximately 24.6°C; a 1°C increase above this threshold lowers productivity by an estimated 4.7 per cent. Precipitation effects are concave, and rainfall shocks of more than one standard deviation below the long-run mean reduce productivity by 6.3 per cent. Irrigation coverage and the use of high-yielding-variety (HYV) seeds significantly attenuate climate damages, providing direct evidence for the adaptation-investment channel. The results survive panel unit-root and cointegration tests, alternative weighting schemes, and the exclusion of states most affected by reorganisation events. The findings imply that India faces measurable adaptation costs in the absence of accelerated investment in irrigation, climate-resilient seed varieties, and weather-indexed crop insurance.

Keywords: - Climate Change, Agricultural Productivity, Panel Data; Fixed Effects, Non-Linear Temperature, India.

I. INTRODUCTION

Agriculture remains a sector of disproportionate social importance for India. Although its share in gross domestic product has fallen steadily since the 1991 economic reforms, the sector continues to provide employment to nearly half of the country's workforce and serves as the principal source of livelihood for rural households across most states (Government of India, 2023). The dependence of Indian agriculture on the south-west monsoon, the seasonality of cropping patterns, and the limited diffusion of irrigation outside the Indo-Gangetic plains together render the sector unusually exposed to climatic variation. The Intergovernmental Panel on Climate Change (IPCC, 2022) projects warming of 1.5–4.5°C across South Asia by 2100 and a more variable monsoon. Estimating the consequences of such warming for agricultural productivity is therefore essential both for evidence-based climate policy and for the design of adaptation programmes.

Two methodological traditions dominate the climate-and-agriculture literature. The Ricardian approach, pioneered by Mendelsohn, Nordhaus, and Shaw (1994), regresses land values or net revenues on long-run climate averages, exploiting cross-sectional variation under the assumption that observed land prices incorporate all relevant adaptation. The new climate-economy approach, exemplified by Deschenes and Greenstone (2007), Schlenker and Roberts (2009), and Dell, Jones, and Olken (2012), uses panel data with unit fixed effects to identify the short-run productivity effects of weather shocks, abstracting from time-invariant location characteristics. The two methods produce systematically different estimates: the Ricardian approach captures long-run adaptation; the panel approach captures the costs of shocks that have not yet been fully adapted to. The present study follows the panel tradition, which is better suited to estimating the marginal cost of further warming.

1.1. Research Problem

Several gaps persist in the Indian climate-economics literature. First, much of the existing Indian evidence relies on Ricardian estimates (Kumar & Parikh, 2001; Sanghi & Mendelsohn, 2008) that may overstate long-run adaptation. Second, where panel methods have been applied, the focus has typically been on agricultural output or yields of a single crop, leaving the broader sectoral effect on value added under-studied. Third, non-linear specifications of the temperature effect central to the international literature since Schlenker and Roberts (2009) remain comparatively rare in Indian work. Fourth, the role of moderating policy variables such as irrigation expansion and HYV adoption has not been systematically integrated within a single estimation framework.

1.2. Research Objectives

The study pursues four objectives:

- To estimate the effect of growing-season temperature and precipitation on agricultural productivity (real value added per hectare) across Indian states over 1990–2023.
- To test for non-linearities in the climate productivity relationship using a quadratic specification and to identify the growing-season temperature optimum.
- To assess whether adaptation investments irrigation, HYV seed adoption, and fertiliser use attenuate the marginal damages of warming.
- To investigate spatial heterogeneity of climate effects across agro-climatic zones.

1.3. Research Hypotheses

Four hypotheses are tested:

- H1: Growing-season temperature exhibits an inverted-U relationship with agricultural productivity, with damages rising sharply beyond a critical threshold.
- H2: Precipitation effects are concave, with both deficient and excess rainfall reducing productivity.
- H3: Irrigation coverage and HYV seed adoption attenuate the marginal damages of temperature shocks.
- H4: Climate damages are larger in agro-climatically marginal regions arid and semi-arid zones than in irrigated humid zones.

1.4. Significance and Organisation

The contribution of the study is fourfold. First, it provides updated estimates of the climate productivity relationship for Indian states using a panel that extends to 2023, capturing recent extreme-weather years including the 2009, 2015, and 2022–23 monsoon failures. Second, by adopting the quadratic non-linear specification of Schlenker and Roberts (2009), it identifies a critical-temperature threshold relevant for Indian growing conditions. Third, the explicit interaction between climate variables and adaptation investments offers direct evidence on the policy levers available to mitigate climate damages. Fourth, the use of panel unit-root and cointegration tests addresses non-stationarity concerns that are often glossed over in the applied literature. The remainder of the paper is organised as follows. Section 2 reviews the literature. Section 3 develops the theoretical framework. Section 4 describes the data and econometric strategy. Section 5 presents the results. Section 6 concludes.

II. LITERATURE REVIEW

2.1. The Ricardian Tradition

Mendelsohn et al. (1994) inaugurated the empirical climate-economics literature by regressing farmland values across U.S. counties on long-run climate normals, controlling for soil and economic variables. Their central finding that climate change would impose moderate net costs on U.S. agriculture, with substantial spatial heterogeneity provoked an influential debate. Subsequent applications to developing countries (Sanghi & Mendelsohn, 2008; Kumar & Parikh, 2001) consistently report larger damages than those estimated for the United States, attributable to greater dependence on rainfed cultivation, less adaptive capacity, and a starting climate closer to the upper limit of crop tolerance. The Ricardian approach has been criticised, however, for assuming costless adaptation and for omitted-variable bias in the cross-section.

2.2. The Panel Tradition

To address these concerns, Deschenes and Greenstone (2007) introduced a panel approach exploiting year-to-year weather fluctuations within U.S. counties. Their estimates differ markedly from Ricardian damages, suggesting that short-run weather shocks impose costs that are not fully reflected in cross-sectional land values. Schlenker and Roberts (2009) extended the methodology to estimate non-linear temperature effects using degree-day exposures and identified critical-temperature thresholds beyond which crop yields decline sharply. Dell et al. (2012) generalised the panel approach to growth at the country level, finding that hot years reduce growth rates in poor countries; Dell, Jones, and Olken (2014) provide a comprehensive review of this literature. The panel approach has since become the dominant framework in climate econometrics.

2.3. Indian Evidence

Indian evidence is mixed but converging on substantial climate sensitivity. Kumar and Parikh (2001), using a Ricardian framework, estimated that a 2°C warming combined with a 7 per cent rainfall increase would reduce Indian farm net revenues by approximately 8.4 per cent. Sanghi and Mendelsohn (2008) extended the Ricardian approach to compare India and Brazil, finding larger damages in India. Auffhammer, Ramanathan, and Vincent (2012) used a panel approach to estimate that declining late-monsoon rainfall and rising minimum temperatures have already lowered Indian rice yields by approximately 1.7 per cent over the 1966–2002 period. Guiteras (2009) projected agricultural losses of 4.5–9.0 per cent by 2050 under medium emission scenarios. More recently, Burgess, Deschenes, Donaldson, and Greenstone (2017) demonstrated that hot years in India sharply raise rural mortality an effect mediated, in part, through reduced agricultural incomes. Krishnamurthy (2017) showed that consumption-insurance against climate shocks remains incomplete in rural India.

2.4. Research Gap

Despite this body of work, three gaps remain. First, panel estimates focused on aggregate agricultural value added rather than the yields of one or two staple crops are scarce. Second, formal panel unit-root and cointegration testing is rarely conducted, even when long panels are used. Third, the interaction between climate variables and adaptation policy is typically explored through descriptive comparisons rather than within an integrated econometric framework. The present paper addresses each of these gaps.

III. THEORETICAL FRAMEWORK

3.1. A Production-Function Approach

The theoretical foundation is a Cobb–Douglas agricultural production function augmented with climate variables (Schlenker & Roberts, 2009; Carleton & Hsiang, 2016). Output Y per hectare in state i and year t is specified as:

$$Y_{it} = A_{it} \cdot g(T_{it}, R_{it}) \cdot K_{it}^{\alpha} \cdot L_{it}^{\beta} \cdot M_{it}^{\gamma} \tag{1}$$

where A is total factor productivity, T is growing-season temperature, R is growing-season precipitation, K is capital (irrigation infrastructure, machinery), L is labour, M is material inputs (fertilisers, HYV seeds), and $g(\cdot)$ captures the climate response function. The climate response is hypothesised to be inverted-U with respect to both temperature and rainfall: a positive marginal effect at low values reflecting beneficial warming or moisture, and a negative marginal effect beyond a critical threshold reflecting heat or flood damage.

3.2. Adaptation Investments

Adaptation enters through three channels. First, irrigation coverage relaxes the rainfall constraint, attenuating both deficient-rainfall and high-temperature damages. Second, HYV seeds shift the production function upward and may extend the temperature range across which yields are sustained, although recent agronomic evidence (IPCC, 2022) suggests modern varieties may also be more vulnerable to extreme heat than traditional ones. Third, fertiliser use partially substitutes for natural soil fertility but exhibits diminishing returns. Adaptation is modelled as an interaction between the climate variables and the relevant policy stocks, permitting a direct test of attenuation.

3.3. Testable Implications

Three testable implications follow. First, the second-order term in temperature should be negative and statistically significant, generating an estimable temperature optimum. Second, irrigation and HYV interactions with temperature should be positive in sign, indicating that adaptation reduces the marginal cost of warming. Third, climate effects should be larger in states with lower baseline irrigation coverage proxying for adaptive capacity generating cross-sectional heterogeneity that the panel design can detect through state-specific interactions.

IV. RESEARCH METHODOLOGY

4.1. Research Design and Approach

The study adopts a quantitative, deductive, panel-data approach (Wooldridge, 2010). The geographic unit is the major Indian state; the temporal unit is the financial year (April–March). The choice of method is dictated by the research questions: identifying the within-state effect of climate variation requires variation across time within each state, which is the defining feature of panel data.

4.2. Data Sources and Sample

The empirical analysis uses an unbalanced panel of twenty major Indian states (Andhra Pradesh, Assam, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Telangana, Uttar Pradesh, Uttarakhand, and West Bengal) for the financial years 1990–91 to 2022–23. Agricultural value added by state at constant 2011–12 prices is sourced from the Central Statistics Office (CSO). Net sown area and irrigation coverage are obtained from the Land Use Statistics published by the Directorate of Economics and Statistics, Ministry of Agriculture. Climate data mean growing-season temperature and total growing-season precipitation are constructed from the gridded daily records of the India Meteorological Department (IMD), aggregated to state boundaries using area-weighted averages of cropland-bearing grid cells. Fertiliser consumption is sourced from the Fertiliser Association of India, and HYV coverage from the Directorate of Economics and Statistics. Some new states (Chhattisgarh, Jharkhand, Telangana, Uttarakhand) enter the panel from their year of formation, producing the unbalanced structure.

Table 1. Variable Definitions and Sources

Variable	Notation	Definition	Source
Productivity	lnAVA	Real agricultural value added per hectare net sown area (₹ at 2011–12 prices)	CSO; DES
Temperature	TEMP	Mean growing-season temperature (°C, June–October)	IMD gridded data
Precipitation	RAIN	Total growing-season rainfall (mm, June–October)	IMD gridded data
Irrigation	IRR	Share of gross cropped area irrigated (%)	DES, MoA&FW
HYV seeds	HYV	Share of gross cropped area under HYV seeds (%)	DES, MoA&FW
Fertiliser	lnFERT	NPK consumption per hectare (kg/ha)	Fertiliser Assoc. of India
Workforce	lnLAB	Agricultural workers per hectare (count)	Census; NSSO

Note. N = 20 states × 34 years (unbalanced). Monetary variables deflated using the agricultural GVA deflator (Base: 2011–12). Author's compilation.

4.3. Empirical Specification

The baseline panel specification, following Schlenker and Roberts (2009) and Burgess et al. (2017), takes the form:

$$\ln(\mathrm{AVA}_{it}) = \alpha_i + \lambda_t + \beta_1 \mathrm{TEMP}_{it} + \beta_2 \mathrm{TEMP}_{it}^2 + \beta_3 \mathrm{RAIN}_{it} + \beta_4 \mathrm{RAIN}_{it}^2 + \gamma X_{it} + \varepsilon_{it} \quad (2)$$

where AVA is real agricultural value added per hectare in state i and year t; α_i denotes state fixed effects controlling for time-invariant factors such as soil quality and topography;λ_t denotes year fixed effects controlling for India-wide shocks such as input-price movements and national policy reforms; X is a vector of time-varying controls including the natural logarithms of fertiliser per hectare, irrigation share, HYV share, and the agricultural labour intensity; and ε is the idiosyncratic error. The temperature optimum, T*, is recovered as :

$$T^* = -\frac{\beta_1}{2\beta_2} \quad (3)$$

To test the adaptation hypothesis, a second specification adds interactions of temperature with irrigation share and HYV share. Standard errors are clustered at the state level to allow for arbitrary within-state serial correlation, following Bertrand, Duflo, and Mullainathan (2004).

4.4. Estimation Procedure and Diagnostic Strategy

The estimation procedure follows the standard sequence for panel data with potentially non-stationary regressors (Wooldridge, 2010). First, panel unit-root tests are conducted using the Levin–Lin–Chu (Levin, Lin, & Chu, 2002) test for the common-root hypothesis and the Im–Pesaran–Shin (Im, Pesaran, & Shin, 2003) test for heterogeneous roots. Second, where the variables are found to be non-stationary, panel cointegration is tested using Pedroni's (2004) residual-based statistics. Third, the choice between fixed-effects and random-effects estimators is made on the basis of the Hausman (1978) specification test. Fourth, post-estimation diagnostics include the modified Wald test for groupwise heteroskedasticity, the Wooldridge test for serial correlation in panels, and a Pesaran cross-sectional dependence test. Fifth, robustness is assessed through:

- Alternative weighting by net sown area,
- Exclusion of states affected by reorganisation, and
- Re-estimation using the Driscoll–Kraay standard errors robust to general cross-sectional dependence.

4.5. Ethical Considerations

The study uses publicly available aggregate secondary data only. No human-subjects research is involved. All sources are duly acknowledged in the references.

V. EMPIRICAL RESULTS AND DISCUSSION

5.1. Descriptive Statistics

Table 2 reports descriptive statistics for the principal variables over the 1990–2023 panel. Real agricultural value added per hectare averaged approximately ₹52,800 (2011–12 prices) but varies substantially across states, with Punjab and Haryana at the upper end and Rajasthan and Jharkhand at the lower end. The mean growing-season temperature is 25.8°C with a standard deviation of 1.9°C across the state-year panel, while growing-season precipitation averages 819 mm with a standard deviation of 326 mm. Irrigation coverage rose from a panel mean of 38.4 per cent in 1990 to 53.7 per cent in 2023; HYV adoption rose from 64.2 per cent to 86.5 per cent over the same window.

Table 2. Descriptive Statistics (State-Year Panel, 1990–2023)

Variable	Mean	Std. Dev.	Min	Max
AVA per hectare (₹'000)	52.8	28.4	9.7	142.6
Temperature (°C)	25.8	1.9	19.4	30.7
Rainfall (mm)	819	326	196	2,184
Irrigation (% GCA)	46.7	21.5	9.2	98.6
HYV share (%)	76.3	13.8	31.4	98.1
Fertiliser (kg/ha)	121.6	68.4	18.2	304.5

Note. N = 642 state-year observations (unbalanced panel). Author's calculations using CSO, IMD, and MoA&FW data.

5.2. Panel Unit-Root and Cointegration Tests

The Levin–Lin–Chu and Im–Pesaran–Shin tests reject stationarity at levels for lnAVA, lnFERT, IRR, and HYV ($p > 0.10$ in both tests), while rejecting non-stationarity in first differences ($p < 0.01$). The climate variables TEMP and RAIN are stationary at levels, consistent with their character as weather realisations. Given the mixed orders of integration, Pedroni's (2004) residual-based panel cointegration tests are applied; four of the seven statistics reject the null of no cointegration at the 5 per cent level, supporting the existence of a long-run relationship. The fixed-effects estimator is therefore implemented on the levels specification, with the understanding that the estimated coefficients capture both short- and long-run responses.

5.3. Hausman Test and Specification Choice

The Hausman (1978) test produces a chi-squared statistic of 38.4 with 9 degrees of freedom ($p < 0.01$), decisively rejecting the random-effects specification in favour of fixed effects. State fixed effects are therefore retained throughout. Year fixed effects are jointly significant ($F = 8.62$, $p < 0.01$) and are similarly retained.

5.4. Baseline Estimates

Table 3 reports the baseline panel fixed-effects estimates. The coefficient on temperature is positive and significant, while the coefficient on temperature squared is negative and significant, confirming the inverted-U shape posited in H_1. The implied growing-season temperature optimum, $T^* = -\frac{\beta_1}{2\beta_2}$, is 24.6°C, indicating that for most Indian states the current growing-season temperature lies at or slightly above the productivity-maximising level. A 1°C increase from a baseline of 26°C approximately the panel mean reduces productivity by an estimated 4.7 per cent. The precipitation coefficients are similarly consistent with H_2: positive in levels, negative in squares, with the implied rainfall optimum at approximately 1,180 mm. Both irrigation and HYV share enter with the expected positive signs and are individually significant at the 1 per cent level.

Table 3. Baseline Panel Fixed-Effects Estimates (Dependent Variable: lnAVA)

Regressor	(1) Baseline	(2) With adaptation	(3) Add ln-controls	(4) Driscoll–Kraay
TEMP	0.218***	0.241***	0.205***	0.205***
$TEMP^2$	−0.0044***	−0.0049***	−0.0041***	−0.0041***
RAIN ($\times 10^{-3}$)	0.412***	0.398***	0.376***	0.376**
$RAIN^2$ ($\times 10^{-7}$)	−0.174***	−0.168***	−0.159***	−0.159**
IRR	0.0083***	0.0091***	0.0079***	0.0079***
HYV	0.0064***	0.0068***	0.0061***	0.0061***
TEMP × IRR	—	0.0011**	0.0010**	0.0010*
TEMP × HYV	—	0.0007*	0.0006	0.0006
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Within R^2	0.642	0.658	0.681	0.681
Observations	642	642	642	642

Note. Cluster-robust standard errors (state level) in columns (1)–(3); Driscoll–Kraay standard errors in column (4). ***, **, * denote significance at 1%, 5%, and 10% respectively. The implied temperature optimum from column (1) is $T^* = 24.6$°C. Source: Author's estimation.

5.5. Adaptation Effects

Column (2) of Table 3 augments the baseline specification with interaction terms between temperature and the adaptation variables. The TEMP × IRR coefficient is positive and significant at the 5 per cent level ($\beta = 0.0011$), and the TEMP × HYV interaction is positive at the 10 per cent level. Interpreting the irrigation interaction, a state with 70 per cent irrigation coverage faces a temperature damage approximately 27 per cent smaller than an otherwise identical state with 40 per cent coverage. The result provides direct empirical support for H_3 and is consistent with the agronomic literature on the role of irrigation in buffering heat stress through evaporative cooling and soil-moisture maintenance.

5.6. Heterogeneous Effects across Agro-Climatic Zones

Re-estimating the baseline model separately for arid/semi-arid states (Rajasthan, Gujarat, Haryana, Punjab, parts of Maharashtra and Karnataka), humid/sub-humid states (Kerala, West Bengal, Assam, Tamil Nadu coastal), and the Indo-Gangetic plain reveals substantial heterogeneity. The temperature damage coefficient is largest in arid/semi-arid states ($\beta2 = -0.0061$), intermediate in the Indo-Gangetic plain ($\beta2 = -0.0042$), and smallest in humid states ($\beta2 = -0.0028$). This pattern is consistent with H_4 and with Burgess et al. (2017), and underscores the unequal climate burden facing different parts of India.

5.7. Diagnostic and Robustness Tests

Diagnostic tests provide reassurance about the validity of the estimates. The modified Wald test rejects homoskedasticity ($p < 0.01$), motivating the use of cluster-robust standard errors. The Wooldridge test rejects no first-order serial correlation ($p < 0.01$), addressed through clustering at the state level. The Pesaran cross-sectional dependence test rejects independence ($p < 0.05$), addressed through the Driscoll–Kraay specification reported in column (4) of Table 3; the principal coefficients are robust to this alternative. Excluding the four states affected by reorganisation (the Andhra Pradesh-Telangana split in 2014 and the Bihar -Jharkhand, Madhya Pradesh-Chhattisgarh, and Uttar Pradesh-Uttarakhand splits in 2000) produces estimates within 8 per cent of the baseline. Net-sown-area weighting produces similar results.

5.8. Discussion

The findings situate Indian agriculture within the global climate-economics literature and extend it in three respects. First, the estimated growing-season temperature optimum of 24.6°C lies below the panel mean of 25.8°C, indicating that most Indian growing regions already operate beyond the productivity-maximising temperature. This finding is consistent with Schlenker and Roberts (2009) for major U.S. crops and with Burgess et al. (2017) for Indian mortality. Second, the magnitude of the estimated damage approximately 4.7 per cent productivity loss per additional degree above baseline is consistent with the cross-country evidence of Dell et al. (2012) and Carleton and Hsiang (2016). Third, and most importantly for policy, the significant adaptation interactions demonstrate that the marginal damages are not fixed: investment in irrigation and seed-system modernisation can meaningfully attenuate the climate burden.

Three caveats merit acknowledgement. First, the panel approach captures the short- and medium-run response to weather variation but cannot identify long-run adaptation through structural transformation, crop-mix shifts, and migration. Hybrid Ricardian panel approaches such as Hsiang (2010) are a promising direction for future work. Second, the use of state-level aggregates masks within-state heterogeneity that finer-grained district-level data could illuminate. Third, the panel period coincides with sustained input subsidy reforms and changes in support-price regimes whose dynamic effects are absorbed into year fixed effects rather than separately identified.

VI. CONCLUSION AND POLICY IMPLICATIONS

This study has estimated the effect of climate variation on Indian agricultural productivity using an unbalanced panel of twenty major states over 1990–2023. Four findings emerge. First, growing-season temperature exhibits a robust inverted-U relationship with agricultural value added per hectare, implying that most Indian states already operate at or above the temperature optimum of approximately 24.6°C. Second, a 1°C rise above this threshold reduces productivity by approximately 4.7 per cent. Third, growing-season rainfall has a similar concave structure, with the optimum at approximately 1,180 mm. Fourth, irrigation coverage and HYV adoption attenuate the marginal damages of warming, providing direct empirical support for the adaptation-investment hypothesis.

Four policy implications follow. First, the climate burden on Indian agriculture is already measurable and is unlikely to be neutralised by autonomous adaptation alone; planned investment in adaptation is essential. Second, accelerating irrigation expansion particularly micro-irrigation in arid and semi-arid zones offers a high-leverage adaptation channel. Third, the development and dissemination of heat-tolerant seed varieties through the Indian Council of Agricultural Research (ICAR) and state agricultural universities should be prioritised, with particular attention to short-duration and stress-tolerant cultivars. Fourth, the scaling-up of weather-indexed crop insurance under the Pradhan Mantri Fasal Bima Yojana, together with improved last-mile payout systems, would address residual risk that adaptation cannot eliminate.

Three avenues for future research are particularly promising. First, district-level analyses using gridded climate data linked to land-use surveys would permit finer-resolution estimates. Second, integration of high-frequency weather data with farm-level panels would help identify the specific agronomic mechanisms heat stress at flowering, soil-moisture loss, pest dynamics that mediate the aggregate productivity response. Third, the interaction between climate adaptation and structural transformation, including out-migration from agriculture, deserves greater attention as a long-run adaptation channel.

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