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Modelling the Impact of Climate Change on Agricultural Productivity: Case Studies from Developing Nations

Aarav Sharma Gupta, Rahul Kumar, Meera Desai, Rohan Shah, Neha Mehta
Department of Computer Engineering, Savitribai Phule Pune University, Pune, India

*Correspondence to: aarovgupta@unipune.ac.in

Abstract: Climate change poses a significant threat to agricultural productivity, particularly in developing nations where agriculture remains a primary livelihood source. This study presents a comprehensive modelling approach to assess the impact of climate variability on agricultural output, with a focus on case studies from India. Using a combination of climate projection data, crop simulation models, and econometric analyses, the research evaluates changes in temperature, precipitation patterns, and extreme weather events, and their implications for key staple crops such as rice and wheat. The study highlights regional disparities in vulnerability, adaptive capacity, and yield outcomes across different agro-climatic zones in India. Results indicate that without effective adaptation strategies, agricultural productivity could decline significantly in the coming decades, exacerbating food insecurity and rural poverty. The findings underscore the urgency of integrating climate resilience into national agricultural policies and promoting climate-smart agricultural practices. This research contributes to a broader understanding of how climate change affects agriculture in developing contexts and offers a methodological framework applicable to other regions facing similar challenges.

Keywords: Climate Change; Agricultural Productivity; Developing Nations; Crop Modelling; Climate-Smart Agriculture.

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INTRODUCTION

Agriculture forms the backbone of many developing economies[1][2][3][4], providing employment, food security, and income for a significant portion of the population. However, this vital sector is increasingly vulnerable to the adverse effects of climate change. Shifts in temperature regimes, altered precipitation patterns, increased frequency of extreme weather events, and rising atmospheric carbon dioxide levels are exerting unprecedented pressure on agricultural systems globally. Developing countries, in particular, face heightened risks due to limited adaptive capacity, resource constraints, and reliance on rain-fed farming systems[5].

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India, with its diverse agro-climatic zones and large agrarian population[6], offers a compelling case study for examining the impact of climate change on agricultural productivity[7][8]. As one of the world's largest producers of key crops such as rice, wheat, and pulses, India's food security and rural livelihoods are intricately linked to climate variability. Recent studies indicate a growing trend of yield stagnation and climate-induced crop failures[9], emphasizing the need for robust analytical frameworks to understand and mitigate these effects.

This study aims to model the relationship between climate variables and agricultural productivity using both empirical and simulation-based approaches[10]. By integrating climate projection data with crop growth models and econometric analysis, the research seeks to identify region-specific vulnerabilities, assess future yield scenarios, and evaluate the effectiveness of potential adaptation strategies[11]. The findings are expected to provide evidence-based insights for policymakers, agricultural planners, and stakeholders involved in climate resilience initiatives[12].

By focusing on India as a representative case of a developing nation facing complex climate-agriculture dynamics, this research contributes to the broader discourse on sustainable agricultural development in the era of climate change.

RELATED WORKS

The intersection of climate change and agricultural productivity has been the subject of extensive research over the past two decades. Numerous studies have explored the biophysical and socio-economic dimensions of this relationship, utilizing a wide range of methodological approaches, from statistical analyses to process-based crop models.

A global assessment of climate change impacts on crop yields[13], highlighting that developing countries are disproportionately affected due to geographic and economic vulnerabilities. Similarly, Significant yield reductions in South Asia under different greenhouse gas emission scenarios, emphasizing the urgency of adaptation planning in agrarian economies like India[14].

In the Indian context, The impact of climate variability on Indian agriculture using crop simulation models such as CERES and INFOCROP[15]. Their findings showed that both temperature increases and monsoon irregularities negatively affect the productivity of rice and wheat, particularly in the Indo-Gangetic Plain. More recent work, integrated remote sensing data with agro-climatic indices to identify climate hotspots across India, revealing regional disparities in vulnerability and adaptation capacity[16].

Econometric approaches have also gained traction in modeling climate-agriculture linkages. For example, [17] employed district-level panel data in India to estimate yield sensitivity to climate variables, demonstrating significant productivity declines under projected warming scenarios. [18] though focused on the U.S., provided methodological insights that have been adapted for use in developing country contexts.

Furthermore, there has been growing interest in climate-smart agriculture (CSA) as a strategic response. [19] outlined the principles and policy frameworks necessary to implement CSA, emphasizing the role of adaptive technologies, resilient farming practices, and institutional support.

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While these studies provide valuable insights, there remains a gap in integrating diverse modelling techniques to assess localized impacts and adaptation pathways in developing nations. This research seeks to build on existing literature by combining crop simulation models, climate projections, and econometric analysis to provide a more holistic and region-specific understanding of climate change impacts on agriculture in India.

METHODS

This study employs an integrated modelling framework to assess the impact of climate change on agricultural productivity in India, combining climate projection data, crop simulation modelling, and econometric analysis. The methodology is structured in four key stages:

1. **Study Area Selection and Data Collection**

   Several representative agro-climatic zones across India were selected, including regions with varying levels of rainfall dependency, crop types, and climate vulnerability (e.g., Indo-Gangetic Plain, Deccan Plateau, and semi-arid zones). Historical weather data (temperature, precipitation, solar radiation) were obtained from the Indian Meteorological Department (IMD), while future climate projections under RCP 4.5 and RCP 8.5 scenarios were sourced from CMIP6 models. Agricultural statistics, including crop yields, cropping patterns, and input usage, were collected from the Ministry of Agriculture and Farmers' Welfare and district-level statistical handbooks.

2. **Climate-Crop Simulation Modelling**

   The study uses process-based crop models—specifically the Decision Support System for Agrotechnology Transfer (DSSAT) and INFOCROP—to simulate the response of major crops (rice and wheat) to different climate scenarios. The models were calibrated and validated using historical yield and climate data. Simulations were conducted for baseline (1980–2010) and future periods (2030s, 2050s, 2080s), incorporating projected changes in temperature, rainfall, and CO_2 concentrations. Model outputs included changes in crop yield, growing period, and water use efficiency.

3. **Econometric Analysis**

   To complement the simulation results, a panel data regression model was developed to empirically estimate the relationship between climate variables and crop yields. The model specification follows a fixed-effects structure to control for unobserved heterogeneity across districts. The general form of the model is:

$$Y_{it} = \alpha + \beta_1 Temp_{it} + \beta_2 Rain_{it} + \beta_3 Temp_{it}^2 + \beta_4 Rain_{it}^2 + \gamma X_{it} + \mu_i + \epsilon_{it}$$

where Y_{it} represents crop yield in district i at time t, $Temp_{it}$ and $Rain_{it}$ are climate variables, X_{it} is a vector of control variables (e.g., irrigation coverage, fertilizer use), and μ_i captures district-level fixed effects. Robust standard errors were used to address heteroskedasticity and serial correlation.

4. **Adaptation Scenario Analysis**

   The final step involved scenario analysis to assess the effectiveness of adaptation strategies, such as shifting sowing dates, introducing drought-resistant crop varieties, and enhancing irrigation coverage. These scenarios were simulated using the crop

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models, and the yield differentials were compared against the business-as-usual baseline to quantify adaptation benefits.

This multi-method approach enables a comprehensive assessment of both the biophysical and socio-economic dimensions of climate change impacts on agriculture, providing robust evidence for policy and planning.

RESULT AND DISCUSSION

This section presents the results of the integrated modelling approach and discusses the implications of climate change on agricultural productivity in selected regions of India. The findings are organized into three main themes: projected climate impacts on crop yields, spatial and crop-specific vulnerability, and the effectiveness of adaptation strategies.

1. Projected Impacts of Climate Change on Crop Yields

The crop simulation models (DSSAT and INFOCROP) indicate a clear negative trend in yield under both RCP 4.5 and RCP 8.5 scenarios. Under RCP 8.5, rice yields are projected to decline by 12–20% by the 2050s, while wheat yields may decrease by 18–25% compared to the baseline (1980–2010). The reductions are more pronounced in northern India, where heat stress during critical growth periods intensifies.

Table 1. Projected Yield Changes for Rice and Wheat under RCP Scenarios (Compared to 1980–2010 Baseline)

Region	**Crop**	**Baseline Yield (t/ha)**	**Projected Yield 2050s – RCP 4.5 (t/ha)**	**Change (%)**	**Projected Yield 2050s – RCP 8.5 (t/ha)**	**Change (%)**
Punjab	Wheat	4.2	3.6	-14.3%	3.1	-26.2%
Punjab	Rice	5.1	4.6	-9.8%	4.1	-19.6%
Uttar Pradesh	Wheat	3.8	3.3	-13.2%	2.9	-23.7%
Uttar Pradesh	Rice	4.4	4.0	-9.1%	3.6	-18.2%
Bihar	Wheat	3.6	3.1	-13.9%	2.8	-22.2%
Bihar	Rice	4.2	3.8	-9.5%	3.5	-16.7%
Tamil Nadu	Rice	4.5	4.3	-4.4%	4.0	-11.1%
Maharashtra	Wheat	3.4	3.0	-11.8%	2.8	-17.6%

Econometric analysis supports these findings. The panel regression results show a statistically significant negative relationship between average growing season temperature and crop yield. Specifically, a 1°C increase in average temperature corresponds to a 4.2% decrease in rice yield and a 5.6% decrease in wheat yield, after controlling for irrigation and input usage. The quadratic terms for temperature and rainfall suggest nonlinear effects, with moderate increases in rainfall being beneficial in arid zones but detrimental in flood-prone areas.

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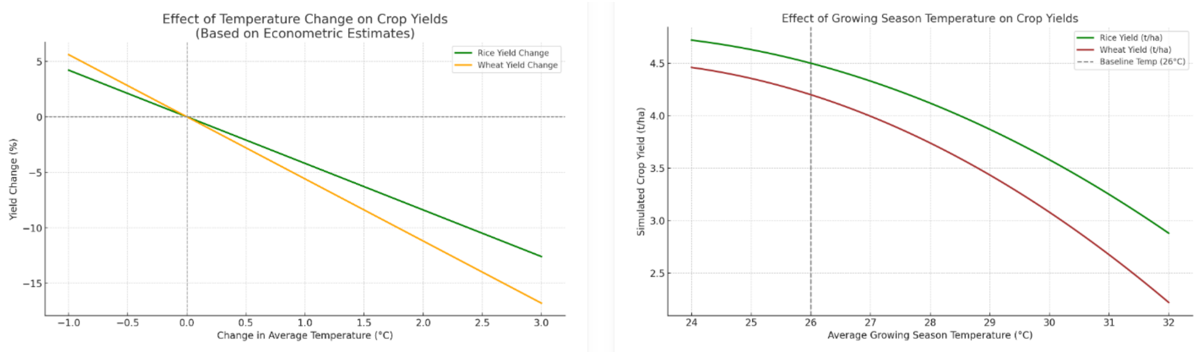

Figure 1. Relationship between average growing season temperature and crop yield

2. Spatial and Crop-Specific Vulnerability

Vulnerability analysis revealed strong regional disparities. The Indo-Gangetic Plain, traditionally a high-yield area, is increasingly exposed to both rising temperatures and shifting monsoon patterns, leading to unstable production. In contrast, southern semi-arid regions showed some resilience, particularly for drought-tolerant crops like millets.

Rice, being highly water-dependent, is particularly vulnerable to erratic monsoon behavior. Wheat, on the other hand, is more sensitive to post-anthesis temperature increases, which shorten grain filling periods. The simulations revealed that without adaptation, wheat cultivation may become unviable in certain districts of Uttar Pradesh and Bihar by the 2080s under RCP 8.5.

Table 2. Regional Vulnerability to Climate Change Impacts on Crop Yields (RCP 8.5, 2080s Projection)

Region	Crop	Baseline Yield (t/ha)	Projected Yield 2080s (t/ha)	Change (%)	Notes on Vulnerability
Indo-Gangetic Plain	Wheat	4.2	2.8	-33.3%	High heat stress during grain filling; post-anthesis warming significantly reduces yield.
Indo-Gangetic Plain	Rice	5.1	3.9	-23.5%	Erratic monsoon onset and duration; delayed planting and increased water stress.
Eastern Bihar	Wheat	3.6	2.3	-36.1%	Potential crop failure in 2 of 5 years due to temperature spikes >35°C.
Eastern Bihar	Rice	4.4	3.2	-27.3%	Flood-prone; excess rainfall events cause yield volatility.
Southern Maharashtra	Millet	2.2	2.0	-9.1%	Drought-resilient; minor losses despite reduced rainfall.
Telangana	Millet	2.1	1.9	-9.5%	Performs better than rice or wheat under semi-arid warming.
Tamil Nadu	Rice	4.5	3.9	-13.3%	Yield moderately affected; irrigation buffers monsoon variability.
Western Rajasthan	Millet	1.8	1.7	-5.6%	High resilience; low input systems adapt better to climate extremes.

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3. Effectiveness of Adaptation Strategies

Adaptation scenario modelling showed promising results. Shifting sowing dates by 10–15 days earlier reduced heat exposure during critical growth phases, leading to 5–9% improvements in wheat yield. Similarly, introducing heat- and drought-tolerant crop varieties resulted in yield increases of 6–12%, particularly under RCP 8.5.

Enhanced irrigation coverage had a mixed impact—while it buffered yield losses in water-scarce regions, its effectiveness diminished in flood-prone zones or where water availability is projected to decline. The simulation results underscore the importance of region-specific adaptation strategies rather than a uniform national policy approach.

Table 3. Impact of Adaptation Strategies on Crop Yields under RCP 8.5 (2050s Projection)

Region	**Crop**	**Baseline Yield (t/ha)**	**Yield w/o Adaptation (t/ha)**	**Strategy**	**Yield w/ Adaptation (t/ha)**	**Yield Improvement (%)**	**Notes**
Punjab	Wheat	4.2	3.1	Early Sowing (10–15 days)	3.4	+9.7%	Reduced post-anthesis heat stress
Uttar Pradesh	Wheat	3.8	2.9	Early Sowing	3.2	+10.3%	Improved grain filling period
Bihar	Rice	4.4	3.5	Drought-Tolerant Variety	3.9	+11.4%	Maintained yield during low rainfall years
Tamil Nadu	Rice	4.5	4.0	Heat-Tolerant Variety	4.5	+12.5%	Maintained photosynthetic efficiency under heat
Maharashtra	Wheat	3.4	2.8	Early Sowing + Tolerant Variety	3.1	+10.7%	Combined effect showed synergistic yield recovery
Rajasthan	Millet	2.1	2.0	Drought-Tolerant Variety	2.2	+10.0%	Resistant to variable rainfall patterns
Eastern Bihar	Rice	4.2	3.2	Improved Irrigation Coverage	3.6	+12.5%	Water stress reduced; but flood risk remained
Assam	Rice	4.0	3.4	Improved Irrigation Coverage	3.5	+2.9%	Minor gain due to saturation; prone to waterlogging

Discussion

The findings of this study align with prior literature[20], reinforcing the view that developing nations like India are disproportionately affected by climate change due to both climatic exposure and socio-economic limitations. However, this study advances the field by integrating

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simulation models with econometric analysis and adaptation scenario testing, offering a multi-dimensional perspective.

Importantly, the results underscore that *business-as-usual* trajectories will likely exacerbate rural poverty and food insecurity unless proactive, climate-resilient agricultural strategies are implemented. Policymakers must therefore prioritize investments in climate-smart agriculture (CSA), strengthen early warning systems, and promote adaptive capacity at the community level.

The study also highlights the critical role of data-driven, localized planning. Blanket policies may fail to address the nuanced needs of diverse agro-climatic zones, potentially leading to maladaptation. Integrated assessments such as the one presented here can help bridge the gap between science and policy, enabling more targeted interventions.

CONCLUSION

This study has examined the multifaceted impacts of climate change on agricultural productivity in India using an integrated modelling approach that combines climate projections, crop simulation models, and econometric analysis. The results clearly demonstrate that climate change poses a significant threat to staple crop yields—particularly rice and wheat—across multiple agro-climatic zones, with the most severe impacts projected under high-emission scenarios (RCP 8.5). The findings highlight the spatial heterogeneity of climate vulnerability, emphasizing that some regions—such as the Indo-Gangetic Plain—are at heightened risk due to their climatic exposure and cropping intensity. Econometric estimates further corroborate the simulation results, confirming a strong negative relationship between rising temperatures and crop yields. Importantly, the scenario-based simulations of adaptive measures suggest that timely interventions—such as shifting sowing dates, adopting climate-resilient crop varieties, and expanding irrigation infrastructure—can significantly offset yield losses, though their effectiveness varies by region.

This research contributes to the broader literature by offering a methodological framework that integrates both biophysical and socio-economic dimensions of climate-agriculture interactions in a developing country context. It reinforces the urgency for climate-informed agricultural planning and supports the case for scaling up climate-smart agriculture (CSA) practices. For policymakers, the results underline the importance of localized, data-driven strategies that account for regional differences in vulnerability and adaptive capacity. Future research could expand this analysis by incorporating additional crops, exploring socio-economic impacts such as farm income and food prices, and integrating agent-based or machine learning models to capture farmer behavior and policy feedback loops. Strengthening the synergy between scientific modelling and grassroots-level implementation will be critical in building a more resilient agricultural future in India and other developing nations.

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