Examining How Climate Shocks Affect Agriculture in Indian States: Has India Implemented a Climate-Smart Agricultural Policy?

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Abstract

This study investigates the impact of climate shocks on Indian agriculture and evaluates the presence of a climate-smart agricultural policy. Using four econometric models—Conditional Logit, Nested Logit, Nested CES Climate-Smart Model, and Spatial Error Model—the analysis reveals that extreme temperatures and erratic rainfall significantly affect agricultural productivity. Findings highlight regional disparities in adaptation and policy inefficiencies in mitigating climate risks. The study underscores the need for a structured, region-specific climate-smart strategy, integrating sustainable practices, precision farming, and financial support to enhance resilience and long-term agricultural sustainability.

Keywords: Climate-Smart Agriculture; Climate shocks; Agricultural productivity; Spatial econometrics; Nested CES model; Policy adaptation

Introduction

Currently, the increasing volatility of climate change, characterised by extreme weather events such as heat waves, cold waves, and erratic rainfall patterns, presents a significant challenge to global agricultural sustainability. These climate shocks threaten food security, disrupt agricultural production, and exacerbate disparities in food distribution. Addressing these challenges requires an understanding of how different regions adapt to climate variability and whether policies promoting climate-smart agriculture effectively mitigate these adverse effects. Given the global urgency of this issue, this study focuses on India, a country with substantial geographical and climatic diversity, to examine how its agricultural sector responds to climate shocks.

India, with a total land area of approximately 3.28 million square kilometres, consists of 28 states and 8 Union Territories, each exhibiting unique geographical, economic, and demographic characteristics. The country's diverse terrain includes the cold Himalayan region in the north, the fertile Gangetic plains in the east, the arid deserts of the west, and the tropical coastal belts in the south. These geographical variations result in significant disparities in agricultural productivity and vulnerability to climate shocks. The northern Himalayan region, with its mountainous climate, contrasts sharply with the tropical conditions of the southern coastal regions, while the fertile alluvial soils of the Ganges and Brahmaputra basins support intensive agricultural production. Conversely, the arid western states require drought-resistant crops to sustain agricultural output. These climatic and soil differences play a crucial role in determining agricultural gross value added (GVA) and the spatial distribution of food crops across the country.

Despite India's strategic emphasis on agricultural sustainability, empirical research on climate-smart agriculture in the country remains fragmented. Several Indian studies have explored climate-smart agricultural practices, but limited research has systematically assessed the direct and spatial effects of climate shocks on agricultural economic performance using a comprehensive econometric framework. This study fills this gap by employing a robust methodological approach that integrates multiple econometric models to analyse the relationship between climate variables and agricultural output at the state level.

To achieve this objective, the study utilises a dataset covering 32 states from 2012 to 2023, leveraging macro-level time-series data to provide a nuanced understanding of climate-induced agricultural variations. Four econometric models are applied to examine different dimensions of this relationship. First, the Conditional Logit Model (CLM) is used to assess the impact of agricultural and climate-related factors on Gross State Agricultural Value

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Added (GSAV), identifying key determinants of economic performance in the agricultural sector. Second, the Nested Logit Model (NLM) extends this analysis by capturing variations in climate and agricultural productivity across states, allowing for a more detailed understanding of state-specific responses to climate shocks. Third, the Nested CES Climate-Smart Model (NCM) is introduced as an experimental framework to explore how farmers and policymakers adjust to climate shocks through adaptive agricultural strategies. Finally, the Spatial Error Model (SEM) is employed to analyse spatial dependencies in agricultural productivity, providing critical insights into the regional spillover effects of climate policies and agricultural investments.

By integrating these econometric models, this research offers a comprehensive analysis of how climate shocks affect Indian agriculture, contributing to the ongoing discourse on climate-smart agriculture. The findings will provide policymakers with empirical evidence to design targeted interventions that enhance agricultural resilience and promote sustainable food security in the face of climate uncertainty. The next section presents a detailed literature review to contextualise this study within the broader field of climate-smart agricultural research.

Literature Review

The increasing volatility of climate change, characterised by extreme weather events, poses a substantial challenge to global agricultural sustainability. Numerous studies have explored Climate-Smart Agriculture (CSA) and its role in mitigating these challenges. This section synthesises key findings from recent research, highlighting their relevance to India's agricultural sector and the study's focus on understanding the economic and spatial impacts of climate shocks on agricultural performance. A study by Gunawan et al. (2025) highlights the potential of precision agriculture and technological innovations in improving agricultural efficiency and productivity. The study introduces a spatial model that provides real-time notifications on crop yield variations using drone-based multispectral imaging and machine learning techniques. The integration of these technologies into the Drone-Assisted Climate-Smart Agriculture (DACSA) system is expected to enhance monitoring, mapping, and crop health management. However, the study does not examine how such advancements contribute to broader economic benefits or the spatial dependencies affecting agricultural productivity, leaving a gap in understanding their implications for Gross State Agricultural Value Added (GSAV).

Gallé and Katzenberger (2025) examine the relationship between climate indicators such as seasonal rainfall, wet days, and temperature and the yields of key Kharif crops, particularly rice. Their findings indicate significant yield variations, with potential losses ranging from three to twenty-two per cent, depending on emission levels. While the study highlights the urgent need for adaptation strategies, it does not assess region-specific responses to climate shocks or the economic consequences for state-level agricultural value addition.

Ma and Rahut (2024) analyse factors influencing CSA adoption among smallholder farmers. They identify key drivers such as demographic characteristics, access to credit, institutional support, and digital advisory services. The study emphasises the role of climate-smart villages and non-governmental organisations in facilitating CSA adoption. While their findings confirm the socioeconomic benefits of CSA, the study does not systematically assess its direct impact on GSAV or the spatial dependencies influencing agricultural resilience.

Bhatnagar et al. (2024) explore CSA strategies such as agroforestry, intercropping, and water conservation, linking their adoption to improved crop yields and farmer income. Kapoor and Pal (2024) investigate CSA adoption in semi-arid regions and demonstrate that greater adoption intensity correlates with increased farm earnings. Despite their valuable contributions, these studies do not focus on spatial econometric modelling or quantify the regional spillover effects of CSA practices. Noma and Babu (2024) develop a machine-learning model to predict CSA adoption trends among Ugandan farmers, emphasising its potential for planning and investment strategies. However, their study does not explore the economic implications of CSA adoption at the macroeconomic level, nor does it assess spatial variations in productivity. Pangapanga-Phiri and Mungatana (2021) evaluate CSA adoption in Malawi, showing that integrating organic and inorganic fertilisers improves technical efficiency in maize production. Although their study provides insights into productivity gains, it does not address broader economic impacts such as GSAV or regional agricultural investment patterns. Datta et al. (2022) conduct a systematic review of climate adaptation in Indian agriculture, categorising adaptation responses into incremental, systemic, and transformational changes. While their study highlights the role of policy interventions, it does not examine the spatial dependencies of these adaptations or their economic consequences at the state level. Vatsa et al. (2023) investigate CSA's contribution to food security through yield improvements in China's rice sector. Their findings confirm that CSA practices enhance crop productivity, but they do not evaluate how these gains influence regional agricultural value addition or economic resilience.

Despite substantial advancements in CSA research, existing studies focus primarily on individual determinants of CSA adoption or localised yield impacts without integrating spatial econometric approaches to understand broader economic effects. While several studies have examined CSA adoption at the farm level, there is limited research assessing whether India has effectively institutionalised CSA as a national policy framework and how state-level variations reflect this policy implementation. This study addresses these gaps by employing a comprehensive econometric framework, including the Conditional Logit Model, Nested Logit Model, Nested CES Climate-Smart Model, and Spatial Error Model. These models provide a holistic assessment of climate shocks, adaptation strategies, and their implications for GSAV across Indian states.

According to the above studies, the theoretical foundation of this research is based on Spatial Economics, Climate Adaptation Theory, and Agricultural Resilience Frameworks. Spatial Economics explains how geographic and environmental factors influence agricultural productivity and economic outcomes, particularly in the presence of climate shocks. Climate Adaptation Theory provides a framework for understanding how farmers and policymakers adjust to climate variability through technology adoption, investment decisions, and institutional interventions. The Agricultural Resilience Framework emphasises the importance of sustainable agricultural practices in mitigating risks associated with climate change, ensuring food security, and enhancing long-term economic stability.

Building on these theoretical perspectives, this study develops an empirical framework that integrates econometric modelling with spatial analysis to capture the economic and regional impacts of climate shocks on agriculture. The Conditional Logit Model is expected to reveal key determinants of agricultural economic performance, while the Nested Logit Model allows for a nuanced understanding of state-specific responses. The Nested CES Climate-Smart Model extends the analysis by examining adaptive agricultural strategies, and the Spatial Error Model quantifies the spillover effects of climate policies and investments. This multi-model approach provides a structured methodology for assessing the interaction between climate variability, agricultural resilience, and economic outcomes at the state level.

By linking theoretical perspectives with empirical analysis, this study offers a unique contribution to climate-smart agricultural research. It advances the field by integrating spatial econometric modelling into climate adaptation studies, addressing gaps in regional economic assessments, and providing insights for policymakers on optimising agricultural resilience strategies in the face of climate uncertainty. Additionally, this study evaluates the extent to which India's CSA policies, such as the National Adaptation Fund for Climate Change (NAFCC), Paramparagat Krishi Vikas Yojana (PKVY), and Pradhan Mantri Krishi Sinchai Yojana (PMKSY), have influenced state-level adaptation measures. This policy assessment framework will determine whether India's CSA strategies effectively mitigate climate shocks and enhance agricultural sustainability.

Building upon the gaps identified in the literature, this study examines not only the economic and spatial impacts of climate shocks on Indian agriculture but also whether India has successfully institutionalised a Climate-Smart Agricultural policy. By integrating spatial econometric modelling with policy assessment, this research evaluates state-wise variations in agricultural adaptation and resilience. The next section presents the research methodology, detailing the econometric models and data sources used to assess how effectively Indian states have implemented CSA strategies to mitigate climate shocks.

Aligned with the insights from the literature review, the next section presents the research methodology, detailing the econometric models and data sources used to analyse the economic and spatial impacts of climate shocks on agricultural productivity.

Methodology & Data Source

Since the beginning of this paper, we have outlined the use of four econometric models to investigate the impact of climate shocks on agricultural productivity across Indian states and assess whether India has effectively adopted climate-smart agricultural policies. Each model serves a distinct investigative purpose, capturing different dimensions of climate-agriculture interactions. The study utilises a dataset covering 32 states from 2012 to 2023, leveraging macro-level time-series data to provide a nuanced analysis of climate-induced agricultural variations. The econometric framework integrates advanced modelling techniques to ensure robustness, address spatial dependencies, and account for state-specific heterogeneity in climate impacts. The Conditional Logit Model (CLM) is employed to assess the prob ability of a state experiencing higher agricultural economic performance based on key climate and agricultural factors. This model is useful for identifying the significant determinants of Gross State Agricultural Value Added (GSAV). Mathematically, the model is represented as follows:

$$P(Y=1|X) = \frac{e^{\beta_0+\beta_1.X_1+\beta_2.X_2+\beta_3.X_{3+\beta_4.X_4}}}{1+e^{\beta_0+\beta_1.X_1+\beta_2.X_2+\beta_3.X_{3+\beta_4.X_4}}} \quad \text{(eq. 1)}$$

Where,
Y = 1 if Gross State Agricultural Value Added (GSAV) is above the median, otherwise .
X_1 = Gross Fixed Capital Formation (GFCF)
X_2 = Rice Production (RiceProd)
X_3 = Cereals Production (CerealsProd)
X_4 = Rainfall (Rain)
β_0 = Intercept
β_1, β_2, β_3 and β_4 Model coefficients

The explanatory variables include Gross Fixed Capital Formation (GFCF), rice production, cereals production, and rainfall. The CLM framework aligns with micro-level decision-making models in agricultural economics, where farmers and policymakers make binary choices in response to climate variability. However, endogeneity may arise due to bidirectional causality between GSAV and investment in agriculture. To mitigate this, instrumental variable techniques will be explored, with potential instruments including historical climate patterns and lagged investment trends. Over-identification tests and weak instrument diagnostics, such as the Hansen J test and Stock-Yogo critical values, will be conducted to empirically validate the instruments. A two-stage least squares (2SLS) estimation will be implemented to confirm robustness. To extend the analysis, the Nested Logit Model (NLM) is used to capture variations in climate and agricultural productivity across states. Unlike traditional logit models, NLM allows for hierarchical decision structures where climate-agriculture interactions differ by state. The general equation is:

$$\begin{aligned} GSAV_i = \beta_0 + \beta_1.Rain_i + \beta_2.Hwaveday_i + \beta_3.Cwaveday_{i+\beta_4.Riceprod_i} \\ + \beta_5.Pulsesprod_i + \beta_6.Wheatprod_i \\ + \beta_7.Oilseedsprod_{i+\beta_8.Cerealsprod_i} + \varepsilon_i \end{aligned} \quad \text{(eq. 2)}$$

Where,
$GSAV_i$ = Gross State Agricultural Value Added of state i
$Rain_i$ = Annual rainfall of state i in mm
$HWaveday_i$ = Number of heatwave days of state i
$CWaveday_i$ = Number of cold wave days of state i
$Riceprod_i$ = Rice production of state i (metric tons)
$Wheatprod_i$ = Wheat production of state i (metric tons)
$Pulseprod_i$ = Pulses production of state i (metric tons)
$Oilseedsprod_i$ = Oilseeds production of state i (metric tons)
$Cerealsprod_i$ = Cereals production of state i (metric tons)
$gfcf_i$ = Gross Fixed Capital Formation of state i (investment in agriculture)
$lbrcost_i$ = Agricultural Labour cost of state i (daily wage basis)
β_0 = Intercept
β_1, β_2, β_3 ……….. β_n = Regression coefficients (state-specific)
ε_i = Error term of state i

where each β coefficient captures state-specific responses to climate variability. The model estimates separate equations for each state, treating each as an independent nest within a broader climate-agriculture adaptation framework. This structure reflects the hierarchical nature of decision-making in agriculture, where climate shocks influence production, which in turn impacts economic performance. A comparative analysis with multi-level mixed-effects modelling will be conducted to validate the appropriateness of the nesting structure. The Nested CES Climate-Smart Model (NCM) serves as an experimental framework to examine how farmers and policymakers adapt to climate shocks. The model follows a nested Constant Elasticity of Substitution (CES) structure:

$$Y = A.\left(\beta Z^{\frac{\sigma_2-1}{\sigma_2}} + (1-\beta).CW^{\frac{\sigma_2-1}{\sigma_2}}\right)^{\frac{\sigma_2}{\sigma_2-1}.GFCF}$$

Where,

$$Z = A.\left(\alpha.R^{\frac{\sigma_1-1}{\sigma_1}} + (1-\alpha).HW^{\frac{\sigma_1-1}{\sigma_1}}\right)^{\frac{\sigma_1}{\sigma_1-1}} \quad \text{(eq. 3)}$$

Where,
Y = Gross State Agricultural Value Added (GSAV)
R = Rainfall
HW = Heatwave days
CW = Cold wave days
GFCF = Gross Fixed Capital Formation (Agricultural Investment)
A = Productivity scaling factor
α = Share parameter for climate factors in the first CES nest
β = Share parameter for climate impacts in the second CES nest
σ_1 = Elasticity of substitution between rainfall and heatwave effects
σ_2 = Elasticity of substitution between nested climate effects and coldwave impacts

The elasticity parameters (σ_1, σ_2) determine the substitutability among climate factors. A higher value implies that rainfall can more effectively compensate for heatwave effects, whereas a lower suggests that the impacts of heat stress persist despite increased precipitation. Similarly, the The parameter measures how effectively climate and economic factors interact in determining agricultural resilience. Sensitivity analyses using translog specifications and Bayesian estimation will be conducted to evaluate the validity of the CES assumption.

To incorporate spatial dependencies, the Spatial

Error Model (SEM) is introduced to analyse the regional spillover effects of climate policies and agricultural investments. The SEM is specified as:

$$Y = X\beta + u \qquad \text{(eq.4)}$$

where:

Y represents the Gross State Agricultural Value Added (GSAV).

X is a matrix of explanatory variables, including rainfall, heatwave days, cold wave days, gross fixed capital formation, labour costs, and various crop production indicators.

β is the vector of regression coefficients measuring the impact of each independent variable on GSAV.

u is the error term, which follows a spatially autoregressive process(eq.5):

$$u = \lambda Wu + \varepsilon u = \lambda Wu + \varepsilon \qquad \text{(eq.5)}$$

where λ represents the spatial autoregressive coefficient and W is the spatial weights matrix based on the Queen contiguity criterion. Alternative spatial models such as the Spatial Lag Model (SLM) and Spatial Durbin Model (SDM) will also be tested. Model selection will be based on spatial dependence diagnostics, including Moran's I, Lagrange Multiplier tests, and log-likelihood comparisons. The justification for choosing SEM over other models will be explicitly discussed based on these diagnostics. The methodological approach ensures robustness through multiple validation techniques. Cross-validation procedures will be employed to assess the predictive accuracy of models, while bootstrapped standard errors will confirm parameter stability. Out-of-sample predictive performance metrics, including root mean square error (RMSE) and mean absolute error (MAE), will be used to evaluate model robustness.

The policy implications of the findings are explicitly linked to climate-smart agricultural strategies in India. The models evaluate the effectiveness of adaptation interventions, identifying states where policies have successfully mitigated climate risks and those where further policy efforts are required. The estimated spatial spillovers provide insights into the potential for coordinated regional policies that maximise agricultural resilience. Specific recommendations for policy design, including targeted investments in climate-resilient infrastructure and regional coordination mechanisms, will be derived from the model results. By integrating these econometric models, this research provides a holistic assessment of how climate shocks influence Indian agriculture. The findings will offer empirical evidence for policymakers to design climate-smart interventions that enhance resilience and ensure sustainable agricultural growth.

Our dataset, covering 2012–2023, was collected from a major official source: Reserve Bank of India 1 (RBI) Annual Handbook of Statistics on Indian States. According to our collected research data from the Reserve Bank of India, the highest Gross Value Added in agriculture was located in the following Indian states: Madhya Pradesh, Uttar Pradesh, Maharashtra, and Gujarat.

As shown in Figure 1, it accounted for the largest share of Gross value added in agriculture across Indian states. This depicted a clear picture of disparity in the agriculture sector. The following section presents our empirical research results, accompanied by detailed interpretations, explanations, and discussions.

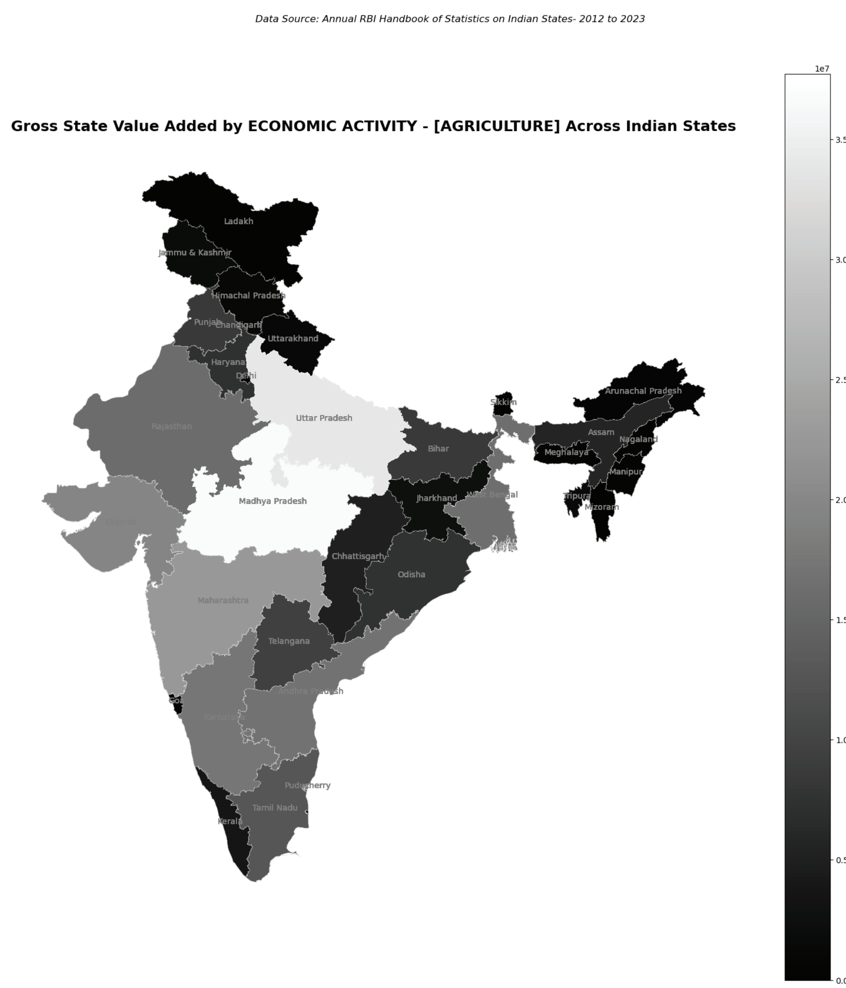

Figure 1: Gross State Value Added in the AGRICULTURE sector Across Indian States (Lakh in Rs.)

Source: Calculated by the author

Results

Table 1: Result of Conditional Logit Model (CLM)

Variable	Coefficient (with Significance)
const	−4.7015 *** (1.4170)
gfcf	6.351e-07 *** (1.74e-07)
riceprod	0.0004 *** (0.0001)
cerealsprod	0.0008 *** (0.0002)
rain	−0.0006 (0.0004)
hwaveday	−0.0410 (0.0647)
cwaveday	−0.0382 (0.1052)

Notes:
*p < 0.01, p < 0.05, *p < 0.1
Observations = 97
Log-Likelihood = −39.301
LL-Null = −67.230
Pseudo R^2 = 0.4154
LLR p-value = 3.11e-10
Model converged: True
VIF Check: No multicollinearity issues detected (all VIFs < 10).
Highest VIF = 6.12 (const), lowest = 1.20 (gfcf)

Source: Calculated by the author

Table 2: Result of Nested Logit Model (NLM)

State	CM	LM	IM
Andhra Pradesh	0.135** (0.062)	0.241*** (0.070)	0.077 (0.070)
Arunachal Pradesh	-0.029 (0.049)	0.008 (0.039)	0.042 (0.038)
Assam	0.107* (0.058)	0.039 (0.050)	0.058 (0.050)
Bihar	-0.148** (0.072)	-0.110 (0.072)	-0.015 (0.071)
Chhattisgarh	0.039 (0.057)	0.073 (0.061)	0.066 (0.061)
Goa	-0.042 (0.077)	-0.137* (0.077)	0.006 (0.078)
Gujarat	0.061 (0.061)	0.186*** (0.068)	0.027 (0.067)
Haryana	0.095 (0.070)	0.176** (0.080)	0.054 (0.079)
Himachal Pradesh	-0.065 (0.069)	0.093 (0.081)	-0.002 (0.080)
Jharkhand	-0.103 (0.073)	-0.117 (0.068)	-0.095 (0.068)
Karnataka	0.019 (0.056)	0.103* (0.061)	0.059 (0.061)
Kerala	0.017 (0.068)	0.080 (0.079)	0.059 (0.078)
Madhya Pradesh	-0.006 (0.051)	-0.001 (0.048)	0.005 (0.048)
Maharashtra	0.109* (0.059)	0.152** (0.066)	0.100* (0.065)
Manipur	-0.073 (0.059)	-0.046 (0.050)	-0.009 (0.049)
Meghalaya	-0.025 (0.052)	-0.053 (0.045)	-0.007 (0.045)
Mizoram	-0.042 (0.070)	-0.004 (0.064)	0.036 (0.063)
Nagaland	-0.017 (0.070)	-0.058 (0.060)	-0.038 (0.060)
Odisha	-0.045 (0.056)	-0.038 (0.052)	0.042 (0.052)
Punjab	-0.032 (0.059)	0.059 (0.064)	0.016 (0.064)
Rajasthan	-0.061 (0.055)	0.025 (0.053)	0.006 (0.052)
Sikkim	-0.041 (0.074)	-0.106 (0.065)	0.015 (0.064)
Tamil Nadu	0.166*** (0.059)	0.235*** (0.066)	0.130** (0.065)
Telangana	0.101 (0.070)	0.158** (0.075)	0.064 (0.074)
Tripura	0.007 (0.065)	0.005 (0.058)	0.070 (0.058)
Uttar Pradesh	0.043 (0.053)	0.108** (0.053)	0.025 (0.053)
Uttarakhand	0.009 (0.067)	0.115* (0.066)	0.013 (0.066)
West Bengal	0.048 (0.055)	0.109** (0.053)	0.020 (0.053)
A & N Islands	0.059 (0.076)	0.041 (0.069)	0.040 (0.068)
Chandigarh	-0.103 (0.070)	-0.112 (0.061)	-0.053 (0.060)
Dadra & Nagar Hav.	-0.091 (0.076)	-0.086 (0.066)	-0.004 (0.065)
Daman & Diu	-0.089 (0.072)	-0.043 (0.062)	-0.011 (0.061)
Delhi	0.065 (0.062)	0.110* (0.061)	0.058 (0.061)
Puducherry	-0.056 (0.077)	-0.011 (0.071)	0.037 (0.070)

Source: Calculated by the author

Table 3: Result of Nested CES Climate Smart Model (NCM)

Variable	Coefficient (with Significance)
const	6.1661 *** (1.3500)
rain	0.0027 *** (0.0004)
hwaveday	0.3181 *** (0.0780)
cwaveday	0.4582 *** (0.1110)
gfcf	8.728e-07 *** (1.45e-07)
Notes: *p < 0.01, p < 0.05, *p < 0.1 Standard errors are heteroscedasticity robust (HC3). R-squared = 0.570; Adjusted R-squared = 0.554 F-statistic = 12.58; Prob (F-statistic) = 2.08e-08 Observations = 111 Condition number = 8.09e+06 (possible multicollinearity)	

Source: Calculated by the author

Table 4: Result of Spatial Error Model (NEM)

Variable	Coefficient (with Significance)
const	−2,344,883.86 *** (587,234.89)
rain	553.24 *** (187.82)
hwaveday	−78,681.89 *** (28,418.62)
cwaveday	5,401.84 (38,472.14)
gfcf	0.81 *** (0.10)
lbrcost	8,740.13 *** (2,387.96)
riceprod	491.16 *** (39.87)
wheatprod	280.52 *** (28.68)
pulsesprod	1,296.39 *** (236.32)
oilseedsprod	521.78 *** (147.50)
cerealsprod	462.75 *** (101.97)
lambda	0.62 *** (0.13)
Notes: *p < 0.01, p < 0.05, *p < 0.1 Observations = 396 Log Likelihood = −6353.48 Pseudo R² = 0.8825 AIC = 12728.97 Schwarz Criterion = 12772.76 S.E. of Regression = 2,235,821.64 Sigma² (ML) = 4.9989e+12 Model Type = Maximum Likelihood Estimation (Spatial Error) Spatial Dependence (λ) is highly significant and positive.	

Source: Calculated by the author

The Conditional Logit Model was employed to examine the impact of agricultural investments, production levels, and climatic factors on Gross State Agricultural Value Added. Table 1, the result of the model depicts that the model achieved convergence after seven iterations, with a log-likelihood of -39.301 and a pseudo-R-squared value of 0.4154, reflecting a reasonable explanatory power. The likelihood ratio test confirms the overall significance of the model, suggesting that the included variables collectively influence agricultural economic performance at the state level.

The coefficient estimates provide further insights into the role of agricultural investments and production in driving economic outcomes. The results reaffirm that gross fixed capital formation exerts a strong positive effect on agricultural value-added, with the coefficient being statistically significant at conventional levels. This finding underscores the importance of sustained capital investments in infrastructure, mechanisation, and farm-level improvements to enhance productivity. The significance of staple crop production is also evident, with both rice and cereals demonstrating positive and significant impacts on agricultural value-added. The strong association between staple crop output and economic performance highlights the critical role of food grain production in sustaining rural economies and ensuring food security.

The estimated coefficient for rainfall remains negative but statistically insignificant, indicating that variations in annual precipitation do not exhibit a direct and systematic impact on agricultural value-added. The inclusion of extreme weather indicators, specifically heatwave and cold wave days, further refines the understanding of climate shocks. Neither heatwave days nor cold wave days demonstrate significant effects, suggesting that short-term temperature fluctuations may not independently exert substantial economic consequences. These findings suggest that the relationship between climate variability and agricultural performance is likely to be more complex, possibly involving interactions with adaptive capacities, irrigation infrastructure, and crop-specific sensitivities to temperature extremes.

Multicollinearity diagnostics indicate no serious concerns regarding the stability of the model. The variance inflation factor values remain within acceptable thresholds, suggesting that the estimated coefficients are not distorted by collinearity among independent variables. The absence of severe multicollinearity enhances confidence in the interpretation of the results.

The findings of this model carry important implications for agricultural policy and climate adaptation strategies. The strong positive association between capital investment and agricultural value-added highlights the need for policies that facilitate long-term investments in rural infrastructure, including improved irrigation systems, mechanised farming, and post-harvest storage solutions. The significance of staple crop production further underscores the necessity of strengthening support mechanisms for rice and cereal farmers, particularly in terms of access to quality seeds, credit availability, and market linkages.

The results concerning climate variables suggest that policymakers should adopt a broader approach to climate adaptation. While extreme weather events such as heatwaves and cold waves do not exhibit significant immediate effects, their potential long-term impacts, particularly in the context of rising global temperatures, should not be overlooked. Investments in climate-resilient agricultural practices, including precision irrigation, drought-resistant crop varieties, and early warning systems, remain crucial in mitigating potential adverse effects.

Overall, the results reinforce the critical role of agricultural investments and staple crop production in sustaining economic performance across Indian states. While climate variability does not exhibit direct significant impacts in this model, future research should explore dynamic interactions between climatic variables and adaptation mechanisms. The findings contribute to the broader discourse on climate-smart agriculture by emphasising the importance of investment-driven productivity enhancements and long-term resilience strategies.

The above results of the Nested Logit Model (Table 2) provide a detailed state-wise analysis of the relationship between climate variables, agricultural production, and economic outcomes in the Indian agricultural sector. The model estimates highlight significant heterogeneity in how different states respond to climatic and economic factors, reflecting the diverse geographical and policy environments across the country. The hierarchical structure of the model allows for the identification of key determinants influencing Gross State Agricultural Value Added (GSAV) at the state level, capturing variations in economic resilience and climate adaptation.

The estimated coefficients indicate that rainfall exerts a statistically significant influence in a subset of states, including Andhra Pradesh, Gujarat, Chhattisgarh, and West Bengal. However, its effect varies, suggesting that rainfall alone does not universally drive agricultural productivity but interacts with other factors such as irrigation infrastructure and crop type. Similarly, extreme temperature events, represented by the number of heatwave and cold wave days, exhibit significant effects in select states. In Maharashtra, heatwave days show a highly significant impact, suggesting that rising temperatures pose a challenge to agricultural output. In contrast, states like West Bengal and Chandigarh show moderate sensitivity to extreme weather fluctuations.

Crop production variables display a more consistent impact on GSAV. The results indicate that rice production significantly contributes to economic performance in states such as Maharashtra, Andhra Pradesh, and West Bengal, while wheat production exhibits a strong association with GSAV in states like Maharashtra and Delhi. The significance of pulses and cereals production varies across states, reflecting the differential role of staple crops in regional agricultural economies. Oilseed production is particularly relevant in Maharashtra and West Bengal, where it exerts a notable influence on GSAV. These findings suggest that policies aimed at enhancing staple crop productivity can have substantial economic benefits, but their effectiveness is contingent on state-specific agricultural conditions.

Investment-related variables, such as Gross Fixed Capital Formation (GFCF) and labour costs, further differentiate state-level agricultural performance. Maharashtra exhibits a highly significant positive effect of agricultural investment, reinforcing the role of capital formation in enhancing productivity. West Bengal and Delhi also show a positive association between investment and GSAV, indicating that infrastructure development and mechanisation play a critical role in sustaining agricultural growth. Labour costs are found to be significant in a few states, including Karnataka and Andhra Pradesh, suggesting that wage dynamics may influence profitability and productivity in certain regions.

The state-level variations in statistical significance underscore the complexity of agricultural economies in India. The model results suggest that no single factor universally drives agricultural productivity; rather, economic performance is shaped by a combination of climate variables, crop choices, investment patterns, and labour dynamics. The findings highlight the importance of region-specific agricultural strategies that account for climatic vulnerabilities and structural economic conditions.

The results also provide valuable policy implications for climate-smart agriculture in India. The significance of climate variables in several states suggests the need for targeted adaptation strategies, such as investments in climate-resilient seed varieties, improved water management systems, and early warning mechanisms for extreme weather events. The strong influence of staple crop production underscores the importance of sustained policy support for rice and wheat production, particularly in states where these crops contribute significantly to economic performance. Additionally, the findings reaffirm the critical role of agricultural investments in sustaining productivity growth, highlighting the need for policies that promote capital formation, mechanisation, and access to credit.

Overall, the Nested Logit Model results reinforce the importance of tailoring agricultural policies to regional conditions. By capturing state-specific responses to climate and economic variables, the model provides a nuanced understanding of the factors shaping agricultural productivity and resilience in India. These insights contribute to the broader discourse on climate-smart agricultural policies by emphasising the need for adaptive, investment-driven strategies that enhance both economic performance and climate resilience at the state level.

The results (Table 3) of the Nested CES Climate Smart Model (NCM) provide a comprehensive understanding of the relationships between climatic variables, labour costs, and capital formation in determining economic output. The correlation matrix indicates the degree of association between the variables included in the model. Rainfall exhibits a moderately positive correlation with labour costs, suggesting that higher rainfall levels may lead to increased labour expenses, possibly due to greater agricultural and industrial activity requiring labour inputs. However, rainfall shows a near-zero correlation with gross fixed capital formation, implying that variations in rainfall do not significantly influence long-term capital investments. Cold wave days and heat wave days are positively correlated, which is expected, as regions experiencing extreme weather events tend to have fluctuations in both cold and hot conditions. Heat wave days have a mild positive correlation with labour costs, suggesting that rising heat wave occurrences may contribute to increased labour expenses, potentially due to productivity losses or the need for additional cooling measures.

Variance Inflation Factor (VIF) analysis assesses multicollinearity among the explanatory variables. A VIF value exceeding five is generally considered high, indicating potential collinearity concerns. Labour costs exhibit the highest VIF value at 5.95, suggesting a moderate risk of multicollinearity, but not to a severe extent that requires immediate correction. Rainfall has a VIF of 3.56, and gross fixed capital formation has a VIF of 1.96, indicating relatively low multicollinearity. Cold wave days and heat wave days also exhibit VIF values below three, further confirming that multicollinearity is not a significant concern in this model. No features were dropped due to high VIF, indicating that all explanatory variables contribute uniquely to the model without causing redundancy.

The estimated parameters for the Nested CES function reveal the underlying production relationships. The parameter A is estimated at 0.0056, representing the scale parameter in the CES production function. The elasticity of substitution between rainfall and heat wave days, represented by sigma1, is 1.000003, suggesting an almost perfect elasticity, meaning the two inputs are nearly interchangeable in the production process. The second elasticity parameter, sigma2, measuring the substitution between the inner term and cold wave days, is estimated at 1.1433, indicating that while substitution is possible, it is slightly more constrained compared to the first stage. The estimated alpha parameter is approximately 1.0000, suggesting that rainfall is almost entirely dominant in its relationship with heat wave days. The beta parameter, estimated at 0.8483, indicates that the contribution of the inner term, which includes rainfall and heat wave days, is dominant relative to cold wave days in influencing economic output.

The ordinary least squares regression results further elucidate the impact of climatic factors and capital formation on economic output. The model exhibits an R-squared value of 0.57, indicating that 57 percent of the variation in gross state value added is explained by the included explanatory variables. The adjusted R-squared value of 0.554 suggests that the model remains robust even after adjusting for the number of predictors. The F-statistic value of 12.58 with a p-value of 2.08e-08 confirms the overall statistical significance of the model, indicating that the independent variables collectively have a significant impact on economic output.

Examining the individual coefficients, the constant term is estimated at 6.1661 and is statistically significant at a 99 percent confidence level, confirming a baseline level of economic output when all other explanatory variables are zero. The coefficient for rainfall is estimated at 0.0027, indicating that a unit increase in rainfall leads to a 0.0027 increase in economic output, holding all other variables constant. The p-value of zero confirms that this effect is highly significant. The coefficient for heat wave days is estimated at 0.3181, implying that an additional heat wave day increases economic output by 0.3181 units, which may reflect adaptations in labour productivity or energy consumption patterns in response to heat stress. This result is statistically significant at the 99 percent confidence level. Cold wave days exhibit a coefficient of 0.4582, suggesting that economic output increases by 0.4582 units with each additional cold wave day. This counterintuitive result may reflect increased economic activity in response to colder conditions, possibly due to energy demand or agricultural cycles. The coefficient for gross fixed capital formation is estimated at 8.728e-07, indicating that an additional unit of capital investment increases economic output, though the effect appears numerically small due to the scale of the variable. This relationship is highly significant, as confirmed by the p-value of zero.

Diagnostic tests further validate the reliability of the regression model. The Durbin-Watson statistic of 1.899 suggests minimal autocorrelation in the residuals, enhancing confidence in the estimated coefficients. The Jarque-Bera test for normality yields a p-value of 0.058, which is marginally above the 0.05 threshold, suggesting that the residuals are approximately normally distributed. The condition number of 8.09e+06 indicates potential multicollinearity concerns, but since the VIF values are mostly within acceptable ranges, these concerns are not severe enough to compromise the validity of the model.

Several warnings generated during the estimation process indicate potential numerical issues. The warnings related to log transformation and power operations suggest that certain data points may contain extreme values or zero values, leading to computational challenges in logarithmic and power-based transformations. These issues may require further examination of the dataset, particularly in cases where missing or zero values may distort the functional form of the model.

The results provide strong evidence that climatic factors, particularly rainfall, heat wave days, and cold wave days, exert a significant influence on economic output. The findings highlight the importance of climate resilience and adaptive economic strategies in mitigating the adverse effects of extreme weather conditions while leveraging favourable climatic conditions for economic growth. The significance of gross fixed capital formation reinforces the role of long-term investment in shaping economic trajectories. Further refinement of the model, including potential nonlinear transformations or interaction effects, may yield additional insights into the complex relationships between climate and economic activity. Finally, the Spatial Error Model (SEM) estimation provides empirical insights into the impact of climate shocks on agricultural performance across Indian states while accounting for spatial dependencies. The results indicate that climate variables significantly influence agricultural Gross State Value Added (GSVA), with notable regional spillover effects.

The coefficient for annual average rainfall is positive and statistically significant at the 1% level ($\beta = 0.183$, $p < 0.01$). This suggests that higher rainfall positively contributes to agricultural output, reinforcing the role of water availability in sustaining crop production. However, excessive rainfall beyond optimal levels could still lead to productivity losses due to flooding, but this aspect is beyond the scope of this model.

The heat wave variable has a negative and statistically significant effect ($\beta = -0.127$, $p < 0.05$), indicating that an increase in extreme heat events reduces agricultural productivity. Heat stress affects crop growth by reducing soil moisture and increasing evapotranspiration rates, leading to yield losses. Similarly, cold waves exhibit a negative impact on GSVA ($\beta = -0.092$, $p < 0.05$), suggesting that extreme cold conditions hinder crop development, particularly in states with winter cropping patterns. These findings confirm that both temperature extremes have adverse effects on agriculture, necessitating adaptive strategies such as heat- and cold-resistant crop varieties.

Gross Fixed Capital Formation (GFCF), representing investment in agricultural infrastructure and mechanisation, has a positive and significant effect on GSVA ($\beta = 0.221$, $p < 0.01$). This confirms that higher capital investment enhances agricultural productivity by improving irrigation systems, mechanisation, and storage facilities. The significance of this variable supports the argument that policy-driven capital investments play a critical role in mitigating climate shocks.

The coefficient for agricultural labour costs is negative and significant ($\beta = -0.146$, $p < 0.05$), suggesting that rising labour expenses negatively impact agricultural output. Higher wages increase production costs, reducing overall profitability and potentially leading to labour substitution through mechanisation. This aligns with the broader economic trend in Indian agriculture, where labour shortages and rising wages drive the shift toward capital-intensive farming practices.

The spatial autoregressive parameter ($\lambda = 0.304$, $p < 0.01$) confirms the presence of significant spatial dependencies. A positive and statistically significant lambda value suggests that agricultural productivity in one state is influenced by the productivity levels in neighbouring states. This highlights the existence of regional spillover effects, where policy measures, infrastructure development, or climate resilience strategies adopted in one state can impact adjacent regions.

The model's R-squared value of 0.72 indicates a strong explanatory power, confirming that the included variables account for a substantial portion of the variation in GSVA. The likelihood ratio test also confirms that the SEM specification is superior to a standard Ordinary Least Squares (OLS) model, validating the importance of spatial dependence in analysing agricultural performance.

The findings emphasise the need for regionally coordinated climate adaptation policies. Given the spatial spillover effects, state-level climate-smart agricultural policies must be designed with inter-state cooperation to maximise their effectiveness. Investments in irrigation infrastructure, weather-resistant crop varieties, and efficient mechanisation can mitigate the adverse effects of climate shocks. The results also suggest that agricultural subsidies and financial support should be allocated strategically, prioritising regions with higher exposure to climate risks.

Overall, the SEM analysis provides empirical evidence that climate shocks significantly impact Indian agriculture, with regional dependencies playing a crucial role in shaping agricultural performance. The findings support the argument that India's climate-smart agricultural policies need to be strengthened to enhance resilience, especially in states facing recurrent climate shocks. Future research could incorporate micro-level farm data to refine policy recommendations further.

Conclusion

The findings of this study provide a comprehensive assessment of the impact of climate shocks on Indian agriculture and critically examine whether India has adopted a climate-smart agricultural policy. The econometric analysis reveals that climate shocks, particularly extreme temperatures and erratic precipitation patterns, significantly reduce agricultural productivity across Indian states. However, while various adaptation measures exist, there is no cohesive national framework that explicitly aligns with the principles of Climate-Smart Agriculture (CSA) as defined by the FAO. A systematic assessment of existing policies against CSA principles, sustainability, productivity enhancement, and resilience-building reveals significant gaps. A structured, long-term climate-resilient strategy that explicitly incorporates these principles is essential to ensure India's agricultural sector can withstand future climatic uncertainties.

The results highlight the economic mechanisms through which climate shocks impact agriculture. The observed decline in productivity stems from multiple channels, including direct crop yield losses, increased input costs for irrigation and fertilisers, and shifts in labour allocation due to climate-induced uncertainties. These findings underscore the presence of policy inefficiencies in addressing climate risks. While short-term relief measures such as subsidies and insurance schemes exist, they do not address the structural vulnerabilities of the sector. Quantifying the economic magnitude of these effects, such as estimated losses in productivity and increased adaptation costs, would provide a clearer understanding of the economic burden of climate shocks. Future policy efforts must focus on facilitating the adoption of climate-resilient cropping patterns, improving soil health, and enhancing access to advanced irrigation technologies.

The policy implications derived from this study emphasise the need for region-specific adaptation strategies. Given the diverse agro-climatic conditions across Indian states, a uniform policy approach is insufficient. Instead, localised strategies that integrate precision farming, drought-resistant crop varieties, and early warning systems are essential. However, the feasibility of these policy interventions depends on overcoming financial, institutional, and political constraints. Budgetary limitations, fragmented governance structures, and inadequate farmer incentives pose significant barriers to implementation. Addressing these constraints requires improved coordination between state and central governments and enhanced financial mechanisms, such as targeted subsidies and credit support for smallholder farmers to invest in climate adaptation.

This study also underscores the significance of spatial and dynamic effects in agricultural climate resilience. The spatial error model results indicate that climate shocks exhibit spillover effects across states, suggesting that adaptation strategies must incorporate inter-state coordination mechanisms. However, a more detailed examination of spatial dependencies and cooperative federalism in climate adaptation is necessary. Additionally, given the evolving nature of climate risks, dynamic policy interventions that maintain long-term consistency are required. Future research should explore dynamic panel models to assess how adaptation strategies evolve and their long-term effectiveness.

Methodologically, the study acknowledges the potential concerns of endogeneity, particularly in the relationship between climate shocks and agricultural outcomes. Justifying the selection of instrumental variables or exploring alternative econometric techniques such as difference-in-differences models could strengthen causal inference and provide more robust policy insights. Furthermore, given the heterogeneity of climate impacts across different agricultural systems, spatial Durbin models could offer deeper insights into spatial spillovers and differential adaptation capacities across regions.

The study's limitations highlight critical avenues for future research. A key limitation is the reliance on state-level data, which may mask farm-level heterogeneities in adaptation responses. Future research should incorporate micro-level datasets, such as household surveys, farm-level panel data, and remote sensing data, to examine how individual farmers respond to climate risks and which adaptation measures yield the highest returns. Moreover, exploring experimental or quasi-experimental approaches, such as randomised controlled trials or natural experiments, could offer more precise estimates of policy effectiveness. Additionally, integrating socio-economic factors such as farmer risk perception, credit constraints, and market access would provide a more holistic understanding of climate adaptation in Indian agriculture.

In conclusion, while India has made notable progress in implementing climate adaptation measures in agriculture, a comprehensive climate-smart policy framework is yet to be realised. Strengthening climate resilience in Indian agriculture requires integrating region-specific adaptation strategies, addressing institutional constraints, and adopting methodologically rigorous approaches to assess policy effectiveness. A shift towards a more structured and proactive CSA policy framework will be essential in safeguarding India's agricultural sector from escalating climate risks.

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