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Assessing the Influence of Financial and Climatic Determinants on Agricultural Productivity in India

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ABSTRACT

This study investigates the relative influence of financial incentives and climatic variability on agricultural productivity in India using annual data from 1978 to 2022. The analysis incorporates paddy yield, institutional agricultural credit, minimum support price (MSP), and all-India rainfall, with financial variables expressed in real terms. Employing Prais–Winsten regression to correct for autocorrelation, the results reveal that rainfall exerts a statistically significant and positive effect on agricultural productivity, whereas credit and MSP, despite positive coefficients, are statistically insignificant. The model explains approximately 42 percent of yield variation and passes standard diagnostic tests for normality and heteroskedasticity, confirming its robustness. These findings underscore that climatic variability continues to dominate agricultural outcomes, outweighing the short-run impact of financial mechanisms. Policy implications point to the urgent need for investment in climate-resilient infrastructure, improved irrigation systems, and regionally customized interventions, while refining MSP and credit delivery to enhance their productivity-enhancing potential. The study concludes that integrating financial support with climate adaptation strategies is critical for achieving

sustainable agricultural growth in India.

INTRODUCTION

Agriculture remains the linchpin of India's rural economy, accounting for nearly one-fifth of national gross value added and engaging more than half of the workforce (Government of India, 2023). Sustained improvements in agricultural productivity are therefore indispensable for food security, rural livelihoods, and inclusive growth. Classical production theory posits that output is determined by land, labour, capital, and technology; yet, in the small-holder context, farmers' input decisions are also shaped by public policy and environmental risk. Over the past five decades, successive governments have expanded institutional credit and implemented minimum-support-price (MSP) schemes to stabilise farm incomes and stimulate investment (Reserve Bank of India, 2024). These interventions are predicated on the hypothesis that relaxing liquidity constraints and guaranteeing price floors will raise the marginal productivity of modern inputs, thereby boosting yields (Stiglitz & Weiss, 1981). Empirical evidence, however, is mixed: some studies report credit-induced yield gains (Bhalla & Singh, 2020), whereas others highlight regional heterogeneity and crowding-out effects (Narayanamoorthy, 2016). A systematic time-series assessment that controls for evolving policy regimes is thus warranted.

Financial incentives alone cannot fully explain yield dynamics because agricultural production in India is intrinsically exposed to climatic variability, particularly the spatial and temporal distribution of the southwest monsoon. Rainfall anomalies influence sowing windows, water availability, and nutrient uptake, making weather a binding constraint on the returns to financial inputs (Gadgil & Kumar, 2006). Climate-shock models further suggest that unpredictable precipitation can dampen farmers' responsiveness to credit and price signals by elevating risk perceptions (Dercon & Christiaensen, 2011). Neglecting this environmental dimension risks biased inference and may lead to misguided policy prescriptions. Consequently, a comprehensive investigation must juxtapose economic incentives with climatic forces to reveal their relative contributions to productivity growth.

Despite extensive cross-sectional research, few studies have examined financial and climatic determinants within a unified time-series framework spanning the Green Revolution to contemporary climate volatility. This article fills that gap by analysing annual data from 1978 to 2022 on crop yields, institutional credit, MSPs for staple cereals, and monsoon rainfall. Employing log-differencing to ensure stationarity and a Prais–Winsten estimator to correct for autocorrelation, the study quantifies the short-run elasticities of yield growth with respect to financial and climatic variables. By disentangling these effects, the paper provides policy-relevant evidence on whether credit expansion and price supports remain effective levers for boosting productivity in the face of increasing climatic uncertainty.

REVIEW OF LITERATURE

The dual influence of financial mechanisms and environmental conditions on agricultural productivity has prompted significant academic inquiry, particularly in developing economies. Scholars have increasingly examined how targeted financial instruments—such as subsidized credit schemes, crop insurance, and procurement price mechanisms—contribute to production outcomes. Dholakia and Sapre (2021) note that public credit delivery systems play a vital role in capital formation and input use intensity, particularly in regions with weak market access. Moreover, Mishra et al. (2020) argue that the impact of financial inclusion is not only immediate but also structural, enhancing long-term resilience of smallholder farmers through access to capital and timely interventions.

From the environmental perspective, there is a consensus that climatic shocks, especially rainfall variability, impose considerable risk to crop yields. Bansal and Srivastava (2018) used spatial econometric models to demonstrate that even moderate variations in monsoon onset and distribution significantly affect rice and wheat outputs in India. Their findings underscore the importance of integrating agro-climatic data into productivity assessments. Similarly, Jain et al. (2022) identified strong negative correlations between anomalous rainfall events and yield performance, reinforcing the need to consider exogenous natural factors alongside financial determinants.

Recent econometric studies have begun to synthesize these two domains using time series analysis. For example, Kumar and Joshi (2023) employed an ARDL framework to test the short- and long-run relationships between rural credit, MSP, and weather volatility, finding that while financial factors have a stabilizing effect, rainfall anomalies consistently override them in rainfed regions. This suggests that the interaction between finance and climate is not merely additive but conditional. The present study adopts a similar empirical approach by utilizing Prais–Winsten regression to control for autocorrelation and distinguish the isolated effects of credit, MSP, and rainfall on agricultural yield in India.

OBJECTIVES

The study was based on the following objectives,

1. To examine the relative influence of financial incentives and climatic variability of agricultural productivity in India

2. To suggest policy measures based on the finding

HYPOTHESIS

Hypothesis of the study is,

H_0: Financial incentives and climatic variability have no significant influence on agricultural productivity in India

RESEARCH METHODOLOGY

The present study evaluates how financial incentives and climatic variability influence agricultural productivity in India. Annual data for four series—paddy yield, institutional agricultural credit, minimum-support price (MSP) for paddy, and all-India rainfall—were compiled for the crop years 1975 – 2024. Yield, Credit and MSP series were drawn from the RBI's Handbook of Statistics on the Indian Economy. Rainfall data were taken from the Indian Meteorological Department. Credit and MSP were converted to real terms using the CPI-IW (base 2015 = 100).

Following Cooray (2008) and Patterson (2000), all variables were first tested for stationarity with the Augmented Dickey–Fuller (ADF) test. The test result is presented in the Table.l

Table No.01 Augmented Dicky Fuller Test

Variable	Level p-value	First Difference p-value	Stationary at
Log_Yield	0.3057	0.01004	1st Diff
Log_Credit (Lagged)	1	$p < 0.0001$	1st Diff
Log_MSP (Lagged)	0.6649	$p < 0.0001$	1st Diff
Rainfall	$p < 0.0001$	-	Level

Source: Researchers' calculations

The stationarity properties of the time series variables were examined using the Augmented Dickey-Fuller (ADF) test under the constant and trend specification. The results revealed that the log-transformed series of agricultural yield, lagged agricultural credit, and lagged minimum support price (MSP) were non-stationary at level, as indicated by their respective p-values exceeding conventional significance thresholds. However, all three variables became stationary upon first differencing, suggesting that they are integrated of order one, I(1). In contrast, the rainfall variable exhibited stationarity in its original level form, with a highly significant ADF p-value ($p < 0.01$), and therefore did not require differencing. Accordingly, the analysis proceeded using first-differenced log values for financial variables (credit and MSP) and agricultural yield, while rainfall was retained in its level form. These transformations ensured the validity of subsequent time series regressions and avoided the risk of spurious inference.

Model adequacy was verified through Jarque–Bera normality, ARCH-LM heteroskedasticity, and Durbin–Watson autocorrelation tests, all of which indicated well-behaved residuals. Estimations were carried out in **Gretl 2023c.**

RESULT AND DISCUSSION

The following section interprets the regression outcomes assessing how financial incentives and climatic variability influence agricultural productivity. The model includes lagged values of credit and MSP, as well as rainfall in its level form, to evaluate both economic and environmental impacts. Table No. 02 presents the results of the Prais–Winsten regression model employed to analyze the effects of financial and climatic variables on agricultural productivity in India.

Table No. 02 Regression Estimates of Financial and Climatic Determinants of Agricultural Productivity

Variable	Coefficient	Std. error	t-stat	p-value
Constant	−0.169139	0.0621826	−2.720	0.0096
Δlog Credit$_{t-1}$	0.0348787	0.0991886	0.3516	0.7270
Δlog MSP$_{t-1}$	0.0260783	0.0673601	0.3871	0.7007
Rain (level)	0.000164322	0.0000523	3.142	0.0032

Model Statistic	Value	Model Statistic	Value
R-squared	0.425	Adjusted R-squared	0.382
F-statistic (3, 40)	3.994	p-Value (F)	0.0141
Std. Error of Regression	0.0458	SE of Regression	0.0457
Rho	-0.0852	Durbin–Watson	1.946

Source: Researchers’ calculations

The results of the Prais–Winsten regression indicate that among the examined determinants, only rainfall exerts a statistically significant and positive effect on agricultural productivity in India. Specifically, the coefficient on rainfall (0.000164, p = 0.0032) suggests that greater rainfall contributes to higher annual yield growth, reinforcing the critical role of climatic conditions. In contrast, the estimated effects of financial incentives—proxied by lagged changes in real agricultural credit and minimum support prices (MSP)—are positive but statistically insignificant, with p-values well above conventional thresholds (0.727 and 0.701, respectively). This implies that, in the short run, variations in credit disbursal and price incentives do not substantially influence yield growth once rainfall is accounted for. The overall model explains approximately 42.5% of the variation in yield growth (Adjusted $R^2 = 0.382$), with a statistically significant F-statistic (p = 0.0141), indicating that the explanatory variables are jointly meaningful. The Durbin–Watson statistic of 1.95 confirms that the model does not suffer from first-order autocorrelation, affirming the appropriateness of the Prais–Winsten correction. These findings suggest that climatic variability remains the dominant driver of agricultural output, underscoring the importance of climate-resilient agricultural policies in India.

Diagnostic Test

To validate the robustness of the regression estimates, standard diagnostic checks were conducted, including tests for normality of residuals and ARCH effects. These diagnostics confirm the appropriateness of the model specification and absence of major violations. Table No. 03 presents the results of diagnostic tests conducted for the selected model.

Table No. 03 Diagnostic Test Results of the Regression Model

Test	Null Hypothesis (H_0)	P-Value	Conclusion
Normality of residual	error is normally distributed	0.156167	Error is Normally Distributed
ARCH Effect	no ARCH effect is present	0.892414	No ARCH effect present

Source: Researchers' calculations

The diagnostic tests indicate that the regression residuals meet two core assumptions for reliable inference. First, the Jarque–Bera normality test yields a p-value of 0.156 (> 0.05), so the null hypothesis that the error term is normally distributed cannot be rejected; the residuals therefore approximate a normal distribution, validating the use of t- and F-statistics for hypothesis testing (Wooldridge, 2020). Second, the ARCH LM test reports a p-value of 0.892, far above conventional significance levels. Consequently, the null hypothesis of no ARCH effect is retained, implying the absence of time-varying conditional heteroskedasticity in the residuals. Taken together, these outcomes confirm that the model's error structure is well-behaved—free of non-normality and conditional variance clustering—thereby lending credibility to the estimated coefficients and their standard errors.

SUGGESTIONS

Based on the empirical evidence, it is recommended that policy efforts prioritize the development and maintenance of climate-resilient infrastructure. Specifically, increased government spending on irrigation systems—such as canals, check dams, and watershed development—can mitigate the adverse effects of rainfall variability on agricultural productivity. Investment in such infrastructure would serve as a stabilizing force, ensuring more consistent output across varying seasonal and climatic conditions. This would also reduce over-reliance on monsoon rains and promote long-term sustainability in agricultural practices.

While Minimum Support Prices (MSP) and agricultural credit remain central components of India's farm support policy, their current structure may limit their productivity-enhancing potential. To enhance their effectiveness, reforms should ensure that MSP better reflects prevailing market prices and input cost structures. Similarly, targeted delivery of agricultural credit—especially toward small and marginal farmers—should be strengthened through improved monitoring and accountability. Complementary measures such as weather-based crop insurance, localized early warning systems, and the promotion of sustainable practices like soil health management and crop diversification should be integrated into broader agricultural policy. Regional customization of these instruments is also essential, given India's climatic and agronomic diversity.

CONCLUSION

This study analyzed the relative influence of financial incentives and climatic variability on agricultural productivity in India over the period 1978 to 2022. Employing Prais–Winsten regression to account for autocorrelation, the findings indicate that rainfall has a statistically significant and positive effect on agricultural yield growth, while the effects of MSP and agricultural credit were statistically insignificant. These results underscore the continued reliance of Indian agriculture on natural factors, particularly rainfall, despite decades of policy-driven financial interventions. Diagnostic tests confirmed the robustness of the model, with normally distributed residuals and no presence of ARCH effects. The outcomes suggest that while financial mechanisms like MSP and credit are essential for income support and risk mitigation, they have not been sufficient in driving productivity gains. Therefore, future agricultural strategies should integrate climatic resilience with refined financial tools to better address the productivity challenge.

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