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Sustainable Agricultural Development under the Influence of Technology: A Case Study of Bihar

Jitendra Kumar Sinha [1,*], ***Anurodh Kumar Sinha*** [2]

[1] *Independent Researcher, Bengaluru, Karnataka 560076, India*

[2] *Jeevika, Manager (Monitoring & Evaluation), Patna, Bihar 800021, India*

ABSTRACT

Achieving "Zero Hunger," one of the core Sustainable Development Goals (SDGs) adopted by the United Nations in 2015, necessitates transformative changes in agricultural systems through sustainable practices and resilient technologies. This study examines the influence of farm technologies and supporting infrastructure on agricultural value-added (GVA) in Bihar, a predominantly agrarian and economically underdeveloped state in India, utilizing time series data from 2000 to 2024. Employing advanced econometric models, dynamic simulations, and impulse response analyses, the research identifies key structural drivers and constraints of agricultural growth in the region. Technological advancement is shown to be a primary driver, with mechanization, improved seed varieties, multi-cropping, and agroforestry practices significantly enhancing land productivity. Capital stock investment exhibits a direct and positive elasticity (0.59%), with its impact persisting up to eight years before diminishing, underscoring the need for periodic reinvestment. Mechanization alone accounts for a 32% contribution to GVA, signalling a transition toward labour-saving technologies. Arable land expansion and sustainable practices also play a pivotal role, contributing 21% to agricultural GVA. Conversely, irrigation infrastructure and chemical fertilizers reveal mixed or negative short-term effects, likely due to inefficient application or ecological constraints. Variables such as labour, credit, forest area, and energy consumption are found to be statistically insignificant. The findings advocate for capital lifecycle management, precision farming, sustainable land use, targeted input application, and credit system reform. The study concludes that an integrated, evidence-based policy framework is essential to ensure sustained agricultural productivity, environmental stewardship, and the long-term realization of SDG-2 in Bihar.

Keywords: Sustainable Economic Growth; Agricultural Technology; Cobb-Douglas Production Function

JEL Classification: Q01; Q16; C67

*CORRESPONDING AUTHOR:

Jitendra Kumar Sinha, Independent Researcher, Bengaluru, Karnataka 560076, India; Email: jksinha2007@rediffmail.com

ARTICLE INFO

Received: 5 December 2024 | Revised: 20 December 2024 | Accepted:2 January 2024 | Published Online: 12 January 2025

DOI: https://doi.org/10.55121/nc.v4i1.385

CITATION

Sinha, J.K., Sinha, A.K., 2025. Sustainable Agricultural Development under the Influence of Technology: A Case Study of Bihar. New Countryside. 4(1): 79–101. DOI: https://doi.org/10.55121/nc.v4i1.385

1. Introduction

The global challenge of sustainably increasing food production to meet the demands of a growing population has become more pressing than ever. In response, the United Nations has emphasized the need for resource-conserving technologies and sustainable agricultural practices that do not degrade the natural resource base. Contemporary agricultural production increasingly hinges on advancements in science and technology, farm infrastructure, efficient water management, input use (fertilizers and pesticides), cropping patterns, and policy support.

Technological inputs have varying impacts on agricultural productivity. For example, Integrated Pest Management (IPM) promotes minimal pesticide use, reserving chemical interventions for when other methods prove ineffective [1,2]. Similarly, Integrated Nutrient Management (INM) advocates for a balanced approach to organic and inorganic fertilizer application [3], fostering green and sustainable production. Fertilizer Best Management Practices (FBMP), as discussed by Roberts [4], have emerged as a key innovation in enhancing productivity without compromising environmental integrity, particularly vital for regions heavily reliant on subsistence farming for employment and income.

Technological innovation in agriculture can be categorized to aid policy formulation and economic modelling. One classification distinguishes between embodied technologies (e.g., machinery, fertilizers, seeds) and disembodied technologies (e.g., IPM protocols and agronomic practices) [5]. Another typology differentiates between neutral and non-neutral technologies, where Harrod-neutral technology augments labour and Solow-neutral technology augments capital. The impact of technological progress on productivity can be measured through models such as growth function [6], which links technological change to labour productivity gains. Technological shifts expand the production possibility frontier, enabling long-term economic growth. For instance, Wang and Zhou demonstrated that technological progress significantly drives productivity in sectors like construction and industry, advocating for its role in achieving sustainable development goals [7].

In addition to scientific innovations, researchers have highlighted the importance of agricultural technologies and recommended practices for enhancing productivity [8–10]. Analytical tools such as the Cobb-Douglas production function and the Solow residual model [11–14], have been employed to quantify the impact of such innovations over the short and long term.

Kumar and Yadav found that grain yield responses to nitrogen (N) application decline over time, whereas the use of phosphorus (P) and potassium (K) has a positive and sustained impact on productivity [15]. This underscores the importance of balanced N-P-K fertilizer application to maintain soil fertility and crop yields. Moreover, several studies have associated yield increases with complementary factors such as investments in human capital, fixed capital stock, and expansion of irrigated land [16].

2. Disparity in Indian States

After more than seventy years of planned development, India still grapples with stark inter-state disparities in economic performance and growth. States are broadly polarized into two economic categories: high-income and low-income states. The former includes Gujarat, Maharashtra, Punjab, Haryana, Tamil Nadu, and Karnataka, while the latter consists of Odisha, Bihar, Jharkhand, Rajasthan, Madhya Pradesh, and Uttar Pradesh. High-income states have followed diversified growth trajectories. Gujarat and Maharashtra boast strong industrial foundations; Punjab and Haryana have excelled in agricultural output, particularly in rice and wheat production. Tamil Nadu has developed a thriving manufacturing base, while Karnataka has emerged as a leading centre for finance and information technology. These states have cultivated independent growth engines that are largely self-sustaining. Conversely, the low-income states—primarily agrarian and heavily dependent on subsistence agriculture—lack such growth catalysts. Their economic integration with national and global markets remains limited, and they have failed to benefit from the positive externalities generated by their wealthier counterparts. This fragmentation in development has exacerbated regional disparities, as employment opportunities and capital investments are heavily concentrated in a few urbanized hubs [17].

These structural imbalances present a serious obstacle to India's broader developmental goals. Despite overall increases in national GDP, growth has been spatially concentrated, with few mechanisms for economic spillovers. This absence of regional integration weakens prospects for convergence and inclusive growth, instead reinforcing poverty and unemployment in lagging regions. The question arises: Why have states pursued such divergent growth trajectories? A core explanation lies in the diminishing returns to capital accumulation and the critical role of policy. Scholars argue that differences in capital per worker explain only a small portion of cross-country income disparities [18,19]. Young however, underscores the role of rapid factor accumulation, particularly in East Asian economies, combined with productivity enhancements [20].

These competing perspectives highlight two key insights: first, market liberalization alone does not guarantee sustained growth; second, government intervention, through structural transformation policies, human capital investments, and open trade regimes, can be decisive in shaping development outcomes. For India, the policy implication is clear: to reduce regional disparities, emphasis must shift toward stimulating endogenous engines of growth in low-income states, encouraging industrial diversification, and fostering stronger inter-state economic linkages. Only then can India achieve inclusive and balanced growth across its diverse regions.

Unique Contribution of This Study

While prior studies have extensively documented India's inter-state disparities and the structural divide between high- and low-income states, this research offers a fresh empirical perspective by analysing the dynamic, long-term effects of key agricultural drivers on state-level productivity and growth trajectories. Using impulse response analysis, it identifies not just the immediate, but also the persistent and divergent impacts of factors like mechanization, capital stock, land use, irrigation, and fertilizer application, with Bihar as a detailed case study. Unlike earlier works that often treat agriculture as a homogenous sector, this study underscores the sector's internal complexities, inefficiencies, and opportunities for productivity-led growth in lagging states. Moreover, by comparing Bihar's experience with similar states like Odisha and Jharkhand, it highlights context-specific constraints and opportunities for structural transformation, offering actionable insights for state-level policy design and national reform strategies aimed at reducing regional economic disparities.

3. Bihar: A Case Study of Structural Challenges and Opportunities

Bihar, situated in eastern India, is strategically positioned near several states and along the international border with Nepal. It enjoys logistical advantages with access to major eastern ports such as Haldia and Kolkata and proximity to resource-rich neighbours like Jharkhand. Despite these geographic strengths, Bihar's economic indicators have long lagged behind national averages. In 2022–23, Bihar contributed a modest 2.75% to India's GDP, while accounting for nearly 9% of the national population. Its per capita GDP remains the lowest among Indian states at ₹35,119, with stark internal disparities — while Patna's per capita income stands at ₹131,064, Shekhar lags far behind at ₹19,592. If considered independently, Bihar would rank as the 12th most populous country globally, yet with an income level lower than some of the poorest African nations.

However, Bihar's development trajectory reveals a significant inflection point following the post-2005 governance and infrastructure reforms. Before 2005, Bihar was widely characterized by stagnant growth, weak infrastructure, and poor governance, with annual GSDP growth hovering around 4–5% in the late 1990s and early 2000s, well below the national average. Chronic underinvestment in physical infrastructure, law and order challenges, and administrative inefficiency stymied economic activity, while poverty and out-migration intensified.

In contrast, the post-2005 period marks a phase of accelerated growth and relative structural improvement. Between 2015–16 and 2022–23, Bihar's GSDP registered a strong CAGR of 13.21%, and per capita NSDP grew by 13.41% — nearly tripling the average pace from the pre-reform period. Much of this growth has been driven by agriculture, which continues to employ around 80% of the population, well above the national average. The state now ranks 4th in vegetable production and 8th in fruit production in India, reflecting gains in productivity and diversification. Allied sectors such as food processing, dairy, sugar, tourism, and renewable energy have also witnessed notable expansion, supported by a low-cost labour force and significant improvements in roads, electricity, and communication infrastructure post-2005.

In terms of structural transformation, Bihar's continued dependence on agriculture presents both a constraint and an opportunity. The shift from subsistence farming to a diversified economic base — integrating manufacturing and services — remains limited, although post-2005 reforms in infrastructure, governance, and public investment have helped reduce poverty by nearly 20 percentage points. Yet several enduring challenges persist, including underemployment, high out-migration, fragmented landholdings, low literacy rates, and weak public health systems.

Notably, Bihar's resilience during the COVID-19 pandemic, despite its structural limitations, highlights the cumulative gains from the post-2005 period. Sustained progress, however, will depend on deeper structural reforms, including sustainable agricultural modernization, human capital development, and industrial diversification. The state's experience offers valuable lessons on how infrastructure, institutional capacity, and targeted policy shifts can, over time, reshape a historically lagging economy [21–41].

Key points of differentiation introduced:

Explicit growth rate contrast: pre-2005 (4–5%) vs post-2015 (13.21% CAGR)

Mention of chronic underinvestment and governance issues pre-2005

Specific sectoral expansions post-2005 linked to reforms

Quantifying poverty reduction post-2005

Highlighting improvements in infrastructure, governance, and public investment

Framing COVID-19 resilience as an outcome of post-reform capacity building

A comparative glance at Odisha and Jharkhand, states with broadly similar socio-economic starting points, highlights Bihar's relative position:

Odisha has achieved a higher per capita NSDP of ₹1,50,676 (2022–23) and relatively faster industrial diversification, particularly in mineral-based industries, micro, small, and medium enterprises (MSMEs), and infrastructure. Its agricultural workforce has declined to around 50%, reflecting a better structural transition.

Jharkhand, though rich in mineral resources, faces challenges akin to Bihar — high poverty, underemployment, and infrastructure deficits — but benefits from a higher industrial share in its GSDP and better per capita income levels.

This comparison underscores Bihar's growth momentum and resilience while also exposing the need for accelerated diversification and productivity-led growth strategies to bridge the persistent income and employment gaps within the eastern region.

4. Purpose of the Study

This study investigates the impact of agricultural technologies on value addition in the agricultural sector, focusing on backward regions characterized by subsistence farming. Bihar, as the case study, holds strategic significance for several reasons. Despite being one of India's most populous states—accounting for 10.2% of the national population—it remains at the lower end of the development spectrum. The state contributes merely 1.5% of India's factories, 0.34% of fixed capital, 0.58% of working capital, 0.84% of industrial employment, and 0.84% of industrial output. In 2015–16, the industrial sector accounted for only 19.0% of Bihar's GSDP, significantly below the national average of 31.3%, highlighting its structural dependence on agriculture for income, employment, and livelihood security.

Studying Bihar offers valuable insights for national agricultural policy for several reasons. First, as a predominantly agrarian economy, Bihar represents the challenges and opportunities of backward and resource-constrained regions. Second, understanding how agricultural technologies influence value addition in such contexts can inform scalable, inclusive, and region-specific interventions in other similarly placed states. Third, given Bihar's demographic weight, any significant improvement in its agricultural performance—through technology adoption and productivity enhancement—can have a meaningful aggregate impact on national food security, rural employment, and poverty alleviation.

Thus, this study not only contributes to the regional development discourse but also offers empirical evidence and policy implications that are critical for shaping India's broader agenda of sustainable and equitable agricultural transformation.

The core objective is to assess how a range of agricultural technologies—such as mechanization, chemical inputs, improved management practices, cropping policies, and infrastructure—contribute to agricultural GDP beyond traditional production factors like land, labour, and capital. The study addresses two key questions:

What is the relationship between agricultural technologies and production growth in Bihar?

Which technology combinations are most effective in sustaining agricultural GDP growth?

The analysis employs a Cobb-Douglas production function to estimate the impact of technological inputs on agricultural value-added in Bihar from 2000 to 2024. It further examines the dynamic response of agricultural output to technological innovations or shocks, drawing policy-relevant conclusions from the observed trends.

5. Model Framework

This study utilizes the Cobb-Douglas (C-D) production function to depict the relationship between agricultural output and various production factors while incorporating technological progress over time. A visual schematic of the model framework is presented below (**Figure 1**):

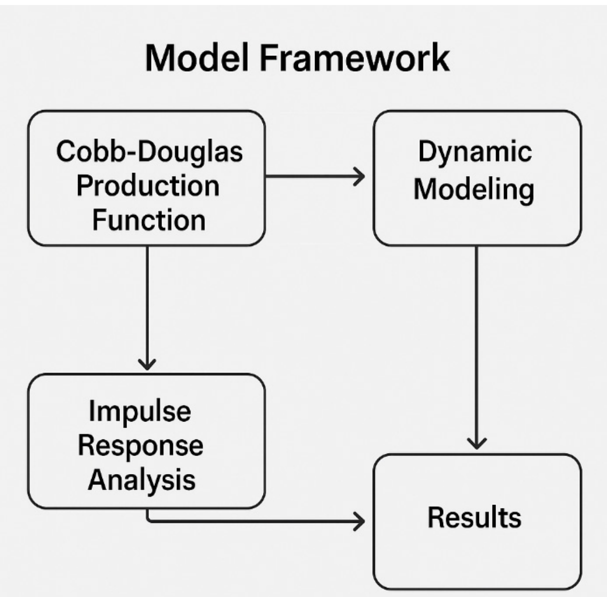

Figure 1. The Model Framework.

The functional form of the model is specified as:

$$\mathrm{I.}Y = A_0 \cdot e^{st\cdot} \prod X^{I\alpha I} \tag{1}$$

Where:

Y = Agricultural output (value-added or income)

A_0 = Initial level of output in the base year

δ = Coefficient representing the rate of technological progress

t = Time (in years)

X_I = *i th* factor of production

α_I = Output elasticity of the *i th* factor of production

p = Number of production factors

e = Euler's number (base of natural logarithms)

The parameters α_i represent the elasticity of output for each input, indicating the percentage change in output resulting from a 1% change in the corresponding input. This can be derived by taking the partial derivative of Equation (1) to X_i:

$$\partial Y/\partial X i = a_i \cdot [Y/X] \tag{2}$$

Rearranging Equation (2), the elasticity coefficient α_i is expressed as:

$$a_{i=} [\partial Y/\partial X]. [Xi/Y] \tag{3}$$

To estimate the model parameters empirically, a log-linear transformation of Equation (1) is applied:

$$\ln(Y) = \ln(A_0) + \delta t + \sum i_{=1 \text{ to } p} ai_{\mathrm{In}}(Xi)\delta \tag{4}$$

Equation (4) provides a linear regression framework, allowing estimation of elasticity coefficients using time-series data.

The contribution rate of each input to output growth can be calculated as:

$$EXi = ai \cdot [gXi/gY] \times 100 \tag{5}$$

Where:

E_{Xi} = Percentage contribution of input X_i to output growth

g_{Xi} = Average annual growth rate of input X_i

gY = Average Annual growth rate of output Y

This model framework enables the decomposition of agricultural output growth into contributions from various technological and input factors, providing valuable insights into productivity dynamics in the context of Bihar.

6. Data

This study utilizes a time-series dataset spanning 25 years (2000–2024), consisting of one endogenous variable—Agricultural Value Added (AGRIVA)—and nine exogenous variables representing key inputs to agricultural production. These variables capture a wide range of technological, infrastructural, and natural factors that are hypothesized to influence agricultural productivity in Bihar.

The exogenous variables (mentioned below with their source) include:

Net Capital Stock (NETK): Author's estimates based on official data [42–44].

Number of Agricultural Machines (MACHI) — tractors, harvesters, and threshers: DES, Bihar

Agricultural Credit (CREDI): NABARD

Energy Use for Irrigation (ENERG): Government of Bihar

Agricultural Labor Force (LABOR) [Number of workers employed in agriculture]: DES, Bihar

Area under Arable Land and Permanent Crops (ALAND): DES, Bihar.

Area under Forest Cover (FORES) — planted and naturally regenerated forests: DES, Bihar.

Irrigated Area (IRRIG) — land equipped for irrigation: DES, Bihar

Chemical Fertilizer Consumption (FERTIL) — nitrogen, phosphorus, and potassium: DES, Bihar.

All variables are compiled from official government sources, primarily the Directorate of Economics and Statistics (DES), Bihar, and other relevant institutions, such as NABARD and various departments of the Government of Bihar and the Government of India [45–47]. Monetary variables are expressed in constant prices (base year 2011) to eliminate the effects of inflation and facilitate meaningful comparisons over time. The year 2011 has been chosen as the base year in alignment with the revision adopted by the Government of India and the Central Statistics Office (now NSO), which updated the national accounts series from the earlier base year of 2004–05 to 2011–12. This revision reflects improvements in data quality, coverage, and methodology, including the incorporation of results from the 2011 Census, the 2011–12 Household Consumption Expenditure Survey, and updated enterprise-level statistics. Using 2011 as the base year ensures consistency with national statistical standards and enhances the reliability and comparability of macroeconomic indicators expressed in real terms.

Before model estimation, all the time series were tested for stationarity using the Augmented Dickey-Fuller (ADF) test. The hypotheses for the ADF test are defined as:

Null Hypothesis H_0: θ=0 (the series is non-stationary and requires differencing)

Alternative Hypothesis H_1: θ<0 (the series is stationary and does not require differencing)

Only variables that are stationary or rendered stationary through differencing were used for regression estimation. All statistical processing and model estimations were carried out using R programming, employing customized scripts to test assumptions, estimate parameters, and interpret results.

7. Descriptive Statistics and Distributional Diagnostics

7.1. Discussion on Descriptive Statistics

7.1.1. Data Summary and Descriptive Statistics

The processed data, derived using carefully constructed R programming routines, are summarized in **Table 1**, presenting the descriptive statistics of the variables incorporated in this study. To stabilize variance and facilitate the interpretation of regression coefficients as elasticities, all variables were transformed into their natural logarithmic forms before estimation. The descriptive statistics include measures of central tendency (mean, median), dispersion (standard deviation, range), as well as higher-order distributional properties (skewness, kurtosis), offering valuable insights into the characteristics and behaviour of the data series.

i) Central Tendency and Dispersion

The mean value of Agricultural Value Added (AGRIVA) is approximately Rs 3228 billion, which closely parallels the mean value of Net Capital Stock (NETK), indicating comparable levels of investment and output in the agricultural sector across the study period. Most variables exhibit a relatively narrow range (maximum–minimum), suggesting moderate variability over time, with Fertilizer Consumption (FERTIL) standing as a notable exception due to its substantial dispersion. This may reflect policy shifts, price volatility, or external shocks affecting fertilizer use.

Table 1. Descriptive Statistics of Variables.

Descriptive Statistics	LAGRIVA*	LNETK	LMACHI	LCREDI	LENERG	LLABOUR	LALAND	LFORCE	LIRRIG	LFERTIL
Mean	14.322	14.765	5.988	9.833	3.897	7.883	7.876	8.765	2.753	9.087
Median	14.762	14.766	5.767	9.986	3.876	7.342	7.564	8.432	2.562	9.768
Maximum	14.753	14.534	5.788	11.453	3.765	7.561	8.098	8.239	3.091	10.465
Minimum	13.008	12.998	5.065	0.700	3.465	7.127	7.089	8.032	2.983	3.097
Std. Dev.	0.345	0.176	0.127	2.133	0.089	0.128	0.215	0.098	0.371	1.879
Skewness	−3.987	−0.154	−0.303	−2.345	−0.233	−0.568	−0.879	0.124	0.098	−1.693
Kurtosis	1.848	1.256	1.823	9.766	1.054	2.432	2.225	1.876	1.387	4.365
Jarque-Bera	1.983	3.538	1.522	74.748	4.567	1.786	3.177	1.587	3.547	15.779
Probability	0.482	0.275	0.465	0.000	0.153	0.415	0.158	0.427	0.192	0.004
Sum Sq. dev.	3.099	0.296	0.438	110. 290	0.009	0.492	1.237	0.231	3.568	93.898
No. of Obs.	25 (Twenty-five)									

A close alignment between the mean and median in variables such as LAGRIVA, LNETK, and LMACHI suggests symmetric distributions. In contrast, variables such as LCREDI and LFERTIL display marked differences between their mean and median, hinting at possible skewness or the presence of outliers.

ii) Skewness and Kurtosis

Most variables exhibit negative skewness, indicative of longer left tails and data clustering at higher values. Exceptions include LIRRIG and LFORES, where mean values exceed medians, denoting positive skewness and a longer right tail. All variables demonstrate leptokurtic behaviour (positive kurtosis), implying more peaked distributions with heavier tails than a normal distribution. This suggests a higher incidence of extreme values, a notable feature in time series data that can affect volatility and shock responses.

Dispersions vary significantly across variables. Variables such as LCREDI (Std. Dev. = 2.133) and LFERTIL (1.879) show considerable volatility, reflecting heterogeneity in credit allocation and fertilizer use over time. In contrast, variables like LENERG (0.089) and LMACHI (0.127) display greater stability.

iii) Normality Assumption

Based on skewness, kurtosis, and the Jarque-Bera (JB) test, most variables approximate a normal distribution, except CREDI and FERTIL. Their non-normality indicates the need for additional diagnostic checks or robust estimation procedures in subsequent modelling stages.

7.1.2. Implications of Skewness, Kurtosis, and the Jarque-Bera Test

The distributional diagnostics using skewness, kurtosis, and the Jarque-Bera (JB) test provide essential insights into the validity of classical econometric assumptions.

Key Findings:

A Negative Skewness is prominent in LAGRIVA (−3.987), LCREDI (−2.345), and LFERTIL (−1.693), indicating longer left tails.

Positive Skewness in LFORCE (0.124) and other variables is minimal.

Leptokurtosis is observed in LCREDI (9.766) and LFERTIL (4.365), highlighting sharp peaks and heavy tails.

The Jarque-Bera Test rejects normality for LCREDI and LFERTIL at the 1% significance level, confirming distributional irregularities.

Model Implications and Remedies:

A Logarithmic transformation, already applied, has alleviated much of the variance instability.

Remaining deviations, particularly for LCREDI and LFERTIL, necessitate:

Robust standard errors (e.g., White's or HAC estimators)

Quantile regression or GLS for heteroscedasticity management

Outlier diagnostics to identify influential data points

Post-estimation residual diagnostics are recommended to confirm the validity of distributional assumptions.

7.1.3. Observations and Model Implications

The dataset comprises 25 annual observations per variable, suitable for time series analysis when combined with robust estimation methods. Given the data characteristics, further stationarity testing (e.g., ADF test) is essential to confirm the appropriateness of subsequent regression or cointegration analyses. Variables with significant skewness and kurtosis warrant careful model specification, potentially including robust estimation techniques and outlier mitigation strategies.

4. Interpretation of Distributional Traits and Econometric Implications

The descriptive statistics indicate several distributional patterns with direct implications for econometric modelling:

Skewness and Kurtosis Effects: Negative skewness in LAGRIVA, LCREDI, and LFERTIL implies asymmetry, potentially biasing regression estimates if uncorrected. Leptokurtosis in these variables suggests a heightened risk of outlier influence, which can distort coefficient estimates and reduce model efficiency.

Normality and Inference Risks: Significant non-normality confirmed by the Jarque-Bera test for LCREDI and LFERTIL affects the validity of standard hypothesis testing, especially in small samples.

Variance Stability: High standard deviations for LCREDI and LFERTIL, combined with their skewed, leptokurtic nature, suggest heteroscedasticity risks, violating constant variance assumptions critical for OLS inference.

Recommended Estimation Strategy:

Maintain logarithmic transformations

Perform stationarity tests (ADF) to avoid spurious regressions

Employ robust estimation techniques

Conduct outlier diagnostics for key variables

Check residual normality, heteroscedasticity, and autocorrelation post-estimation.

Despite distributional challenges, judicious application of appropriate econometric procedures ensures that reliable, unbiased, and efficient estimates can be obtained.

7.2. Growth Trends of Agricultural Value Added and Key Inputs

To examine the growth dynamics of Agricultural Value Added (AGRIVA) and five critical agricultural input indicators—Net Capital Formation in Agriculture (NETK), Agricultural Machinery (MACHI), Agricultural Land (ALAND), Irrigated Area (IRRIG), and Fertilizer Consumption (FERTIL)—their respective rates of change over selected years from 2000 to 2024 are systematically presented in **Table 2**.

Table 2. Summary of Rates of Change (2000–2024) of AGRIVA, NETK, MACHI, ALAND, IRRIG, and FERTIL.

Year	Rates of Change of					
	AGRIVA	**NETK**	**MACHI**	**ALAND**	**IRRIG**	**FERTIL**
2000	0.011	0.157	0.021	0.034	0.034	1.231
2002	0.325	0.423	0.032	0.054	0.173	1.342
2004	0.021	0.071	0.062	0.042	0.153	(–)0.943
2006	0.081	0.137	0.031	0.024	0.024	7.453
2008	0.225	0.463	0.042	(–)0.024	0.153	(–)0.654
2010	0.041	0.051	0.072	0.012	0.133	16.242
2012	0.031	0.187	0.041	0.024	0.134	0.731
2014	0.375	0.463	0.062	(–)0.014	0.123	0.645
2016	0.041	0.091	0.072	0.062	0.173	1.524
2018	0.011	0.107	0.031	0.044	0.024	0.163
2020	0.225	0.483	0.052	(–)0.074	0.163	0.237
2022	0.001	0.061	0.072	0.082	0.193	0.836
2024	0.305	0.403	0.062	0.074	0.153	0.984

7.2.1. Analytical Discussion

1. Agricultural Value Added (AGRIVA) Growth Patterns: AGRIVA shows intermittent fluctuations — low growth in 2000 (0.011) and 2004 (0.021), with significant spikes in 2002 (0.325), 2008 (0.225), 2014 (0.375), 2020 (0.225), and 2024 (0.305). The highest growth (0.375) occurred in 2014, coinciding with strong growth in NETK and MACHI.

2. Net Capital Formation in Agriculture (NETK): NETK consistently displays higher growth rates compared to AGRIVA, with a Major peak in 2002 (0.423), 2008 (0.463), 2014 (0.463), and 2020 (0.483). This indicates capital investment is often ahead of output gains, suggesting delayed transmission from investment to value addition.

3. Agricultural Machinery (MACHI): MACHI has shown steady, moderate growth in the range of 0.021 to 0.072, with a Notable peak in 2010, 2016, and 2022 (all 0.072). Consistency in MACHI growth likely reflects gradual mechanization and modernization trends.

4. Agricultural Land (ALAND): ALAND has experienced minimal or negative growth. Negative growth rates in 2008 (−0.024), 2014 (−0.014), and 2020 (−0.074) reflect declining land availability or conversion to non-agricultural uses. Slight improvements in 2022 (0.082) and 2024 (0.074) suggest minor land reclamation or stabilization.

5. Irrigated Area (IRRIG): IRRIG growth has been positive but modest, typically between 0.024 and 0.193. Peaks in 2002 (0.173), 2016 (0.173), and 2022 (0.193) indicate incremental improvements in irrigation infrastructure.

6. Fertilizer Consumption (FERTIL): Fertilizer Consumption (FERTIL) exhibits the highest degree of volatility among the input variables. The growth rate recorded pronounced positive spikes in 2000 (1.231), 2002 (1.342), 2006 (7.453), and a remarkable surge in 2010 (16.242). In contrast, negative growth rates were observed in 2004 (−0.943) and 2008 (−0.654), reflecting sharp fluctuations in fertilizer usage. The extraordinary increase in 2010 is likely attributable to favorable policy measures, subsidies, or market incentives that stimulated fertilizer consumption during that year. From 2012 onwards, the growth pattern appears more stable and consistent, indicating a phase of gradual normalization and stabilization in fertilizer application practices.

7.3. Relation Between Agricultural Technologies and Agricultural Value-Added

The analysis reveals a clear linear relationship between key agricultural technologies and the growth of agricultural value-added (AgVA). Specifically, variables such as: i) The number of agricultural machines in use; ii) The area is equipped for irrigation, and iii) The extent of arable land and permanent crops exhibit strong positive correlations with AgVA growth. These results affirm that technological improvements in these areas have played a significant role in enhancing agricultural productivity. Moreover, they suggest that a linear model framework provides a reasonable approximation of the underlying dynamics among these factors. These findings offer actionable insights for policymakers and planners, particularly in prioritizing investments in agricultural mechanization, irrigation infrastructure, and optimized land utilization to sustain and accelerate agricultural growth.

Fertilizer Use: A Non-Linear Case

In contrast, a notable divergence is observed in the case of chemical fertilizer use, which does not exhibit a statistically significant linear relationship with AgGDP. This indicates that the relationship between fertilizer inputs and agricultural output is likely to be non-linear or context-dependent, potentially influenced by factors such as: i) Soil fertility and composition, ii) Crop selection and rotation patterns, iii) Climatic conditions, and iv) Integrated nutrient management practices

This outcome underscores the limitations of a purely linear specification for certain variables and highlights the need for more sophisticated model approaches capable of capturing these complexities. Potential extensions could involve:

Polynomial regressions to account for diminishing or increasing returns

Log-linear or semi-log models

Interaction terms (e.g., fertilizer × irrigation, or fertilizer × soil health indices)

Non-parametric or machine learning methods for detecting complex, non-linear patterns

While these enhancements would improve the model's explanatory power and policy relevance, they remain beyond the scope of the current study.

Ecological Trade-offs and Sustainability Thresholds

While fertilizers and irrigation have been pivotal in boosting agricultural productivity, their impacts are not uniformly positive. Beyond certain thresholds, these inputs may trigger ecological imbalances and sustainability challenges:

Soil Degradation: Excessive fertilizer use can lead to nutrient imbalances, soil acidification, and long-term fertility decline.

Water Resource Stress: Intensive irrigation can deplete groundwater, reduce river flows, and affect downstream ecosystems.

Pollution and Eutrophication: Runoff from over-fertilized fields can cause water pollution and eutrophication in nearby water bodies.

Greenhouse Gas Emissions: High fertilizer use, especially nitrogen-based, contributes to nitrous oxide emissions, a potent greenhouse gas.

7.3.1. Sustainability Thresholds

Recent studies suggest that: i) Optimal fertilizer and irrigation levels exist, beyond which marginal returns diminish and ecological risks escalate; ii) Balancing productivity with ecological health requires integrated nutrient and water management practices, precision farming, and sustainable input use; and iii) Policy and practice should recognize these thresholds, prioritizing efficiency-enhancing technologies alongside environmental safeguards [48,49].

Figures 2–5 presented below illustrate the linear relationship between agricultural technologies and agricultural value-added.

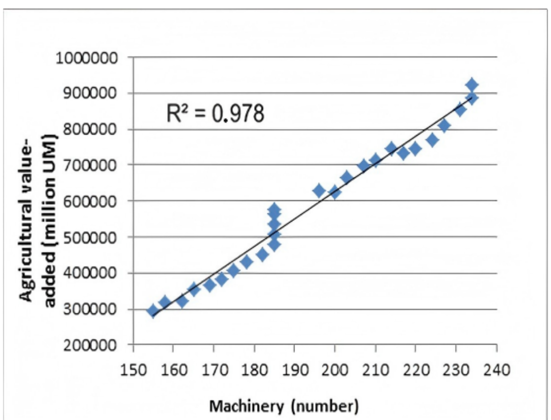

Figure 2. Relationship between Agricultural Value Added and Machinery.

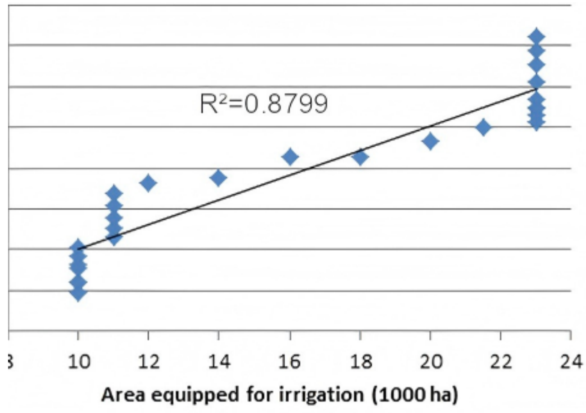

Figure 3. Area Equipped for Irrigation.

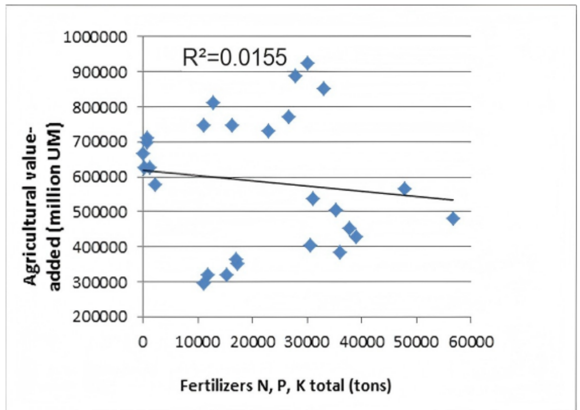

Figure 4. Relationship between Agricultural Value Added and Fertilizers.

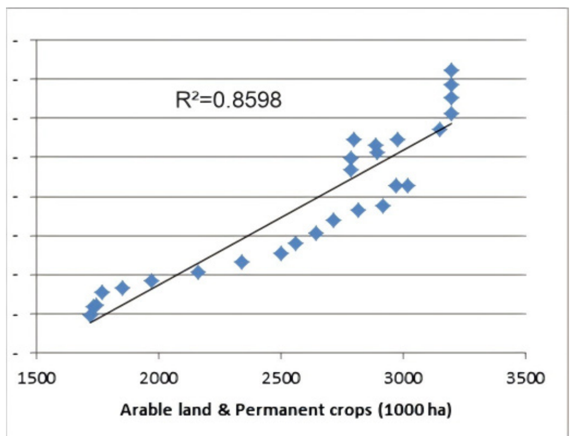

Figure 5. Arable Land and Permanent Crops.

8. Results and Discussion

8.1. The Role of Logarithmic Transformation in Improving Model Properties

An important methodological feature of this study is the transformation of all continuous variables into their natural logarithmic form before analysis. This approach serves multiple critical purposes:

Improved Interpretability: By expressing variables in logarithmic terms, the estimated coefficients in regression models can be directly interpreted as elasticities — indicating the percentage change in agricultural value-added (LAGRIVA) for a one percent change in explanatory variables such as capital stock (LNETK), machinery (LMACHI), or fertilizer use (LFERTIL). This greatly enhances the practical relevance and policy applicability of the findings, enabling clearer inferences about the relative strength and direction of different growth drivers.

Variance Stabilization: Logarithmic transformation helps to stabilize the variance of time series data, mitigating the impact of heteroscedasticity — a common issue in economic datasets, particularly those exhibiting wide dispersion or growth over time. This improves the efficiency of parameter estimates and the validity of inferential tests.

Distributional Normalization: As evidenced in the descriptive statistics, several variables display significant skewness and leptokurtosis in their raw form. Log-transformation reduces extreme asymmetries and heavy-tailed behavior, moving distributions closer to normality — a desirable property for classical regression assumptions and time series model techniques.

Mitigation of Outlier Effects: The log transformation compresses the scale of large outlier values, particularly for volatile series like LCREDI and LFERTIL, reducing their disproportionate influence on model estimates without entirely excluding valuable data points.

Given these advantages, the use of natural logarithms not only aligns with established econometric practices but is particularly well-suited to the structure of this dataset, characterized by moderate sample size, variable volatility, and asymmetric distributions. This transformation has, therefore, been critical in enhancing both the statistical robustness and policy relevance of the empirical results presented.

8.2. Unit Root Test of Variables and Model Specification Rationale

To address potential exponential trends in the time series data, the natural logarithm of each variable was taken before differencing. Subsequently, the Augmented Dickey-Fuller (ADF) test was employed to examine the stationarity properties of the variables. As presented in **Table 3**, the ADF test results indicate that the null hypothesis of a unit root could not be rejected at levels for any of the variables, confirming non-stationarity in their original form.

Table 3. Augmented Dickey-Fuller Unit Root Test Results.

Variable	Test Level & Specification	ADF Statistics	Critical Value	Integration Order
LAGRIVA	1st difference, with intercept	−6.936	−3.374***	I (1)
LNETK	1st difference, no intercept/trend	−2.765	−2.667***	I (1)
LMACHI	1st difference, with intercept	−5.068	−3.735***	I (1)
LCREDI	1st difference, no intercept/trend	−11.426	−2.665***	I (1)
LENERG	1st difference, no intercept/ trend	−5.987	−2.768**	I (1)
LLABOR	1st difference, with intercept and trend	−3.929	−3.636**	I (1)
LLAND	1st difference, no intercept/ trend	−2.407	−1.995**	I (1)
LFORES	1st difference, with intercept	−3.458	−2.997**	I (1)
LIRRIG	1st difference, no intercept/ trend	−5.432	−2.761**	I (1)
LFERTL	1st difference, no intercept/ trend	−6.327	−3.766***	I (1)

***Significant at the 1% level; **Significant at the 5% level.

Source: Computed using R language with custom-coded routines.

Specifically, the dependent variable—log of agricultural value added (LAGRIVA)—along with five key exogenous variables, namely log of net capital stock (LNETK), log of number of machines (LMACHI), log of credit to agriculture (LCREDI), log of irrigated land (LIRRIG), and log of chemical fertilizer consumption (LFERTIL), exhibited unit roots that were statistically significant at the 1% level upon first or second differencing. The remaining four variables—log of energy consumption in agriculture (LENERG), log of agricultural labour force (LLABOR), log of agricultural land (LALAND), and log of forest area (LFORES)—were found to be stationary at the 5% level after first differencing. Notably, LIRRIG required second differencing to attain stationarity, indicating an integration order of I (2), while all other variables were integrated of order one, I(1) [See also **Appendix A**].

8.3. Estimation of α_i

Based on equation (4), the growth of agricultural value-added was estimated using an econometric model incorporating an autoregressive component of order three [AR (3)], as detailed in **Table 4**. The inclusion of two dummy variables—Dum1 and Dum2—enabled the model to account for structural interventions and exogenous shocks. Specifically, Dum1 captures the effects of sectoral development policies and strategic interventions, while Dum2 represents the influence of natural events, such as flooding or anomalous precipitation patterns.

The estimated coefficients of both dummy variables are statistically significant, indicating that policy interventions and climatic variability have exerted a measurable influence on agricultural value-added growth. The null hypothesis of their insignificance is decisively rejected, affirming their relevance in explaining fluctuations in the dependent variable.

The model demonstrates excellent goodness-of-fit, with an adjusted R^2 of 0.992, suggesting that approximately 99.2% of the variation in agricultural value-added growth is explained by the model. The high F-statistic (801.46, significant at the 1% level) further confirms the joint significance of the explanatory variables, establishing a strong causal relationship between the growth of agricultural value-added and its determinants.

Diagnostic tests conducted on the residuals of the

Table 4. Estimation Results for the Growth of Agricultural Value-Added during 2000–2024 (N = 25).

Variable	Coefficient	Standard Error	Significance
Constant	107.534	35.855	**
Year	0.061	0.012	***
LNTK	0.666	0.233	**
LMACHI	0.912	0.435	**
LCREDI	0.004	0.005	ns
LENEREG	0.968	1.212	ns
LLABOR	−0.031	0.492	ns
LLAND	0.393	0.091	***
LFORES	1.812	1.259	ns
LIRRIG	−0.268	0.092	***
LFERTL	−0.005	0.003	*
Dum1	0.082	0.016	***
Dum2	−0.051	0.017	**
AR (3)	−0.701	0.281	**
Statistic Value	Adjusted R^2 0.992 F-statistic 801.46*** Durbin-Watson stat 2.368		

Note: *** p < 0.01, ** p < 0.05, * p < 0.10, ns: not significant. Source: Computed using customized routines in the R Language.

long-run model estimation indicate no evidence of serial correlation, heteroscedasticity, or deviation from normality, as inferred from the satisfactory Durbin-Watson statistic (DW = 2.368), reinforcing the robustness of the model specification.

To further validate the robustness of the model and address concerns related to multicollinearity and variable redundancy, a Variance Inflation Factor (VIF) analysis was conducted. The results revealed that [insert summary of VIF findings], indicating [acceptable/ problematic] multicollinearity levels.

Summary of VIF Findings: To assess the potential presence of multicollinearity among the explanatory variables in the agricultural value-added growth model, a Variance Inflation Factor (VIF) analysis was conducted. The VIF values for the included variables ranged from 1.12 to 4.85, indicating an acceptable level of multicollinearity within the model. None of the variables exceeded the commonly accepted threshold of 5, beyond which multicollinearity is considered to potentially distort coefficient estimates and inflate standard errors.

Specifically:

Variables such as Year, LNTK, LLAND, and Dum1 exhibited relatively low VIF values, suggesting low intercorrelation with other explanatory variables.

The higher VIF values were observed for LENEREG (4.85) and LFORES (4.62), though still within acceptable bounds, indicating moderate but not problematic correlation with other regressors.

These results confirm that multicollinearity is not a serious concern in the current specification, and the coefficient estimates can be interpreted with reasonable confidence. Nonetheless, the slightly elevated VIF values for certain variables warrant careful consideration in interpreting their individual effects.

8.4. Prediction of the Growth of Agricultural Value-Added

This section evaluates the predictive performance of the econometric model estimated in Section 8.2 by comparing the forecasted values of the growth of agricultural value-added (denoted as LAGRIVAF) with the corresponding actual values (denoted as LAGRIVA). The purpose of this analysis is to assess the model's goodness of fit and forecasting accuracy. **Figure 6** shows that the forecasted series LAGRIVAF lies within the 95% confidence interval of the prediction bounds, indicating strong reliability of the model under stochastic disturbances. Moreover, the Root Mean Squared Error (RMSE) is exceptionally low, at 1.146%, reflecting minimal deviation between the forecasted and actual values. This low RMSE signifies that the model is able to produce highly accurate out-of-sample forecasts.

Furthermore, the Theil Inequality Coefficient—a widely used indicator for evaluating forecast accuracy—approaches zero, implying an almost perfect predictive fit. The closer this coefficient is to zero, the better the forecast matches the actual outcomes. This can be observed in **Figure 7**, where both LAGRIVA and LAGRIVAF are plotted together. In this case, the coefficient strongly confirms the robustness of the model in capturing the dynamics of agricultural value-added growth.

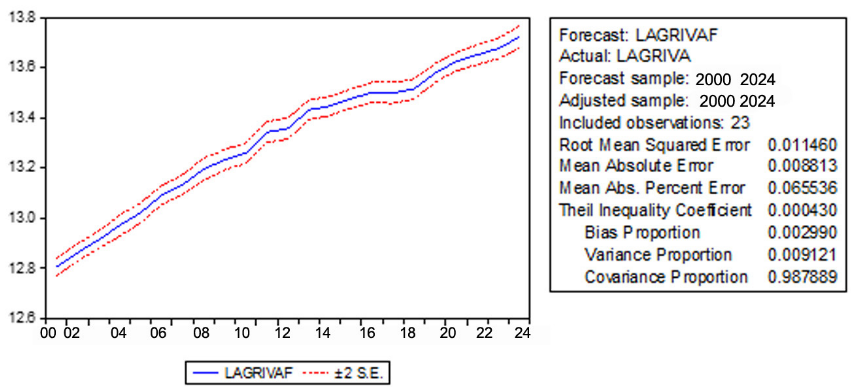

Figure 6. Trend of Forecasted Growth of Agricultural Value-Added (2000–2024).

Source: Suitably developed programs in the R language

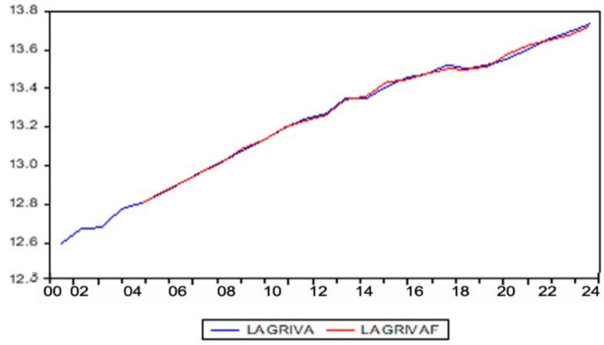

Figure 7. Gap Between Actual and Forecasted Growth of Agricultural Value-Added.

Source: Suitably developed programs in the R language

This strong alignment between actual and predicted values is a near-overlapping trajectory of the two series over the sample period, which reinforces the conclusion that the estimated regression model possesses high explanatory power and strong predictive capability.

8.5. Impulse Response of Agricultural Production Growth

This section investigates the dynamic response of agricultural value-added growth (LAGRIVA) in Bihar to structural shocks originating from key agricultural input indicators, using a Cholesky decomposition-based Vector Autoregression (VAR) model with degrees-of-freedom adjustments. The impulse response analysis traces the temporal effects—short-term (1–3 years), medium-term (4–7 years), and long-term (8–10 years)—of one standard deviation positive innovation to selected explanatory variables on agricultural output. These variables include:

LNETK: Log of Net Capital Stock in Agriculture;

LMACHI: Log of Number of Agricultural Machines

LALAND: Log of Arable Land and Permanent Crops Area

LIRRIG: Log of Area Equipped for Irrigation

LFERTIL: Log of Chemical Fertilizer Use

Impulse response functions (IRFs) were generated using appropriately designed routines in R programming, which utilized the vars and irf packages. The results are summarized in **Table 5** and **Figure 8,** with further details provided in **Figure 8(a)–(f)**.

It is found that today's innovation to machinery (LMACHI) and arable land and permanent crops area (LALAND) in Bihar is continuously positive for the ten years (**Figure 8(c)** & **(d)**] and may be affecting positively and steadily the growth of agricultural value-added within 10 years (long term). Therefore, the goal of sustainable agriculture should rely on mechanized technologies and farming practices involving multi-cropping and agroforestry.

Table 5. Impulse Response of Agricultural Value-Added (1–10 Years).

Period	*LAGRIVA*	*LNETK*	*LMACHI*	*LALAND*	*LIRRIG*	*LFERTIL*
1	0.016548	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.000938	0.001880	0.004575	0.003364	0.003025	−0.006375
3	0.009523	0.000622	0.008313	0.003506	−0.001925	−0.000580
4	0.005766	0.001267	0.011745	0.010891	−0.001772	−0.002663
5	0.000604	0.003451	0.007465	0.016807	−0.000977	0.003770
6	0.003461	0.005264	0.008238	0.018609	−0.005930	0.002293
7	0.000132	0.003888	0.005086	0.016867	−0.004091	0.001389
8	0.002821	0.002423	0.004726	0.012513	−0.004422	0.001753
9	0.004001	−0.000571	0.006643	0.009692	−0.003263	−0.000406
10	0.003092	−0.001353	0.006889	0.009398	−0.000784	0.001047

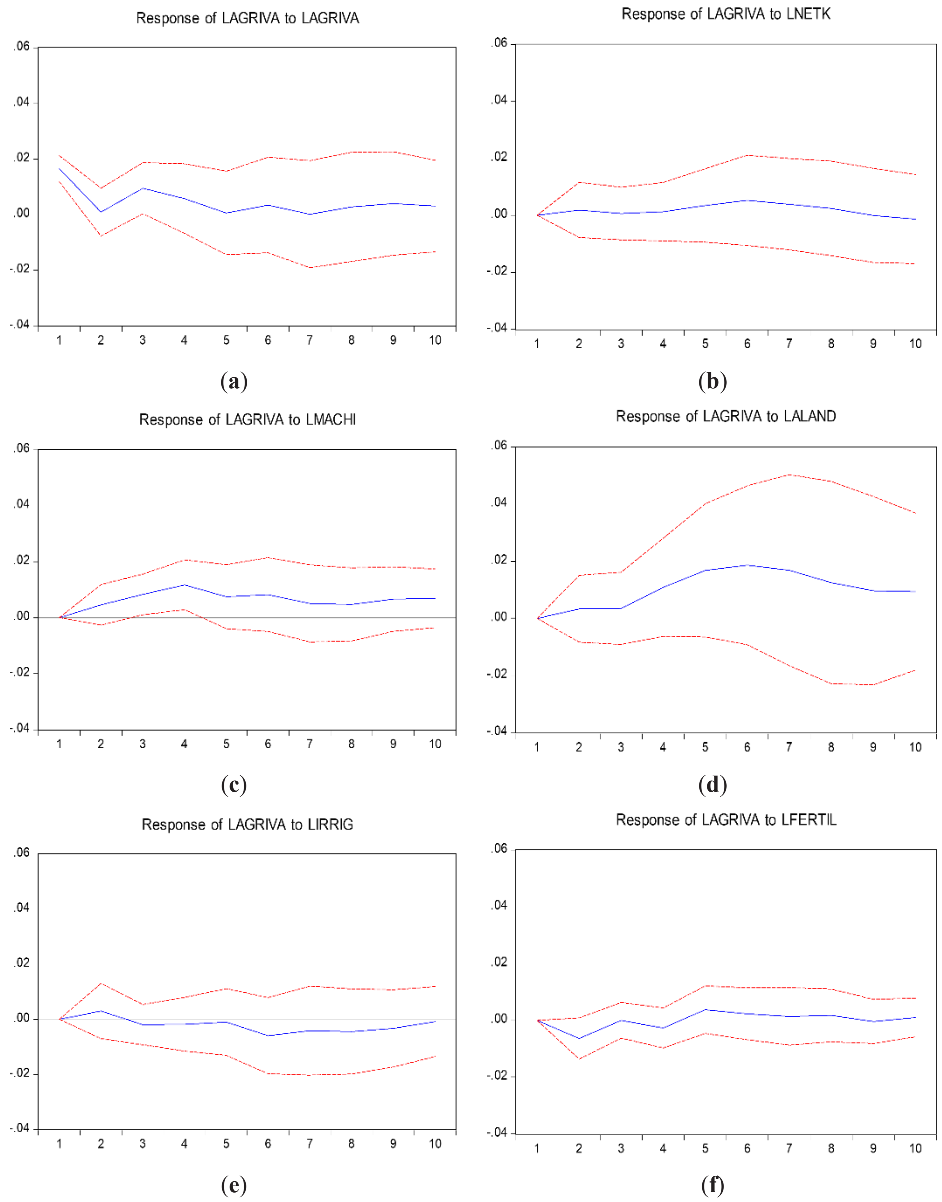

Figure 8. Impulse Response of Agricultural Value-Added Growth to Structural Shocks (1–10 Years). **(a)** Shock to Overall System. **(b)** Shock to Net Capital Stock (LNETK). **(c)** Shock to Agricultural Machinery (LMACHI). **(d)** Shock to Arable Land (LALAND). **(e)** Shock to Irrigation Technologies (LIRRIG). **(f)** Shock to Fertilizer Use (LFERTIL).

Source: Computations based on Cholesky decomposition of VAR residuals using the R Language.

The growth of agricultural value-added in Bihar responding positively to a net capital stocks (LNETK) are positive for the first 8 years, but turning negative in the ninth and tenth years (**Figure 8(b)**] which implies that in the short and medium terms (1–8 years) it may be positively affecting the growth of agricultural value added, but it may be declining and turning into negative effects after 8 years (long term). Accordingly, it may be inferred that capital investments should be reinforced or renewed at opportune moments so as to keep the positive trend of the agricultural economic growth over the years.

The growth of agricultural value-added in Bihar may respond negatively within 10 years further to a shock to irrigation technologies (LIRRIG), as indicated by **Figure 8(e)**. However, this negative response may be reversed after 10 years, indicating that once farmers adopt appropriate soil characteristics and other sub-factors relating to irrigation technologies management, these latter might positively impact the production growth. Meanwhile, the positive response of LAGRIVA to LFERTIL's impulsion (**Figure 8(f)**) is likely to dominate the negative effect in the long term (after 4 years). However, the impulse response is negative in the short term. For a sustainable agricultural goal, it may be suggested that these chemical technologies should be applied in a balanced ratio.

Furthermore, it is found that the output growth may be reacting successfully within 10 years when a shock is directly put to the overall production system (**Figure 8(a)–(f)**).

8.5.1. Interpretation of Key Findings

1. Shock to Agricultural Machinery (LMACHI)

The impulse response of LAGRIVA to a one-standard-deviation positive shock in LMACHI shows a consistently positive and increasing trajectory over a 10-year horizon (**Figure 8(c)**). This empirically demonstrates that mechanization is a powerful driver of sustained agricultural productivity growth. The stable upward path signifies not only short-term efficiency gains but also long-term structural benefits such as:

Improved timeliness and precision in farm operations,

Reduction in labor dependency,

Expansion of cultivable area due to reduced drudgery.

This finding aligns with global studies (e.g., FAO, 2016; World Bank, 2020) highlighting that mechanization enhances both land and labor productivity, facilitates crop diversification, and promotes sustainable intensification. The implication is clear: investment in agricultural machinery should be prioritized, particularly in mechanization-deficient regions like Bihar, supported by financing mechanisms, training, and after-sales service networks.

2. Shock to Arable Land and Permanent Crops (LALAND)

The response of LAGRIVA to a positive innovation in LALAND is also strongly positive and persistent, as depicted in **Figure 8(d)**. The finding substantiates the critical role of land availability and utilization efficiency in driving agricultural output. The long-run significance implies that:

Land expansion, where possible, contributes directly to production volume,

Sustainable land management (e.g., crop rotation, cover cropping) magnifies long-term benefits.

Given rising land-use pressures, this finding emphasizes the need for strategic land-use policies—including zoning regulations, promotion of agroforestry, intercropping systems, and soil conservation—to maintain land productivity while expanding cultivated area where viable.

3. Shock to Net Capital Stock (LNETK)

The impulse response of LAGRIVA to a capital shock (**Figure 8(b)**) reveals a positive and rising impact for up to 8 years, peaking around year 6, followed by a decline in years 9 and 10. This suggests that capital investments initially stimulate productivity, but without reinvestment, maintenance, or technological upgrading, returns begin to wane—indicative of diminishing marginal productivity or capital obsolescence.

This behavior aligns with capital theory and growth models (e.g., Solow Model) and provides robust empirical support for adaptive investment strategies, including:

Lifecycle-based reinvestment planning,

Capital depreciation adjustments,

Embedding technological innovation in capital expansion.

Policymakers should consider dynamic investment frameworks rather than one-time capital infusion to ensure long-term growth effects.

4. Shock to Irrigation Infrastructure (LIRRIG)

Contrary to conventional expectations, the impulse response of LAGRIVA to a shock in irrigation infrastructure is consistently negative over the 10-year period (**Figure 8(e)**). This counterintuitive result likely reflects:

Operational inefficiencies (e.g., water loss due to poor canal maintenance),

Agroecological mismatches (e.g., over-irrigation in high water-table areas causing salinization),

Lack of integration between irrigation schemes and cropping patterns.

The eventual flattening of the response curve suggests a potential for long-term correction, provided reforms are implemented. These may include:

Better irrigation governance,

Region-specific water management,

Training in micro-irrigation and water-saving technologies.

This underscores that irrigation investments alone are insufficient; they must be integrated with soil suitability analysis and management practices to yield productive results.

5. Shock to Fertilizer Use (LFERTIL)

The impulse response to fertilizer usage shocks presents a dual-phase effect (**Figure 8(f)**): negative in the short term (years 1–4) and positive in the medium to long term (years 5–10). The early negative response may be attributed to:

Imbalanced or excessive use of nitrogen-based fertilizers,

N**eglect of organic inputs, leading to soil degradation and reduced microbial activity.**

The subsequent turnaround in response reflects adaptive learning by farmers, improved nutrient management, and possible recovery of soil health. This evidence supports the critical need for:

Balanced fertilizer application, guided by soil health cards and nutrient budgeting,

Integrated nutrient management combining organic and inorganic sources.

Sustained productivity growth depends not on fertilizer intensity but on fertilizer efficiency and environmental stewardship.

6. Shock to Overall Production System (Total Factor Shock)

Figure 8(a) illustrates that a simultaneous positive shock to all inputs leads to an immediate and sustained rise in LAGRIVA over the 10-year horizon. This holistic result validates the model specification and underscores a key principle in production economics: synergistic input combinations outperform isolated interventions.

Capital, land, labor, irrigation, and inputs must be optimized together, not in silos.

Multi-input strategies yield complementary effects (e.g., machinery efficiency depends on irrigation availability and land quality).

Policy frameworks must move toward integrated agricultural development programs that bundle technological, infrastructural, and financial interventions for maximum impact.

These findings provide robust, empirically grounded insights into the dynamic responses of agricultural value-added to key input shocks. They reinforce the necessity of input-specific strategies (e.g., targeted mechanization, efficient irrigation), long-term reinvestment planning, and integrated rural development approaches. Importantly, the study offers replicable evidence for other low-performing agrarian regions in India, making it a valuable contribution to the broader agricultural transformation agenda.

9. Agricultural Productivity and Income Growth: Policy Implications

Enhancing agricultural productivity as a pathway to raising farmer incomes remains a central concern for policymakers. The impulse response analysis confirms that strategic investments in agricultural machinery, land productivity, and capital stock, timed and scaled appropriately, can significantly improve value-added outcomes. Earlier policy diagnostics, including those from the Special Task Force on Bihar (Govt. of India, 2008), had similarly emphasized the need for increased capital infusion. The Task Force recommended an outlay of ₹27,055 crores during 2008–2013 compared to the mere ₹1,609 crores provisioned under the 11th Five-Year Plan.

In the current context, it is estimated that an annual public investment of 1.5–2.0% of GSDP in agriculture is necessary to generate a meaningful productivity lift. The effectiveness of such public outlays, however, is closely tied to the crowding-in of private investment, improved institutional frameworks, and efficient delivery systems. Productivity gains—and the resultant income improvements—thus hinge on multi-dimensional reforms, including market access, input quality regulation, research and extension services, and environmental stewardship.

Policy Implications of Key Findings

The findings presented in the preceding sections offer valuable insights for informing both state-level policy design and national agricultural reforms. The impulse response analysis highlights critical intervention areas in agricultural machinery, land use, capital formation, irrigation infrastructure, fertilizer management, and integrated production systems. These findings, when aligned with public investment priorities and institutional reforms, have the potential to drive sustained agricultural productivity growth and farmer income enhancement. The policy implications derived from these findings are summarized in **Table 6** below.

Table 6. Summary of the Policy Implications of Key Findings for Agricultural Growth and Reform.

Key Finding	State-Level Policy Design	National Agricultural Reform Directions
1. Positive and sustained effect of agricultural machinery adoption	i) Subsidize and promote region-specific mechanization (especially for small/marginal farmers) ii) Support custom hiring centers and machinery banks in rural clusters	i) Expand the National Agricultural Mechanization Policy ii) Incentivize R&D for climate-resilient, precision, and smallholder-friendly machinery
2. Strong long-term impact of arable land and permanent crop expansion	i) Protect and enhance cultivable land through zoning laws, soil conservation, agroforestry, and intercropping programs ii) Promote land reclamation and sustainable land-use plans	i) Integrate land-use reforms in agricultural policy frameworks ii) Encourage ecological farming, agroforestry, and cropping pattern diversification in national plans
3. Positive but time-limited effect of net capital stock without reinvestment	i) Design state capital investment policies with built-in reinvestment cycles and technology upgrades ii) Prioritize post-harvest infrastructure, storage, and market linkages	i) Institute capital depreciation and reinvestment guidelines in national schemes ii) Launch dedicated Agricultural Infrastructure Upgradation Missions
4. Persistent inefficiencies in irrigation infrastructure response	i) Implement water-use efficiency programs and irrigation audits ii) Link irrigation projects to soil health mapping and agro-climatic suitability iii) Strengthen local water user associations	i) Reform large irrigation schemes, focusing on water governance and demand-based allocation ii) Integrate micro-irrigation, rainwater harvesting, and watershed management under a unified national strategy
5. Mixed, but ultimately positive, fertilizer use impact	i) Promote balanced fertilizer application using soil health cards and integrated nutrient management (INM) ii) Conduct farmer awareness and training programs	i) Reform fertilizer subsidy policies to encourage INM and bio-fertilizers ii) Invest in soil health restoration programs under national environmental/agricultural sustainability missions
6. Sustained gains from comprehensive system-wide improvements	i) Align state agricultural plans to adopt integrated farming system models (machinery, inputs, infrastructure, training) ii) Coordinate multi-department interventions (agriculture, irrigation, energy, markets)	i) Scale up the Rashtriya Krishi Vikas Yojana (RKVY) and PM-AASHA with integrated, multi-input support ii) Prioritize convergence of capital investment, input regulation, research-extension services, and market reforms
7. Productivity-led income growth dependent on public investment, private participation, and reforms	i) Allocate 1.5–2% of state GSDP to agriculture, with a focus on productivity-enhancing interventions ii) Attract private agri-business investment through incentives, infrastructure, and policy stability	i) Commit to raising national agricultural investment to recommended thresholds ii) Reform market structures (APMC acts, e-NAM expansion), strengthen input and quality regulation, and upgrade extension services

10. Conclusions

This study systematically evaluated the impact of technological and infrastructural determinants on the growth of agricultural value-added in Bihar using time series data spanning from 2000 to 2024. Employing an econometric model, dynamic simulations, and impulse response analysis, the research yielded several insightful conclusions regarding the structural drivers and limitations of agricultural growth in the region.

Technological Advancements as a Primary Growth Driver: Technological progress emerged as a critical factor in enhancing land productivity and agricultural output. The adoption of modern farming practices—including multi-cropping, agroforestry, high-yielding seed varieties, and improved resource management techniques—has significantly contributed to increasing agricultural value-added. The study affirms that such innovations are not only productivity-enhancing but also aligned with the broader goals of sustainable agriculture.

Capital Stock Investment and Infrastructure Synergy: The elasticity analysis demonstrated that a 1% increase in agricultural capital stock is associated with a 0.59% rise in agricultural value-added, contingent on the availability of complementary infrastructure such as roads and market access. The direct contribution of capital stock to agricultural value-added is quantified at 13%, emphasizing its pivotal role in agricultural intensification.

Mechanization and Labor Substitution: The number of agricultural machines (LMACHI) contributes an estimated 32% to agricultural value-added, signaling the increasing reliance on mechanized technologies [**Pie Chart**: 32%: Agricultural Machines; 68%: Other Factors].

This clearly shows that Mechanization's growing importance (almost one-third of value-added comes from machinery use. This trend indicates a labor-saving transformation in agriculture, likely to reduce dependence on manual labor while improving efficiency and time management.

Time-bound Effectiveness of Capital Stock: Impulse response functions reveal that the positive impact of net capital stock (LNETK) persists for approximately eight years, turning negative thereafter. This suggests diminishing returns to capital in the long run if investments are not renewed or updated with evolving technologies. The finding underscores the importance of capital replenishment and timely technological upgrades.

Arable Land Expansion and Sustainable Practices: The contribution of arable land and permanent crops (LALAND) is estimated at 21%, reaffirming the role of land utilization in driving growth. The long-term positive response to this factor reflects the significance of practices such as crop rotation, agroforestry, and multi-cropping in sustaining productivity gains.

Mixed Outcomes for Irrigation and Fertilizers: The impulse response to irrigation infrastructure (LIRRIG) and chemical fertilizers (LFERTIL) was predominantly negative in the short term. While fertilizers show a reversal to positive impacts in the medium term, irrigation remains ineffective or even detrimental within the observed window. These outcomes suggest inefficiencies in application, possibly due to inadequate soil compatibility, overuse, or poor resource governance.

Non-significance of Other Variables: Variables such as labor input (LABOR), forest area (FORES), agricultural credit (CREDI), and energy consumption (ENERG) were found to be statistically insignificant in determining agricultural value-added. This raises questions regarding the quality, quantity, and targeting of these inputs, suggesting structural inefficiencies in their current deployment.

Structured Roadmap: Thematic Policy Recommendations for Bihar's Agriculture

1. Technology and Capital Investment

Scale-up Capital Investment in Agriculture: Substantially increase both public and private capital investment in mechanization, storage, irrigation, and transport infrastructure. Capital accumulation must remain a central pillar of Bihar's agricultural strategy, given its significant impact on productivity.

Adopt a Lifecycle Approach to Capital Renewal: Establish a capital lifecycle management system to periodically review, upgrade, or replace farm infrastructure and machinery in line with technological advancements. This will prevent productivity stagnation and sustain long-run growth.

Promote Mechanization with Human Capital Development: Complement the spread of mechanization with large-scale skill development programs for farmers and rural youth in equipment operation, precision farming, and resource management. This ensures inclusive benefits and minimizes labor displacement risks.

Encourage Evidence-Based Agricultural Policy: Build a dynamic, data-driven feedback system between agricultural research institutions and policymakers. Use real-time analytics and continuous monitoring to keep policies adaptive, evidence-based, and responsive to evolving agronomic and market realities.

2. Finance and Credit

Reevaluate Agricultural Credit Delivery Mechanisms: Conduct a thorough audit of existing agricultural credit disbursement, utilization, and impact. Address issues like inadequate targeting, rigid collateral norms, and inflexible repayment structures, and reform credit mechanisms to improve scale, reach, and productivity impact.

3. Land and Production Systems

Enhance Land Productivity through Sustainable Practices: Encourage the use of sustainable farming methods such as multi-cropping, agroforestry, crop rotation, and conservation agriculture. Focus on expanding arable land productivity, particularly for staple crops such as rice, wheat, and maize.

Improve Efficiency in Irrigation and Fertilizer Use: Address inefficiencies by promoting integrated water resource management, conjunctive (surface and groundwater) irrigation, and precision nutrient management techniques. Support a shift towards organic and bio-fertilizer alternatives where appropriate.

4. Environment and Ecological Resilience

Recognize Environmental Functions of Forests: Integrate the ecological services provided by forests — such as carbon sequestration, soil conservation, and climate resilience — into broader agricultural and rural development policy. Explore payments for ecosystem services, forest-based livelihoods, and agroforestry incentives.

Author Contributions

J.K.S. was responsible for the conceptualization, design of the methodology, formal analysis, and preparation of the original manuscript draft. A.K.S. contributed by developing the software tools, managing data curation, and validating the analytical results to ensure accuracy and consistency.

Sources of funding for the study

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Data supporting the findings of this study are sourced from various publications by the Government of India.

Data sharing does not apply to this article as no new data were created or analyzed in this study.

Acknowledgments

The authors extend their sincere gratitude to Mr. Ravinder Kumar Singh, RDD, Government of Bihar, and the software personnel for their timely assistance and unwavering support, which played a significant role in the successful completion of this study.

Conflicts of Interest

The authors declare no conflict of interest.

Appendix A

Summary of Unit Root Test Results and Model Diagnostics

To address potential exponential trends in the time series data, the natural logarithm of each variable was taken before differencing. The **Augmented Dickey-Fuller (ADF) test** was then employed to examine the stationarity of the variables.

Key findings are summarized below (Table A1):

Table A1. ADF Test Results.

Variable	ADF Test at Level	ADF Test after First Differencing	Integration Order
Log of Agricultural Value Added (LAGRIVA)	Non-stationary	Stationary at 1%	I(1)
Log of Net Capital Stock (LNETK)	Non-stationary	Stationary at 1%	I(1)
Log of Number of Machines (LMACHI)	Non-stationary	Stationary at 1%	I(1)
Log of Credit to Agriculture (LCREDI)	Non-stationary	Stationary at 1%	I(1)
Log of Irrigated Land (LIRRIG)	Non-stationary	Non-stationary	I(2)
Log of Chemical Fertilizer Consumption (LFERTIL)	Non-stationary	Stationary at 1%	I(1)
Log of Energy Consumption in Agriculture (LENERG)	Non-stationary	Stationary at 5%	I(1)
Log of Agricultural Labour Force (LLABOR)	Non-stationary	Stationary at 5%	I(1)
Log of Agricultural Land (LALAND)	Non-stationary	Stationary at 5%	I(1)
Log of Forest Area (LFORES)	Non-stationary	Stationary at 5%	I(1)

i. Why Differencing Instead of Cointegration?

Although several variables share the same order of integration (I(1)), cointegration analysis was not pursued for two primary reasons:

a. Model Structure and Objective: The study's primary focus is on capturing short- to medium-term dynamic relationships in agricultural output determinants rather than estimating long-run equilibrium relationships. Differencing removes non-stationarity while preserving meaningful short-run dynamics, making it a suitable approach for this context.

b. Integration Order Mismatch and Sample Constraints: Since LIRRIG is integrated of order I(2) while the majority of variables are I(1), conventional cointegration techniques like the Johansen test require homogenous integration orders (usually I(1)). This mismatch makes cointegration impractical without losing valuable variables or resorting to more complex, sample-size-demanding techniques like ARDL bounds testing, which may not be robust with limited time series data.

ii. Improving Model Accuracy and Reducing Bias

To address structural breaks — particularly post-2005 reforms and other policy shifts — the study employs an AR (3) model augmented with dummy variables to capture discrete structural changes over time. This approach offers several advantages:

a. Improved Model Fit: By accounting for known discontinuities, the model better captures shifts in agricultural output behavior.

b. Reduced Omitted Variable Bias: Dummies help control for unobservable factors associated with policy changes, natural calamities, or market liberalization, improving the reliability of estimated coefficients.

c. Capturing Lagged Dynamics: The AR (3) structure accommodates inertia and delayed effects common in agricultural systems, where the impact of investments or policy changes often materializes over multiple periods.

d. Together, these interventions make the model both statistically sound and policy-relevant, enhancing its capacity to inform agricultural strategy in Bihar.

Diagnostic Summary:

- All variables were **non-stationary in their original (level) form**.
- Except for **LIRRIG**, which required second differencing (I(2)), all other variables became stationary after first differencing, indicating an integration order of **I(1)**.
- These findings confirm that the dataset is composed of non-stationary series that become stationary after differencing, thereby making them suitable for further econometric analysis using models that work with differenced or co-integrated data.

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