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RESAERCH NOTE

Agricultural Production and Cost Efficiency in India: A State- and Crop-Level Analysis, 2000–2021

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ABSTRACT

This study examines the evolution of agricultural cost, allocative and technical efficiency in India from 2000 to 2021, a period marked by significant technological and structural changes shaped by successive agricultural revolutions and policy shifts. While past decades saw remarkable gains in crop output and productivity, recent trends highlight growing concerns over input inefficiencies, rising production costs, and sustainability challenges. Utilizing Farrell's efficiency framework and Data Envelopment Analysis (DEA), I estimate and decompose cost, allocative, and technical efficiencies for 16 major crops across 15 Indian states. The analysis reveals notable crop-level variations, offering critical insights into whether inefficiencies arise from suboptimal input allocation or technical constraints. By providing a comprehensive assessment of production and cost efficiency in Indian agriculture, the findings aim to inform policy, guide resource allocation, and support strategies for long-term equitable agricultural growth.

Keywords: Cost, allocative and technical efficiency, input distance functions, production and cost theory

JEL codes: C67, D24, O3, Q18

I

INTRODUCTION

India's agricultural sector has undergone significant structural and technological transformations since independence in 1947. Initially characterized by subsistence-level productivity, the sector transitioned through various phases marked by substantial gains in food grain production and diversification into high-value crops. Innovations and institutional support across different agricultural revolutions such as the Green Revolution for food grains, Yellow Revolution for oilseeds, White Revolution for dairy, Blue Revolution for fisheries, and Golden Revolution for horticulture have collectively enhanced output levels (Fan et al., 2000). These shifts underscore the critical role of technology adoption and policy frameworks in driving agricultural growth.

Structural changes including widespread adoption of high-yielding varieties, mechanization, irrigation expansion, and intensified use of chemical fertilizers and pesticides have contributed to improvements in total factor productivity (Yotopoulos and Lau, 1973; Fan, Hazell, and Thorat, 2000). These developments unfolded within the broader planning framework of the Five-Year Plans and, more recently, strategic visions such as the NITI Aayog's Three- Year Action Agenda and the Fifteen-Year Vision[2]. However, these gains have often been accompanied by increased input

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[2]Initially, agricultural policies and Five-Year Plans focused on ensuring food security and reducing poverty. In recent years, India has shifted away from the centralized Five-Year Plan model that guided its economic development since

intensities, raising important questions about production costs and the sustainability of prevailing practices.

Since the 1990s, inefficiencies in input use have become more apparent, with challenges such as groundwater depletion, excessive fertilizer application, and cropping system imbalances particularly the dominance of rice-wheat monoculture in northern India highlighting the limits of past strategies (Adamopoulos and Restuccia, 2014). This shift in discourse from output maximization to resource-use efficiency signals a more nuanced understanding of agricultural performance, especially given agriculture's continuing importance for rural employment and income in India's lagging regions (Sinha and Sharma, 2020).

Despite the critical importance of these issues, empirical studies on Indian agriculture tend to emphasize output and input intensities, with limited attention to cost, allocative, and technical (CAT) efficiency across crops (Bhattacharyya, et al., 2017). These studies often lack insight into whether producers operate close to the cost and production frontier, masking spatial variations and the rationale behind input use decisions.

To address this gap, I apply Farrell's (1957) efficiency framework using Data Envelopment Analysis (DEA), a nonparametric method that avoids imposing functional form assumptions (Banker et al., 1984; Shaik, 2013; Shaik, 2015). This approach allows estimation of cost efficiency (CE), allocative efficiency (AE), and technical efficiency (TE) for 16 major crops across 15 Indian states from 2000 to 2021. By decomposing CE into AE and TE, I identify whether inefficiencies stem from suboptimal input allocation or technical limitations, offering a more complete understanding of production behavior and economic decision-making.

The study's primary objective is to estimate and compare variations in cost, allocative, and technical efficiency across major agricultural crops in India. This comprehensive analysis aims to enhance understanding of agricultural efficiency in India and provide evidence-based insights to guide policy and resource allocation decisions.

II

THEORY OF PRODUCTION, COST, AND EFFICIENCY MEASUREMENT

The concept of technical efficiency is rooted in the input distance function, which is based on production theory (Fuss and McFadden, 1978). This function establishes a relationship between a vector of outputs, denoted as $y =$

1951. The 12th Five-Year Plan (2012–2017) was the last, and in 2015, the Planning Commission was replaced by the NITI Aayog (National Institution for Transforming India). NITI Aayog introduced a more flexible and adaptive planning framework, including the Three-Year Action Agenda (2017–2020), a Seven-Year Strategy (2017–2024), and a Fifteen-Year Vision Document. These changes reflect a broader shift toward decentralized, innovation-driven, and outcome-based economic planning.

$(y_1, y_2, \dots, y_M) \in R^M$, and a vector of non-allocable inputs, denoted as $x = (x_1, x_2, \dots, x_N) \in R^N$.

This relationship is represented by the production function as follows:

$$(1)\, y = f(x)$$

This production function defining the relationship between input and output quantities based on production theory, is modelled using the Data Envelopment Analysis (DEA) framework. In DEA, the technology that transforms inputs into outputs is represented by an input, output, or graph set. Here, the relationship between output and input is defined by the input set, $L(y, x)$. The technical efficiency measure is computed either using Shephard's concept or Farrell's concept of efficiency, both of which are defined by the distance function. The input set is:

$$(2) \qquad L(y, x) = \{x\text{: } y \text{ is produced by } x;\}$$

The set follows the properties of strong disposability assumptions of outputs and inputs, and constant returns to scale (CRS) or variable returns to scale (VRS) as in Fare et.al., (1994).

The input distance function, represented by the input set defined in equation (1), is used in the estimation of efficiency. The input distance function captures the scalar shrinkage of inputs. The reference technology, denoted as T, defined by all the DMUs, forms the basis in the estimation of each DMU's efficiency. The input distance function with strong disposability assumption is represented as:

$$(3) \qquad L(y, x) = \{x\text{: } y \text{ is produced by } x;\}$$

$$or$$

$$\begin{aligned} \min_{\lambda, z} \lambda \ s.t. \quad & y \leq Yz \quad \text{where} \quad Y = (y^1, y^2, \dots, y^T) \\ & \lambda x \geq Xz \qquad\qquad X = (x^1, x^2, \dots, x^T) \\ & z = 1 \end{aligned}$$

Cost and allocative efficiency are estimated based on the cost theory (Shephard, 1953 and Shephard, 1970), which establishes the relationship between a vector of non-allocable inputs, denoted as $x = (x_1, x_2, \dots, x_N) \in R^N$, given a vector of output, $y = (y_1, y_2, \dots, y_M) \in R^M$, and dependent on a vector of input prices, denoted as $w = (w_1, w_2, \dots, w_N) \in R^N$.

The cost function based on cost theory is represented as:

$$(4) \qquad c = f(w, y)$$

Here, c is the cost and computed as the product of input quantity, x, and input price, w.

Following Fare et al (1994) and the cost function defined above, consider the cost minimization set that transforms inputs into outputs and is provided with input prices. In DEA, the cost minimization set is defined by the minimum cost piece-wise technology required to produce an output vector. Relative to the input set, the cost minimization, denoted as $cm(w, y)$, with known x and w is:

$$(5) \qquad cm(w, y) = \min_{z,x} \{wx: x \epsilon L(y, x)\}$$

$$or$$

$$\min_{z,x} wx \;\; s.t. \quad y \leq Yz \quad \text{where} \quad Y = (y^1, y^2, \ldots, y^T)$$

$$\lambda x \geq Xz \qquad X = (x^1, x^2, \ldots, x^T)$$

$$z = 1$$

The input cost efficiency is estimated as the ratio of cost minimization, $cm(w, y)$, to observed cost and is defined as:

$$(6) \qquad C^T(w, x, y) = \frac{cm(w,y)}{wx}$$

This input cost efficiency, denoted as $C^T(w, x, y)$, is decomposed into 1) scalar reduction in inputs defined by technical efficiency, denoted as, $L^T(y, x)$ and 2) using inputs in a wrong mix attributed to input allocative efficiency, denoted as $A^T(w, x, y)$. The input allocative efficiency is defined as:

$$(7) \qquad A^T(w, x, y) = \frac{C^T(w,x,y)}{L^T(y,x)}$$

Equations (3, 6 and 7) are estimated separately by crop and every year from 2001 to 2021.

III

DATA CURATION, SOURCES, AND CONSTRUCTION OF VARIABLES

For this analysis, I utilized data from the Comprehensive Scheme for Studying the Cost of Cultivation of Principal Crops in India (Government of India, 2020), which offers detailed estimates of cultivation costs and production across multiple states and crops. The scheme follows a three-stage stratified random sampling design, as outlined by the Directorate of Economics and Statistics. In the first stage, tehsils (administrative units) are selected; this is followed by the selection of clusters of villages in the second stage, and finally, operational holdings within these clusters are sampled in the third stage. The sampling framework also incorporates agro-climatic zoning based on factors such as soil type, climate, and prevailing cropping patterns to ensure representativeness across diverse agricultural conditions.

The data are collected from approximately 8,100 sample operational holdings across nineteen states, using the Cost Accounting Method. This method involves maintaining continuous debit and credit entries to capture daily expenditures and receipts, enabling a comprehensive computation of total cultivation costs and farm-level net returns. The scheme is implemented in collaboration with sixteen State Implementing Agencies, which include agricultural universities and affiliated research institutions.

For the purposes of this study, I curated plot-level panel data covering the years 2001 to 2021. The dataset includes information on nineteen crops cultivated across eighteen Indian states, although not all crops are grown in every state or in every year. The crops analyzed include - cereals: Bajra, Barley, Jowar, Maize, Paddy (Rice), and Wheat; pulses: Arhar (redgram), Gram (Bengalgram), Masur (Lentil), Moong (Greengram), and Urad (Blackgram); oilseeds: Groundnut, Rapeseed & Mustard, Sesamum, and Soybean; fibres: Cotton and Jute; and commercial crops: Sugarcane and Potato. The states included in the analysis are Andhra Pradesh, Assam, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Kerala, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttarakhand, Uttar Pradesh, and West Bengal.

To facilitate model estimation, I aggregated the plot-level data to the tehsil level. I focused exclusively on observations with non-zero input and output values and ensured that both quantities and prices were valid. Output quantities are measured in quintals, and prices are reported in rupees per quintal (Rs/quintal). Input quantities are recorded in hectares for land, hours for labor and capital services, and kilograms (kg) for seeds and fertilizers. Input prices are expressed in rupees and correspond to their respective quantity units. The specific input-output variables for major crops include output measured in quintals, land use in hectares, labor input in hours, capital input in hours, seed usage in kilograms, and fertilizer usage in kilograms.

Furthermore, cost information is provided for land (in rupees per hectare), labor (in rupees per hour), capital (in rupees per hour), seed (in rupees per kilogram), and fertilizer (in rupees per kilogram).

This structured and multi-dimensional dataset enables a consistent and detailed estimation of cost, allocative and technical efficiency across both crops and states of Indian agriculture.

IV

EMPIRICAL ANALYSIS AND RESULTS

This section presents the empirical analysis, starting with the coefficient of variation (CV) for key variables, including output quantity, input quantity, and input prices across crops and years. The CV is used as a standardized, dimensionless measure of dispersion, which allows for systematic comparisons across variables with differing units and magnitudes.

Following this, I estimate and compare three main efficiency measures: cost efficiency, allocative efficiency, and technical efficiency. These measures are calculated separately for each crop and year, from 2001 to 2021, providing detailed insights into performance trends within Indian agriculture. The cost efficiency is estimated using equation 6, allocative efficiency using equation 7, and technical efficiency using equation 3.

The efficiency scores are assessed under two production assumptions: constant returns to scale (CRS) and variable returns to scale (VRS). CRS assumes proportional changes in output relative to inputs, reflecting an optimal scale of operation. In contrast, VRS allows for deviations from this proportionality, acknowledging that farms may operate at sub-optimal scales due to technological, resource, or size constraints. As a result, VRS yields higher efficiency estimates, as it accounts for the heterogeneity present in agricultural production environments.

This approach facilitates a thorough and consistent estimation of efficiency metrics, forming the basis for the subsequent discussion of results.

4.1.Coefficient of variation of variables used in the efficiency analysis

To assess and compare variability across key inputs, outputs, and prices within Indian agriculture, I use the coefficient of variation (CV) as a central statistical metric. The CV, presented as a percentage, is a unitless measure of dispersion, allowing for comparisons between variables that differ in scale or measurement units. A low CV indicates relative stability and predictability, while a high CV suggests increased volatility and associated risk.

Table 1 provides the CV estimates for the primary crops and their respective input-output categories over the period from 2000 to 2021. A CV of 0.57 indicates a 57% variation, while a CV of 1.23 suggests a 123% variation from the mean. These metrics are essential for evaluating the extent of variability and, by extension, economic risk across various crops and their corresponding inputs and outputs. The appendix contains A-Table 1, which provides similar statistics broken down by state for maize and soybean.

Regarding output variability, potato (CV: 0.80) and pea (CV: 1.1) exhibit the highest volatility, reflecting substantial fluctuations in yield due to local agro-ecological conditions and production practices. In contrast, crops such as jute (CV: 0.47) and soybean (CV: 0.50) show more stability in output.

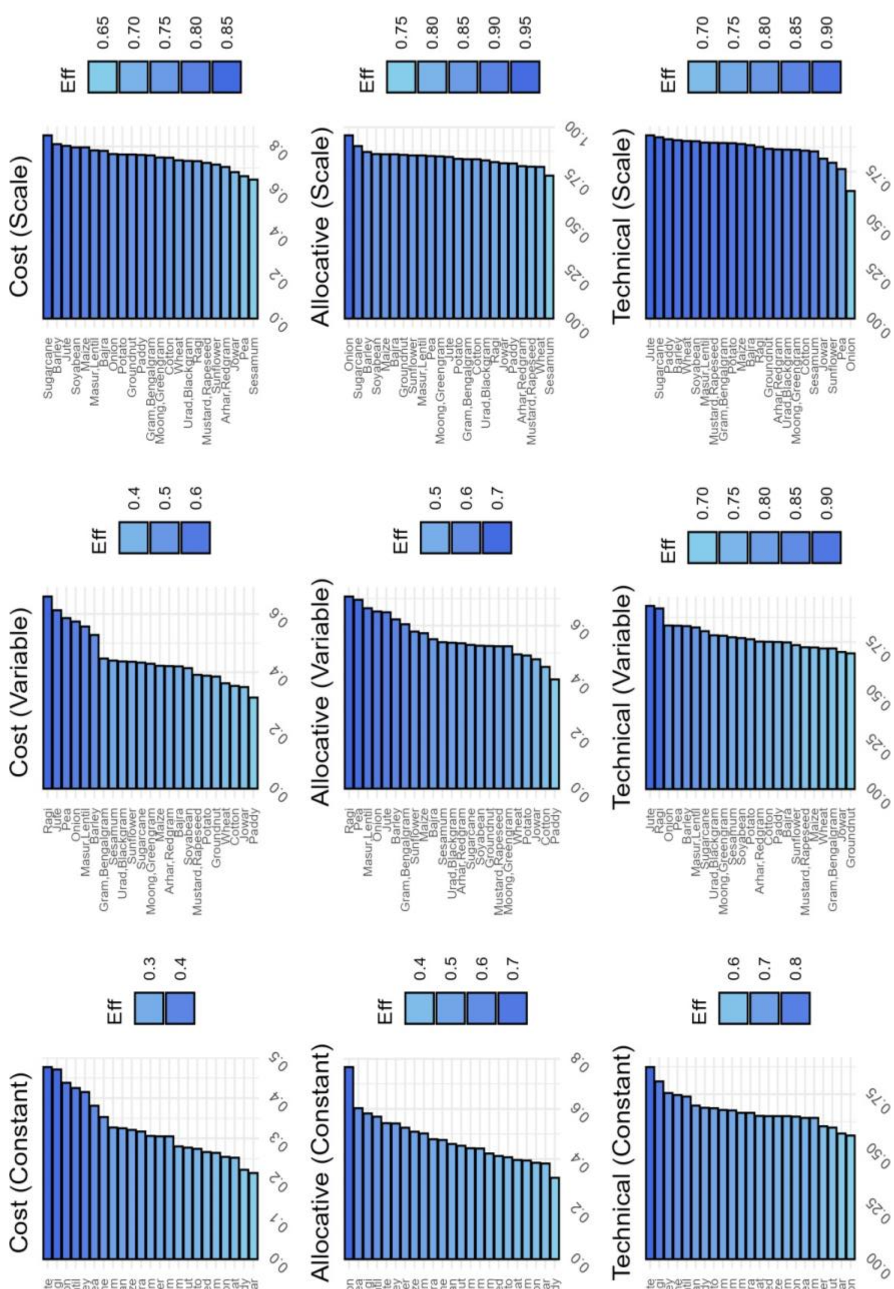

FIGURE 1. BAR CHART OF AVERAGE COST, ALLOCATIVE AND TECHNICAL EFFICIENCY BY CROP, 2001 TO 2021

Land use variability is significant for potato (1.53) and pea (1.23), indicating fluctuating land requirements and intensity of cultivation. In contrast, jute (CV: 0.47) and soybean (CV: 0.50) demonstrate more consistent land utilization. Labor input variability is notable for crops like onion (0.38) and soybean (0.48), which show stable labor requirements. However, pea (1.12) and potato (0.82) exhibit greater variability due to region-specific cultivation and post-harvest practices. Capital input CVs reveal significant disparities: paddy (2.25) and arhar (2.04) are capital-intensive crops marked by considerable fluctuations, while soybean (0.86) and wheat (0.90) show more stable capital needs. Seed usage also varies significantly. Potato has a high CV (2.25), reflecting intensive and variable seed requirements, while crops like soybean (0.55) and jute (0.57) require fewer variable seed inputs, which reduces production uncertainty. Fertilizer input variability is also notable. Potato (1.74) and arhar (1.53) exhibit high CVs, indicating uncertainty in fertilizer requirements, whereas soybean (0.56) and jute (0.59) show more predictable fertilizer needs, presenting less financial risk from a cost management perspective.

When analyzing cost structure, land costs are most variable for potato (2.02) and pea (1.32), driven by regional pricing disparities. Labor costs for onion (0.33) and soybean (0.48) are stable, but for paddy (0.71) and potato (0.52), they fluctuate more due to labor-intensive cultivation methods. Capital costs show high variability for sugarcane (1.45) and potato (0.96), whereas soybean (0.64) and moong (0.54) demonstrate lower volatility, offering more predictable financial outcomes. Seed price volatility is particularly high for paddy (6.62) and sugarcane (3.93), which presents challenges for cost planning. Conversely, seed prices for soybean (0.43) and jute (0.62) remain more stable. Fertilizer price volatility is high for potato (2.48) and arhar (1.54), but more predictable for soybean (0.70) and jute (0.73).

Synthesizing these findings, crops such as potato (output CV: 0.80), pea (1.39), arhar (1.11), and paddy (1.00) are characterized by significant variability across outputs, input quantities, and prices, which increases production and financial risk for farmers. Potato's high CVs for both output and major inputs (seed and fertilizer prices, both at 2.48) mark it as a high- risk crop. In contrast, crops like soybean (0.57), jute (0.52), and wheat (0.91) show consistently low variability, making them more stable options for producers seeking predictability in both yields and costs. This stability reduces economic risk and supports long-term farm management and financial planning.

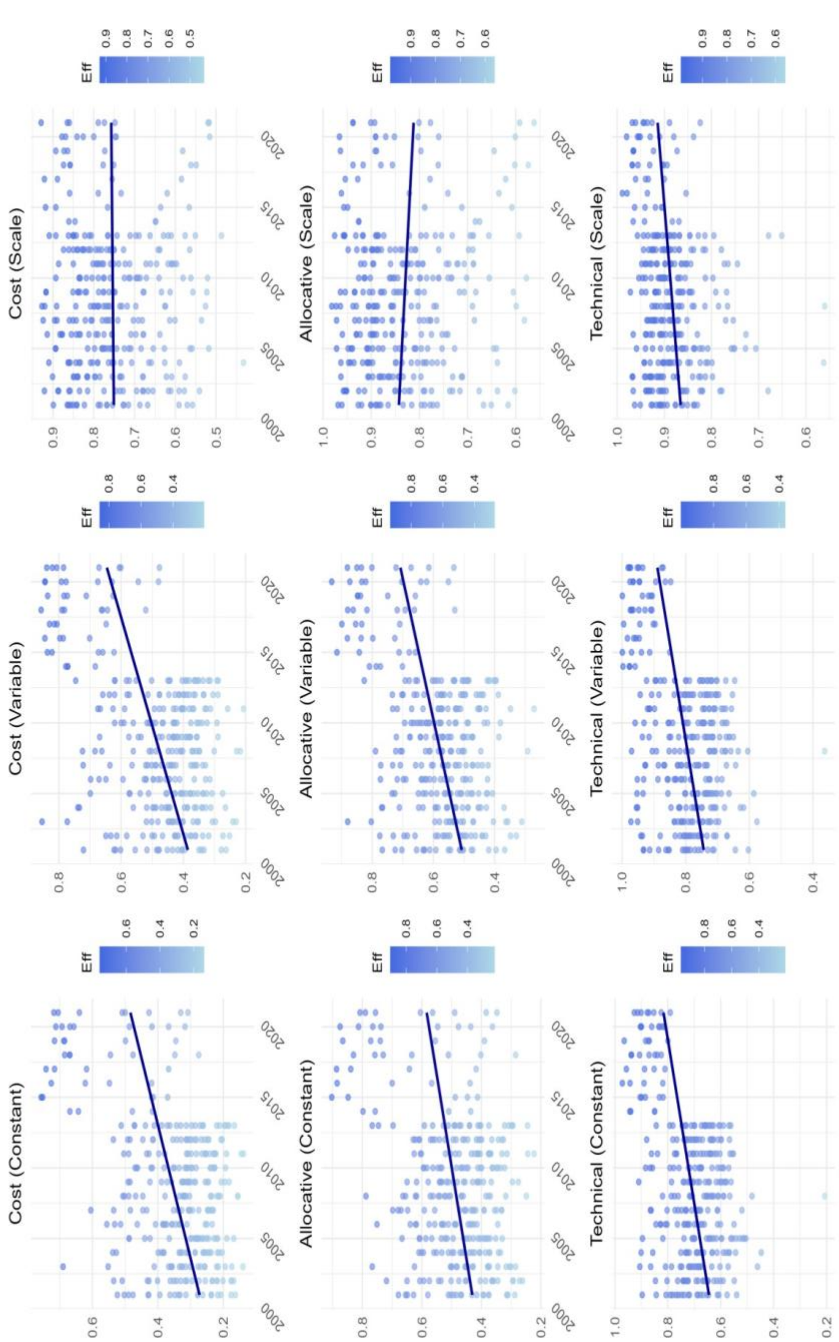

FIGURE 2. TREND LINE OF AVERAGE COST, ALLOCATIVE AND TECHNICAL EFFICIENCY BY CROP, 2001 TO 2021

4.2.Comparative cost, allocative and technical efficiency across crops

This section systematically examines and compares cost, allocative, and technical efficiencies for various crops, considering different assumptions about production scale, including constant, variable, and scale efficiencies. The efficiency metrics, summarized in Table 2 and illustrated in Figure 1, describe crop performance over the period from 2001 to 2021.

Figure 2 visually traces the temporal trends of cost, allocative, and technical (CAT) efficiency across the crops studied. For further reference, A-Table 2 in the appendix provides similar statistics by state for maize and soybean. Efficiency measures serve as key indicators of agricultural performance. Cost efficiency reflects how efficiently a crop's output is produced relative to input expenditure. Allocative efficiency measures the optimal allocation of resources such as land, labor, and capital in line with prevailing market prices. Technical efficiency quantifies a crop's ability to maximize output from given inputs, minimizing waste. The joint interpretation of these efficiency measures offers a comprehensive view of crop performance, highlighting the relationship between economic and technological factors at different scales of production.

The analysis of efficiency patterns across selected crops shows that Arhar (redgram) experiences significant improvements in cost, allocative, and technical efficiency as production scale increases. Under constant returns to scale, the crop shows a cost efficiency of 0.280, allocative efficiency of 0.422, and technical efficiency of 0.650. At the scale efficiency frontier, these values rise to 0.705, 0.797, and 0.863, respectively, indicating substantial gains from economies of scale and more effective resource utilization.

Similarly, Bajra (pearl millet) also shows positive scale effects. The initial efficiencies in cost (0.317), allocative (0.479), and technical (0.665) rise with increased scale, reaching 0.780, 0.859, and 0.885, respectively. This progression underscores the crop's responsiveness to larger- scale production and suggests significant productivity potential under expanded cultivation.

Barley follows a similar trajectory, with cost, allocative, and technical efficiencies improving from 0.415, 0.542, and 0.755 under constant returns to 0.811, 0.871, and 0.910 at the scale efficiency frontier. This consistent improvement further confirms the advantages of scale in realizing efficiency gains.

Cotton, despite showing modest baseline efficiencies in cost (0.254), allocative (0.385), and technical (0.648), also benefits significantly from increased scale, with efficiencies rising to 0.748, 0.833, and 0.857, respectively. These results reflect the challenges faced by smaller producers and emphasize the benefits of capital- and input-intensive production systems at larger scales.

TABLE 1. COEFFICIENT OF VARIATION OF OUTPUT AND INPUT QUANTITY AND PRICES, 2001 TO 2021, BY CROP

Crop/ States		Quantity						Price				
		Output	Land	Labor	Capital	Seed	Fertilizer	Land	Labor	Capital	Seed	Fertilizer
Arhar, Redgram	10	1.11	1.08	0.93	2.04	1.01	1.53	1.35	0.52	0.89	0.71	1.54
Bajra	6	0.70	0.63	0.57	1.52	0.69	0.91	0.87	0.56	0.75	0.52	1.15
Barley	2	0.83	0.84	0.67	1.13	0.80	0.94	0.98	0.55	1.06	0.40	1.03
Cotton	11	0.76	0.54	0.58	1.23	1.34	0.83	0.98	0.62	1.14	0.66	0.96
Gram, Bengalgram	13	0.85	0.73	0.69	1.20	0.82	1.04	1.05	0.59	1.05	0.45	1.20
Groundnut	10	0.88	0.73	0.63	1.33	0.74	1.14	1.05	0.59	1.23	0.51	1.00
Jowar	6	0.83	0.70	0.62	1.71	0.81	1.11	1.18	0.53	0.83	0.84	1.31
Jute	3	0.52	0.47	0.47	1.22	0.57	0.59	0.77	0.50	1.14	0.62	0.73
Maize	15	1.05	0.71	0.79	1.96	0.66	1.14	1.27	0.67	0.90	0.98	1.42
Masur, Lentil	5	0.83	0.76	0.69	1.43	0.87	0.80	0.86	0.50	0.78	0.46	0.88
Moong, Greengram	6	0.91	0.86	0.72	1.92	0.93	1.16	1.21	0.54	0.70	0.56	1.28
Mustard, Rapeseed	12	1.01	0.87	0.76	1.30	1.01	1.04	1.17	0.61	0.90	0.98	1.08
Onion	2	0.78	0.81	0.38	1.14	0.78	0.58	0.90	0.33	1.43	0.39	0.66
Paddy	19	1.00	0.66	0.61	2.25	0.77	1.30	1.32	0.71	0.96	6.62	1.42
Pea	3	1.39	1.23	1.12	1.61	1.26	1.21	1.32	0.47	0.72	0.53	1.44
Potato	5	1.59	1.53	0.82	1.26	2.25	1.74	2.02	0.52	0.96	0.66	2.48
Ragi	5	0.76	0.71	0.70	1.46	0.95	0.84	1.02	0.60	1.12	1.77	1.00
Sesamum	8	0.95	0.87	0.69	1.70	1.06	1.13	1.23	0.54	0.97	0.79	1.35
Soyabean	4	0.57	0.50	0.48	0.86	0.55	0.56	0.80	0.50	0.64	0.43	0.70
Sugarcane	6	0.84	0.72	0.81	1.12	1.18	0.93	1.24	0.62	1.45	3.93	0.97
Sunflower	3	0.82	0.72	0.56	1.60	0.71	0.77	0.99	0.54	1.00	0.54	0.80
Urad, Blackgram	13	1.01	0.80	0.76	1.95	0.96	1.17	1.35	0.66	0.83	0.55	1.39
Wheat	14	0.91	0.66	0.57	0.90	0.63	0.96	1.25	0.59	1.01	0.46	0.97

Onion presents a unique case. While allocative efficiency is notably high at the outset (0.767), technical efficiency (0.562) lags behind. As the scale of production increases, cost efficiency improves from 0.438 to 0.765, and allocative efficiency peaks at 0.958. However, technical efficiency remains low, rising to 0.651. This divergence suggests that resource allocation is highly effective, but technological or agronomic limitations may hinder the full realization of production potential.

Figure 1 presents nine efficiency metrics - cost, allocative, and technical assessed under constant, variable, and scale assumptions as detailed in Table 2. Each metric is depicted with a distinct scale, where darker shades indicate higher efficiency values and lighter shades represent lower performance. These visualizations are aligned with the results in Table 2, providing further clarity to the analysis. Figure 2 illustrates the temporal evolution of these efficiency metrics from 2001 to 2021, revealing upward trends in cost, allocative, and technical efficiency under both constant and variable returns to scale. Notably, cost efficiency at scale remains stable, while allocative efficiency at scale shows a downward trend, contrasted by increases in technical efficiency at scale over the observed period.

The aggregated findings reveal a clear pattern in which most crops demonstrate improvements in cost and technical efficiency as production scales increase. Barley and wheat, in particular, achieve notably high technical efficiencies at larger scales, which aligns with their suitability for intensive, large-scale production. In contrast, onions stand out for their superior allocative efficiency, reflecting farmers' ability to align input use with market signals, even when technical performance is less optimal.

Crops like Arhar, Bajra, and Cotton also exhibit scale-related efficiency gains, though the magnitude and pace of improvement vary. These differences are influenced by both the inherent characteristics of the crops and regional agro-economic factors that shape the responses to scaling.

In general, the trend toward higher production scale is associated with better resource allocation, cost reduction, and increased output. However, the observation that allocative efficiency often outpaces technical efficiency indicates a persistent gap in fully optimizing output, despite effective resource allocation.

V

CONCLUSIONS

This study provides a comprehensive analysis of efficiency in Indian agriculture, focusing on cost, allocative, and technical efficiency measures for various crops over the period from 2001 to 2021. The application of the coefficient of variation (CV) as a standardized measure of dispersion reveals significant variability in outputs, inputs, and prices across different crops. These findings highlight the economic risks associated with crop production in India.

TABLE 2. MEAN COST, ALLOCATIVE AND TECHNICAL EFFICIENCY BY CROP, 2001 TO 2021

Crop	Constant			Variable			Scale		
	Cost	Allocative	Technical	Cost	Allocative	Technical	Cost	Allocative	Technical
Arhar, Redgram	0.280	0.422	0.650	0.421	0.535	0.752	0.705	0.797	0.863
Bajra	0.317	0.479	0.665	0.420	0.550	0.748	0.780	0.859	0.885
Barley	0.415	0.542	0.755	0.528	0.623	0.831	0.811	0.871	0.910
Cotton	0.254	0.385	0.648	0.353	0.448	0.751	0.748	0.833	0.857
Gram, Bengalgram	0.327	0.502	0.642	0.447	0.605	0.717	0.759	0.833	0.896
Groundnut	0.277	0.453	0.598	0.385	0.525	0.692	0.763	0.856	0.866
Jowar	0.214	0.382	0.571	0.349	0.476	0.699	0.681	0.812	0.816
Jute	0.477	0.543	0.873	0.613	0.649	0.934	0.803	0.845	0.935
Maize	0.321	0.509	0.650	0.422	0.572	0.722	0.796	0.859	0.891
Masur, Lentil	0.425	0.569	0.739	0.557	0.664	0.824	0.782	0.853	0.898
Moong, Greengram	0.305	0.442	0.676	0.429	0.524	0.782	0.749	0.848	0.861
Mustard, Rapeseed	0.266	0.412	0.650	0.391	0.524	0.723	0.724	0.794	0.897
Onion	0.438	0.767	0.562	0.574	0.652	0.834	0.765	0.958	0.651
Paddy	0.222	0.325	0.688	0.313	0.402	0.750	0.761	0.811	0.915
Pea	0.381	0.603	0.642	0.586	0.695	0.833	0.662	0.850	0.763
Potato	0.274	0.407	0.686	0.388	0.490	0.764	0.763	0.835	0.895
Ragi	0.471	0.582	0.808	0.660	0.707	0.921	0.732	0.818	0.876
Sesamum	0.264	0.394	0.665	0.440	0.539	0.774	0.646	0.747	0.853
Soyabean	0.325	0.460	0.698	0.414	0.526	0.770	0.796	0.860	0.905
Sugarcane	0.353	0.476	0.746	0.433	0.529	0.805	0.852	0.902	0.925
Sunflower	0.305	0.525	0.604	0.436	0.578	0.734	0.716	0.853	0.795
Urad, Blackgram	0.306	0.443	0.678	0.437	0.537	0.784	0.733	0.827	0.862
Wheat	0.252	0.396	0.651	0.362	0.494	0.717	0.736	0.793	0.906

The results indicate that crops such as potato, pea, arhar, and paddy exhibit substantial volatility in both output and key input costs, making them high-risk crops for farmers. In contrast, crops like soybean, jute, and wheat show low variability in outputs, input quantities, and prices, marking them as more stable and less risky choices for farmers seeking predictability in production and cost management.

The analysis of efficiency metrics reveals that most crops show improvement in cost and technical efficiency as the scale of production increases. However, allocative efficiency exceeds technical efficiency, suggesting that resource allocation tends to align well with market prices, but there is still room to enhance output from available inputs. The findings also show that larger-scale production is associated with improved cost reduction, output maximization, and better resource utilization, particularly for crops such as barley and wheat.

In contrast, crops like onion exhibit high allocative efficiency but lag in technical efficiency. This highlights the gap between effective resource allocation and the potential for maximizing output. The study further illustrates that while scale efficiencies improve across many crops, the gap between allocative and technical efficiency persists, reflecting the challenges in fully optimizing production despite efficient resource allocation.

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APPENDICES

APPENDIX TABLE 1. MEAN OUTPUT AND INPUT QUANTITY AND PRICES BY STATE FOR MAIZE AND SOYBEAN,2001 TO 2021

State	Output (Quintals)	Land (Hectare)	Labor (Hours)	Capital (Hours)	Seed (Kgs)	Fertilizer (Kgs)	Land (Rs/Hec)	Labor (Rs/Hour)	Capital (Rs/Hour)	Seed (Rs/Kg)	Fertilizer (Rs/Kg)
						Maize					
Andhra Pradesh	43.3	1.1	631.8	77.6	22.5	198.6	12,159	23.2	140	96	3,612
Bihar	21.9	0.6	349.5	25.1	12.0	78.3	3,184	10.8	109	68	1,454
Gujarat	13.3	0.7	417.2	21.8	15.3	91.0	2,967	14.2	155	86	1,510
Himachal Pradesh	8.2	0.6	211.5	3.7	18.0	37.3	1,969	17.5	250	25	451
Jharkhand	9.8	0.4	276.3	4.4	9.1	31.5	3,223	19.0	290	88	693
Karnataka	39.7	1.3	811.1	58.1	20.7	179.3	8,373	15.9	132	96	3,439
Madhya Pradesh	18.6	1.1	480.2	9.0	22.9	67.9	4,778	18.5	266	67	1,227
Maharashtra	31.8	0.7	382.6	35.9	12.7	152.4	8,528	43.1	405	260	4,657
Odisha	22.2	0.6	468.0	6.7	12.0	83.0	6,903	32.1	478	233	2,692
Punjab	20.2	0.5	167.0	16.3	10.6	105.3	6,139	46.7	330	252	2,659
Rajasthan	7.3	0.4	237.9	8.1	12.2	30.8	1,308	15.8	178	29	460
Tamil Nadu	33.0	0.8	446.7	92.7	15.4	180.8	6,368	28.4	99	165	3,299
Telangana	50.0	1.0	339.5	17.9	22.3	310.6	22,681	78.2	686	282	8,423
Uttar Pradesh	7.3	0.4	243.4	12.4	8.3	29.7	1,939	13.5	149	32	438
Uttarakhand	4.5	0.4	142.1	5.9	8.0	44.5	910	8.8	104	17	603
	21.7	**0.8**	**419.7**	**33.4**	**15.9**	**98.5**	**4,912**	**17.6**	**168**	**71**	**1,783**
						Soybean					
Chhattisgarh	10.8	1.2	400.7	10.6	111.2	85.6	5,295	12.3	266	23	1,896
Madhya Pradesh	19.7	1.7	551.1	18.5	149.4	67.6	8,844	14.4	211	24	1,296
Maharashtra	12.2	0.9	438.4	13.6	68.5	63.0	3,548	16.9	211	30	1,215
Rajasthan	9.4	0.9	312.5	12.0	84.4	32.1	3,426	17.0	243	28	689
	15.4	**1.2**	**481.6**	**15.7**	**106.8**	**63.6**	**5,969**	**15.7**	**214**	**27**	**1,231**

APPENDIX TABLE 2. MEAN COST, ALLOCATIVE AND TECHNICAL EFFICIENCY BY STATE FOR MAIZE AND SOYBEAN, 2001 TO 2021

	Constant			Variable			Scale		
State	Cost	Technical	Allocative	Cost	Technical	Allocative	Cost	Technical	Allocative
					Maize				
Andhra Pradesh	0.266	0.752	0.355	0.410	0.783	0.503	0.721	0.954	0.743
Bihar	0.317	0.724	0.439	0.419	0.777	0.523	0.796	0.923	0.832
Gujarat	0.206	0.450	0.466	0.248	0.546	0.453	0.860	0.833	0.936
Himachal Pradesh	0.359	0.615	0.611	0.435	0.709	0.626	0.834	0.863	0.921
Jharkhand	0.567	0.834	0.676	0.660	0.911	0.714	0.856	0.909	0.906
Karnataka	0.288	0.711	0.402	0.416	0.735	0.545	0.741	0.963	0.760
Madhya Pradesh	0.396	0.632	0.605	0.467	0.692	0.652	0.862	0.921	0.906
Maharashtra	0.633	0.929	0.688	0.726	0.958	0.757	0.884	0.968	0.895
Odisha	0.799	1.000	0.799	0.850	1.000	0.850	0.945	1.000	0.945
Punjab	0.613	0.951	0.648	0.646	0.997	0.648	0.948	0.954	0.956
Rajasthan	0.334	0.549	0.624	0.445	0.666	0.652	0.789	0.818	0.907
Tamil Nadu	0.263	0.721	0.363	0.338	0.768	0.426	0.828	0.932	0.864
Telangana	0.515	0.923	0.556	0.722	0.923	0.774	0.742	1.000	0.743
Uttar Pradesh	0.342	0.517	0.659	0.440	0.655	0.655	0.806	0.793	0.938
Uttarakhand	0.119	0.456	0.286	0.148	0.595	0.246	0.845	0.774	0.987
	0.321	**0.650**	**0.509**	**0.422**	**0.722**	**0.572**	**0.796**	**0.891**	**0.859**
					Soybean				
Chhattisgarh	0.115	0.553	0.240	0.161	0.638	0.267	0.689	0.849	0.797
Madhya Pradesh	0.375	0.706	0.529	0.456	0.744	0.601	0.833	0.946	0.866
Maharashtra	0.276	0.698	0.389	0.359	0.789	0.444	0.778	0.880	0.860
Rajasthan	0.381	0.667	0.558	0.585	0.843	0.668	0.681	0.794	0.826
	0.325	**0.698**	**0.460**	**0.414**	**0.770**	**0.526**	**0.796**	**0.905**	**0.860**