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# Comparative analysis of resource use efficiency and productivity among AI-adopting and non-adopting sugarcane farmers in Western Maharashtra

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**Abstract**

The present study examined resource-use efficiency and productivity differentials between AI-adopting and non-adopting sugarcane farmers in Western Maharashtra during the agricultural year 2025-26. Primary data were collected from 90 farmers (45 AI and 45 non-AI) selected from nine tehsils across Pune, *Satara* and Solapur districts. Cobb-Douglas production functions were estimated separately for each system. The AI model explained 87 per cent of output variation, while the non-AI model explained 84 per cent. In AI cultivation, machine power, phosphorus, potassium, plant-protection expenditure and micronutrient expenditure exerted positive and statistically significant effects on output, whereas irrigation expenditure showed a negative significant relationship. Under non-AI cultivation, manure, phosphorus and potassium had positive significant effects, while irrigation expenditure was negatively significant. Resource-use analysis for AI sugarcane indicated under-utilisation of manure, machine power, nitrogen, phosphorus and potassium, with particularly high MVP/MC ratios for phosphorus (51.78), potassium (42.00) and machine power (26.55). Plant protection and micronutrient expenditure were over-utilised, and irrigation recorded a negative MVP/MC ratio. In non-AI cultivation, manure, machine power, phosphorus and potassium were under-utilised, while human labour, nitrogen, irrigation, plant protection and micronutrients showed ratios below unity. AI farmers obtained substantially higher physical productivity (248.23 t/ha versus 177.89 t/ha) and a higher B:C ratio at Cost C (2.02 versus 1.47). The results underscore the productivity advantage of AI-based practices and the scope for reallocation of under-utilised inputs in both systems.

**Keywords:** Resource-use efficiency, Input elasticities, Cobb-Douglas production function, AI sugarcane, MVP/MC ratio, Western Maharashtra

## 1. Introduction

Sugarcane is a major commercial crop of Maharashtra, occupying about 13–14 lakh hectares and contributing substantially to farm income and the sugar industry. Western Maharashtra accounts for nearly 65–70 per cent of the state's sugarcane area and production owing to better irrigation facilities and a well-developed network of sugar factories. Cultivation is both input- and labour-intensive, and the efficient allocation of land, labour, water, fertilisers and plant-protection chemicals is central to profitability.

Artificial Intelligence (AI) tools—including IoT sensors, satellite-based advisories, drones and data-driven decision support—are increasingly being applied to sugarcane production. Pilot work at Krishi Vigyan Kendra, Baramati, in collaboration with technology partners, has demonstrated yield gains and reductions in water and chemical use under AI-assisted management. At the same time, the technology alters the structure of input requirements and the marginal productivities of labour, machinery, nutrients and irrigation.

Input elasticities derived from a production function quantify the percentage change in output associated with a one-per-cent change in a given input, holding other factors constant. When combined with market prices, elasticities permit calculation of marginal value products and assessment of allocative efficiency. Measuring elasticities alongside efficiency ratios therefore provides a clearer picture of resource performance than production trends alone.

District- and system-level analysis is useful for identifying differences between technological regimes within a local agricultural setting. Accordingly, this study examines resource-use efficiency and productivity differentials between AI-adopting and non-adopting sugarcane farmers in Western Maharashtra for the agricultural year 2024-25. Specifically, it estimates Cobb-Douglas production functions and computes MVP/MC ratios to describe input responsiveness and allocative efficiency under the two systems.



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## 2. Data and methodology

Primary data relating to production aspects (input quantities, prices and output) of AI and non-AI sugarcane were collected through the survey method for the year 2025-26 with the help of schedules specially designed for the purpose. Western Maharashtra was purposively selected as it is the principal AI and non-AI sugarcane-growing region of the state. Three districts—Pune, *Satara* and Solapur—were selected. From each district three tehsils were chosen on the basis of maximum area under both systems (Baramati, Indapur and Daund in Pune; Khatav, Koregaon and Phaltan in *Satara*; Madha, Karmala and Malshiras in Solapur). From each tehsil five AI and five non-AI growers were selected randomly, resulting in a total sample of 90 farmers (45 AI and 45 non-AI). The list of AI sugarcane growers was obtained from the AI Sugarcane Project (Farm of the Future), KVK Baramati.

### *2.1 Production function specification*

To estimate resource-use productivity, the Cobb-Douglas production function of the following type was used:

$$Y = aX_1^{b_1}X_2^{b_2}X_3^{b_3}X_4^{b_4}X_5^{b_5}X_6^{b_6}X_7^{b_7}X_8^{b_8}X_9^{b_9}...X_n^{b_n}e^u$$

Where,

Y = Output of the main produce (t/ha)
$X_1$ = Human labour (days/ha)
$X_2$ = Manures (t/ha)
$X_3$ = Machine labour (hr/ha)
$X_4$ = Nitrogen (kg/ha)
$X_5$ = Phosphorus (kg/ha)
$X_6$ = Potassium (kg/ha)
$X_7$ = Irrigation charges (₹/ha)
$X_8$ = Plant protection charges (₹/ha)
$X_9$ = Micronutrient charges (₹/ha)
u = Error term
*a* = Intercept
$b_i$ = Regression coefficients (partial elasticities of production)

The logarithmic transformation of equation (1) was estimated by ordinary least squares. The coefficient of multiple determination ($R^2$), adjusted $R^2$ and the *F*-statistic were used to evaluate goodness of fit.

### *2.2 Resource-use efficiency*

To estimate resource-use efficiency, the following formula was used:

$$MVP = [\ bi\ \frac{\bar{Y}}{\bar{X}i}]\ Py$$

Where,

$b_i$ = Elasticity of production of the $i^{th}$ input
$\bar{Y}$ = Geometric mean of output
$\bar{X}_i$ = Geometric mean of the $i^{th}$ input
$P_y$ = Per unit price of output

The ratio of Marginal Value Product (MVP) to Marginal Cost (MC) was then computed for each input. An MVP/MC ratio greater than unity indicates under-utilisation of the resource; a ratio less than unity indicates over-utilisation; and a ratio equal to unity indicates optimal allocation.

## 3. Results and Discussion

The relationship between inputs and output, together with the associated efficiency ratios, was analysed for AI and non-AI sugarcane in Western Maharashtra. The results are presented below.

### *3.1 AI sugarcane production function*

The estimated production function for AI sugarcane explained 87 per cent of the variation in yield. Machine power, phosphorus, potassium, plant-protection expenditure and micronutrient expenditure recorded positive and statistically significant elasticities, indicating that a one-per-cent increase in these inputs raised output, holding other factors constant. Irrigation expenditure entered with a negative and significant coefficient, consistent with over-application of water relative to the response surface. Human labour and nitrogen showed positive but relatively smaller effects. The sum of the partial elasticities pointed to favourable scale characteristics under AI management.

These results are consistent with the lower absolute quantities of several inputs used by AI farmers (human labour 115.93 days/ha versus 136.37 days/ha under non-AI; nitrogen 404.48 kg/ha versus 546.32 kg/ha; phosphorus 142.53 kg/ha versus 210.67 kg/ha) while still achieving substantially higher physical output (248.23 t/ha versus 177.89 t/ha).

### *3.2 Non-AI sugarcane production function*

The production function estimated for non-AI sugarcane explained 84 per cent of the variation in yield. Manure, phosphorus and potassium registered positive and statistically significant elasticities. Irrigation expenditure again showed a negative significant relationship. Human labour, nitrogen, plant protection and micronutrients displayed weaker or negative associations with output at the prevailing mean levels, suggesting over-application of these resources under conventional management.

### *3.3 Resource-use efficiency in AI sugarcane*

The allocative efficiency of resource use in AI sugarcane production was evaluated by estimating the ratio of Marginal Value Product to Marginal Cost (MVP/MC) for each critical input using equation (2). The results are presented in Table 1.

An examination of Table 1 reveals that the ratio of MVP to MC was greater than unity for human labour (1.31), manures (10.35), machine power (26.55), nitrogen (2.19), phosphorus (51.78) and potassium (42.00). Because these values exceed 1.0, the resources were under-utilised at the geometric-mean levels prevailing in the sample. Phosphorus and potassium, in particular, displayed very high ratios, indicating substantial scope for additional application from an economic standpoint. Conversely, the MVP/MC ratios were less than unity for plant-protection charges (0.33) and micronutrient charges (0.75), and negative for irrigation (−0.28), confirming excess utilisation of these inputs.

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**Table 1.** Resource-use efficiency in AI sugarcane production

| Sr. No. | Particulars | Unit | bi | MVP (Rs) | MC (Rs) | MVP/MC | Remark |
|---|---|---|---|---|---|---|---|
| 1 | Human labour ($X_1$) | Days | 0.071 | 526.37 | 400 | 1.31 | Under-utilised |
| 2 | Manures ($X_2$) | Ton. | 0.535 | 18645.25 | 1800 | 10.35 | Under-utilised |
| 3 | Machine ($X_3$) | Hrs. | 0.798 | 21246.81 | 800 | 26.55 | Under-utilised |
| 4 | Nitrogen ($X_4$) | Kg. | 0.012 | 26.31 | 12 | 2.19 | Under-utilised |
| 5 | Phosphorus ($X_5$) | Kg. | 0.534 | 3210.63 | 62 | 51.78 | Under-utilised |
| 6 | Potassium ($X_6$) | Kg. | 0.371 | 2268.35 | 54 | 42.00 | Under-utilised |
| 7 | Irrigation ($X_7$) | ₹ | −0.0036 | −0.285 | 1 | −0.28 | Over-utilised |
| 8 | Plant protection ($X_8$) | ₹ | 0.0027 | 0.333 | 1 | 0.33 | Over-utilised |
| 9 | Micronutrients ($X_9$) | ₹ | 0.0044 | 0.759 | 1 | 0.75 | Over-utilised |

*Note: Geometric mean levels of inputs and output and unit output price were used to compute MVP.*

### *3.4 Resource-use efficiency in non-AI sugarcane*

The allocative efficiency of resource use in non-AI sugarcane cultivation was evaluated using the same MVP/MC framework. The results are presented in Table 2.

An examination of Table 2 reveals that the MVP to MC ratio was greater than unity for manures (12.94), machine power (24.56), phosphorus (20.86) and potassium (30.30), signalling under-utilisation. Human labour (−5.21), nitrogen (0.044), irrigation (−0.15), plant protection (−0.20) and micronutrients (0.28) exhibited ratios below unity (or negative), indicating over-utilisation at the prevailing levels.

**Table 2.** Resource-use efficiency in non-AI sugarcane production

| Sr. No. | Particulars | Unit | bi | MVP (Rs) | MC (Rs) | MVP/MC | Remark |
|---|---|---|---|---|---|---|---|
| 1 | Human labour ($X_1$) | Days | −0.46 | −2087.8 | 400 | −5.21 | Over-utilised |
| 2 | Manures ($X_2$) | Ton. | 1.003 | 23300.8 | 1800 | 12.94 | Under-utilised |
| 3 | Machine ($X_3$) | Hrs. | 1.03 | 19648.9 | 800 | 24.56 | Under-utilised |
| 4 | Nitrogen ($X_4$) | Kg. | 0.00048 | 0.5355 | 12 | 0.044 | Over-utilised |
| 5 | Phosphorus ($X_5$) | Kg. | 0.44 | 1293.39 | 62 | 20.86 | Under-utilised |
| 6 | Potassium ($X_6$) | Kg. | 0.54 | 1636.65 | 54 | 30.30 | Under-utilised |
| 7 | Irrigation ($X_7$) | ₹ | −0.0032 | −0.157 | 1 | −0.15 | Over-utilised |
| 8 | Plant protection ($X_8$) | ₹ | −0.0027 | −0.205 | 1 | −0.20 | Over-utilised |
| 9 | Micronutrients ($X_9$) | ₹ | 0.0030 | 0.2835 | 1 | 0.28 | Over-utilised |

*Note: Geometric mean levels of inputs and output and unit output price were used to compute MVP.*

### *3.5 Comparative assessment of productivity and efficiency*

A comparison of the two production systems reveals several consistent patterns. First, AI farmers achieved markedly higher physical productivity (248.23 t/ha) than non-AI farmers (177.89 t/ha) while using lower quantities of human labour, setts, manure, major nutrients, micronutrients, irrigation and plant-protection inputs. Machine use was only marginally higher under AI. Second, both systems exhibit under-utilisation of manure, machine power, phosphorus and potassium, implying that additional application of these inputs would raise returns. Third, irrigation is over-utilised in both systems, as indicated by negative MVP/MC ratios. Fourth, plant protection and micronutrients are over-utilised under AI as well as non-AI management, although the absolute expenditure levels differ.

The higher goodness-of-fit of both models ($R^2$ = 0.87 for AI and 0.84 for non-AI) indicates that the specified inputs account for a substantial share of yield variation. The productivity differential in favour of AI is therefore attributable not only to differences in input quantities but also to more precise timing and placement of inputs guided by sensor-based and advisory systems. Cost of production per tonne was correspondingly lower under AI (₹1,549.75) than under non-AI (₹2,116.24), and the B:C ratio at Cost C stood at 2.02 for AI against 1.47 for non-AI.

## 4. Conclusions

The study estimated input elasticities and resource-use efficiency for AI and non-AI sugarcane cultivation in Western Maharashtra using Cobb-Douglas production functions. Under AI management, machine power, phosphorus, potassium, plant protection and micronutrients contributed positively and significantly to output, while irrigation showed a negative significant elasticity. Under non-AI management, manure, phosphorus and potassium were the principal positive contributors, and irrigation again entered with a negative coefficient.

Resource-use efficiency analysis demonstrated that both groups under-utilise manure, machine power, phosphorus and potassium, while over-utilising irrigation. AI farmers additionally under-utilise nitrogen and, to a modest extent, human labour, whereas non-AI farmers over-utilise human labour and nitrogen. Rationalisation of irrigation and chemical plant-protection use, together with expanded application of the under-utilised nutrients and machine power, can raise both technical and economic efficiency.

Overall, AI-based sugarcane cultivation exhibited a clear productivity and profitability advantage over the conventional system. Effective training, technical guidance and reliable digital connectivity remain necessary for farmers to realise the full benefits of the technology.

## 5. Suggestions

On the basis of the empirical findings the following recommendations are offered:

1. Farmers should adopt soil-test-based and sensor-guided fertiliser recommendations that increase phosphorus, potassium and manure applications toward the levels indicated by the efficiency ratios, while avoiding excess nitrogen and irrigation.
2. Micro-irrigation systems and AI-assisted irrigation scheduling should be promoted to correct over-irrigation and improve water-use efficiency.



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3. Expansion of farm mechanisation, guided by the high MVP/MC ratios for machine power in both systems, will raise productivity and reduce labour pressure during peak periods.
4. Krishi Vigyan Kendras and state extension agencies should intensify training on the use of AI tools, data entry, interpretation of advisories and integrated nutrient and pest management for sugarcane.
5. Improvement of rural internet connectivity and provision of affordable AI hardware and software packages, supported by targeted subsidies, will lower the barriers to adoption identified by AI farmers (lack of training, technical knowledge and connectivity).

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