



RESEARCH ARTICLE

Estimation of technical efficiency of integrated smart farming: Evidence from Tamil Nadu

Dhanush T¹, Selvam S², Prahadeeswaran M¹, Murugananthi D³ & Kalpana M⁴

¹Department of Agricultural Economics, Tamil Nadu Agricultural University (TNAU), Coimbatore 641 003, Tamil Nadu, India

²Department of Agricultural Economics, Agriculture college and Research Institute, Tamil Nadu Agricultural University (TNAU), Kudumiyamalai, Pudukottai 622 104, Tamil Nadu, India

³Directorate of Agribusiness Development, Tamil Nadu Agriculture University (TNAU), Coimbatore 641 003, Tamil Nadu, India

⁴Department of Physical Sciences and Information Technology, Tamil Nadu Agriculture University (TNAU), Coimbatore 641 003, Tamil Nadu, India

*Correspondence email - selvamseconomics@tnau.ac.in

Received: 03 April 2026; Accepted: 22 June 2026; Available online: Version 1.0: 24 July 2026

Cite this article: Dhanush T, Selvam S, Prahadeeswaran M, Murugananthi D, Kalpana M. Estimation of technical efficiency of integrated smart farming: Evidence from Tamil Nadu. Plant Science Today. 2026; 13(sp5): 1-7. <https://doi.org/10.14719/pst.14831>

Abstract

The study examines the technical efficiency and adoption dynamics of integrated smart farming system in Erode district of Tamil Nadu. Smart farming is represented as a bundled, firm-supported system integrating drip irrigation, fertigation and real-time digital advisory. The primary data were gathered from 120 farmers (60 adopters and 60 non-adopters) in 2025–26 (agricultural year) with stratified random sampling design. Data envelopment analysis (DEA) in variable returns to scale (VRS) and bias corrected using Simar and Wilson bootstrapped DEA were employed to estimate technical efficiency. Bootstrap truncated regression was used to analyse determinants of efficiency and a binary Logit model was used to analyse adoption behaviour. The outcomes revealed a mean technical efficiency of 0.62, representing a 38 % unrealised production potential. Fertiliser accounted for 93.30 % of the input slack, indicating mismanagement as a potentially important source of inefficiency. Education and technology adoption intensity are found to be significant drivers of efficiency. The extension linkage, perceived usefulness and technological awareness are key factors in the decision to adopt the smart farming technologies. The results underscore the need for the adoption of integrated technology packages, capacity development of farmers and extension support to improve the efficiency and productivity of farms.

Keywords: bootstrapped DEA; data envelopment analysis; logit model; smart farming; technical efficiency; truncated regression

Introduction

Horticulture in Tamil Nadu is increasingly characterised by a high-input, capital-intensive production system and is highly responsive to precision-based interventions. Smart farming, broadly defined as the integration of digital technologies with agricultural systems to enhance production efficiency and decision-making, has gained considerable global attention (1, 2). The western part of Tamil Nadu is an interesting empirical setting where such firms as Mobitech Wireless Solutions Private Limited provide comprehensive support for smart farming by integrating drip irrigation, fertigation and mobile advisory services. The smart farming concept in this study is not considered as the use of single precision tools, but as a firm-mediated, bundled system that integrates physical infrastructure and real-time digital decision support. This conceptualisation is new in that it moves beyond a technology being simply an input and towards an integrated service ecosystem that increases decision-making, efficiency in the use of inputs and farm productivity. Despite the increased amount of work, there is a significant gap in research, as most studies have focused on a single technology rather than on the evaluation of a system of smart farming technologies that includes the support of the farming companies, especially in the Indian horticulture sector (3). Besides, the socio-economic factors impacting efficiency and

adoption of such bundled systems are poorly understood, despite a rich literature on technology adoption in developing countries (4). In this context, the present study seeks to: (i) to estimate the technical efficiency of smart farms and to identify the factors affecting the technical efficiency. (ii) to identify the factors influencing the adoption of smart farming technologies.

Materials and Methods

Research design

Erode district is located between 10° 36' and 11° 58' N latitude and 76° 49' and 77° 58' E longitude, at a mean sea level of 171.91 m, in the western part of Tamil Nadu. The district covers an area of 5722 sq. km, accounting for approximately 4.4 % of the total geographical area of the state. It is bordered by Karnataka state to the north-west, Coimbatore district to the west, Tiruppur district to the south and Namakkal and Karur districts to the north-east and east. The eastern part of the district experiences a dry climate, while the western part has a semi-dry climate. The district receives rainfall from both south-west and north-east monsoons, with a normal annual rainfall of approximately 732.5 mm (actual rainfall in 2023–24: 807.5 mm). The dominant soil types are red loam and red sandy soil, which are well-suited for horticultural crops

including banana. Banana is the most important commercial crop in the district, with 20075 hectares under cultivation and a total production of 710750 tonnes in Fasli 1432 (2022–23), making Erode one of the leading banana-producing districts in Tamil Nadu (5).

For this study, a two-stage stratified random sampling was used. In the first stage, Erode district was purposively selected, based on expert consultation, owing to its high concentration of smart farming adopters and the operational presence of Mobitech Wireless Solutions Private Limited, which provides its integrated smart farming package (drip irrigation, fertigation and mobile advisory services) on a subscription-fee basis to enrolled farmers. This subscription cost was included in the input cost data collected during the survey. The sampled farmers predominantly cultivated the Grand Naine (G9) variety of banana, which is the commercially dominant cultivar in the region. Crop homogeneity in the district due to the uniform cultivation of Grand Naine banana allowed for more credible and meaningful cross-farm efficiency comparisons. In the second phase, four blocks (Anthiyur, Gopichettipalayam, Sathiyamangalam and T.N. Palayam) were identified, in consultation with experts and the technology provider. The sampling frame for each block included all the banana growers. The farmers were classified into two groups, namely smart farming adopters and non-adopters. A simple random sampling method was used to select 15 adopters and 15 non-adopters from each stratum, resulting in a total sample of 120 farmers (60 adopters and 60 non-adopters).

Pre-tested personal interview schedules were used to collect primary data during the 2025–26 agricultural year. The survey gathered detailed information on per-acre input use and costs (labour, fertilisers, plant protection chemicals and machinery), total output value and area under banana cultivation. Socio-economic and behavioural variables such as age, education, farming experience, farm size, primary occupation, technological awareness, perceived usefulness, extension contact, risk orientation and government support were also systematically collected to support efficiency and adoption analysis. The study was conducted with the informed consent of all participating farmers. Ethical clearance was obtained from the Institutional Ethics Committee of Tamil Nadu Agricultural University (TNAU), Coimbatore, in accordance with guidelines for social science research involving human participants.

Data envelopment analysis

Efficiency measurement represents a significant advancement over traditional performance evaluation methods by simultaneously considering both inputs and outputs, offering a more comprehensive assessment of production performance. The conceptual roots of modern efficiency analysis are from Farrell who developed the frontier approach, which measures efficiency against best performing units (6). This was extended by Charnes et al. developed the original DEA model under constant returns to scale (CRS) (7) and further by Banker et al. generalised it to accommodate variable returns to scale (VRS) (8). This framework is a much more appropriate one for multiple inputs and outputs than simple ratio-based measures and is relevant for many complex systems including 'smart farming'.

There are two types of methods for efficiency estimation: parametric and non-parametric. The parametric approach to the study of Inefficiency is called Stochastic Frontier Analysis, in which a production function is postulated and a stochastic error term is

introduced to account for Inefficiency and random shocks. Statistically sound but make strong and sometimes restrictive assumptions and is often limited in handling multiple outputs. The non-parametric approach (Data Envelopment Analysis) has the advantage of not making any functional form assumptions and instead builds an empirical efficiency frontier via linear programming.

Considering the multi-dimensionality of smart farming systems, this study uses the method of data envelopment analysis (DEA). Smart farms require several inputs (labour, fertilisers, plant protection chemicals and machinery), output and various technological practices. The DEA is able to effectively reflect this complexity by comparing farms to best performers. In addition to this the study uses an input-oriented model which assumes that the farmer has more control over the inputs and a variable returns to scale (VRS) specification to take account of the different sizes and operational conditions of farms.

An input oriented VRS DEA model is given below for n smart farm, where each unit producing s number of output by using m different inputs with $s + m$ constraints (9).

$$\text{Maximize } \theta \quad (\text{Eq. 1})$$

Subject to:

$$\sum \lambda_j Y_{rj} \geq Y_{r0} \quad (r = 1, \dots, s) \quad (\text{Eq. 2})$$

$$\sum \lambda_j X_{ij} \leq \phi X_{i0} \quad (i = 1, 2, \dots, m) \quad (\text{Eq. 3})$$

$$\sum \lambda_j = 1 \quad (\text{Eqn. 4})$$

$$\lambda_j \geq 0 \quad (j = 1, 2, \dots, n) \quad (\text{Eq. 5})$$

Where:

θ = Technical efficiency score for smart farm under evaluation ($0 < \theta \leq 1$)

y_{rj} = amount of output r produced by smart farm j (Output value - y_{1j})

x_{ij} = amount of input i used by smart farm j (Labour cost - x_{1j} , fertiliser cost - x_{2j} , plant protection cost - x_{3j} and machinery cost - x_{4j})

n = number of smart farm s (60)

s = number of output (1)

m = number of inputs (4)

The technical efficiency score θ_i ranges from 0 to 1, with higher values indicating greater efficiency. A smart farm is considered technically efficient if $\theta_i = 1$.

Conventional DEA has been used extensively as a technical efficiency measurement and is a deterministic model which is susceptible to sampling fluctuation, noise and outliers. Furthermore, standard two-stage analyses which estimate DEA scores as a function of explanatory variables can lead to biased and statistically problematic results in a typical setting. To address these drawbacks, Simar and Wilson developed an approach based on the bootstrap to correct for biases in efficiency scores and to provide valid inference using a truncated regression and confidence intervals with high levels of confidence (10, 11). The bootstrap DEA framework overcomes limitations of the traditional DEA methodology by taking sampling variability into account and providing better statistical inferences for efficiency estimates. It is especially useful in agronomic applications, where production

processes depend on the ambient conditions and on the occasional presence of measurement noise and on the inter-farm variability. Empirical results have demonstrated the more robust inference on the determinants of efficiency and the more accurate benchmarking of efficiency that bootstrap DEA offers in situations where sample sizes are small and operational conditions are varied.

These methodological improvements are of relevance in the context of smart farming systems, where several inputs are used and output as well as different technology adoption rates are varying. Farms vary widely in terms of their endowments, managerial ability and institutional support and consequently in their performance. In such a diversified scenario of Tamil Nadu, results of conventional DEA approach may lead to overestimation of efficiency and miss the actual differences in performance. Hence, this research uses the essence of the bootstrapped DEA proposed by Simar and Wilson to derive the efficiency score and provide statistically reliable estimates (10, 11). This method helps to ensure the empirical soundness of the analysis and helps to better capture the factors affecting technical efficiency in integrated smart farming systems.

Bootstrap data envelopment analysis procedure

Step 1: Compute original DEA efficiency scores $\tilde{\theta}_j$ for all smart farming adopters

Step 2: Generate bootstrap samples using smooth bootstrap procedure:

$$\tilde{\theta}_j^* = \tilde{\theta}_j + \varepsilon_i^* \quad (\text{Eq. 6})$$

Where, ε_i^* is drawn from kernel density estimation of $(\tilde{\theta}_j - 1)$ (Eq. 7)

Step 3: Construct pseudo-dataset and compute bootstrap efficiency scores

Step 4: Repeat bootstrap procedure B times (B = 2000 iterations)

Step 5: Calculate bias-corrected efficiency scores:

$$\tilde{\theta}_j^{\text{corr}} = \tilde{\theta}_j - \text{Bias}_j \quad (\text{Eq. 8})$$

Where:

$$\text{Bias}_j = (1/B) \times \sum (\tilde{\theta}_j^* - \tilde{\theta}_j)$$

(Eqn. 9)

Step 6: Construct confidence intervals:

$$[\tilde{\theta}_j^{\text{corr}} - z(\alpha/2) \times \tilde{\sigma}_j, \tilde{\theta}_j^{\text{corr}} + z(\alpha/2) \times \tilde{\sigma}_j] \quad (\text{Eq. 10})$$

Where

$\tilde{\sigma}_j$ is the bootstrap standard error of $\tilde{\theta}_j$

The bias-corrected efficiency score is given by:

$$\tilde{\theta}_j^{\text{corr}} = 2\tilde{\theta}_j - \tilde{\theta}_j^* \quad (\text{Eq. 11})$$

Where

$\tilde{\theta}_j^{\text{corr}}$ = Bias-corrected efficiency score

$\tilde{\theta}_j$ = Original DEA efficiency score

$\tilde{\theta}_j^*$ = Mean of bootstrap efficiency scores

Simar-Wilson bootstrap truncated regression

Estimated efficiency scores are naturally bounded between 0 and 1 and exhibit serial correlation because they are jointly determined relative to a common production frontier. This contradicts classical assumptions of independence and unboundedness as needed for

typical regression procedures. Thus, the application of ordinary least squares (OLS) results in biased and inconsistent results, while Tobit models, which were developed for censored data, are not suitable to account for the dependency structure of the scores resulting from the DEA. The Simar-Wilson truncated regression approach, however, is a well-founded solution, accounting explicitly for the truncation of the dependent variable and correcting for serial correlation by a bootstrap procedure. In addition, Simar-Wilson suggests that efficiency scores be converted to inefficiency scores (scores ≥ 1) by taking their reciprocal as this is more appropriate for the needs of truncated regression. One of its essential features is that it can be specified with a natural left-truncation of 1, which is suitable for the model's distributional assumption that underlies the estimation of the model. Moreover, working with inefficiency can prevent boundary issues with efficiency scores that are constrained to a close interval between 0 and 1. This also allows easier interpretation of results, since any change in the explanatory variables can be directly interpreted as a change in inefficiency from the best-practice frontier. Prior to estimation, Kolmogorov-Smirnov test was conducted to examine the normality of the variables used in the second-stage regression analysis. The results revealed that education and perceived usefulness were not normally distributed ($p < 0.05$), whereas age, farm size, extension/industrial contact, technical efficiency score and the variable represented by risk orientation followed an approximately normal distribution ($p > 0.05$). Since the normality assumption was not satisfied for all explanatory variables, the bootstrap truncated regression approach was employed. The bootstrap procedure is robust to departures from normality and provides consistent statistical inference for DEA efficiency scores, making it appropriate for the present study.

Factors influencing the adoption of smart farming technology-logit model

To design interventions that target the smart farming technology adoption, it is essential to understand what factors influence it. As a result, the binary logit model was used in this study to identify and analyse the key determinants of the adoption of smart farming, due to the binary nature of the outcome of interest. The dependent variable was coded as 1 for smart farming adopters and 0 for non-adopters. The independent variables were selected from literature and comprised of extension/industrial contact, perceived usefulness, technological awareness, education, income, age, farm size, risk orientation and government support. The model provided an explanation of what factors are influencing the adoption of smart farming based on these observed variables and their relationship with the latent performance capacity. This approach enabled the understanding of the dynamics of smart farming adoption in a statistically sound and policy-relevant way in relation to the region of Tamil Nadu.

$$Li = \ln(P_i/(1-P_i)) = \beta_0 + \sum(\beta_j X_j) + \varepsilon_i \quad (j = 1 \text{ to } 8) \quad (\text{Eq. 12})$$

where,

Li = the latent variable representing the underlying smart farming adoption level

P_i = Probability that the smart farming adoption

β_0 to β_8 are the coefficients to be estimated,

where

β_0 = Constant

β_1 to β_4 capture the effects of behavioural variables: extension/industrial contact, perceived usefulness, technological awareness and education (years of schooling),

β_5 to β_8 correspond to socio-economic variables: income (rupees), age (years), farm size (acres) and risk orientation (Sujan Singh Scale) (12), a widely used scale in Indian extension research developed at Punjab Agricultural University comprising 10–12 statements on a five-point Likert-type format (Strongly Agree/Agree/Undecided/Disagree/Strongly Disagree) measuring farmers' tendency to take calculated risks in farming and technology adoption decisions,

X_1 = Extension/industrial contact (count)

X_2 = Perceived usefulness (1–5 Likert scale)

X_3 = Technological awareness (1–5 Likert scale)

X_4 = Education (years of schooling)

X_5 = Income (annual income in rupees)

X_6 = Age (years)

X_7 = Farm size (acres)

X_8 = Risk orientation (Sujan Singh Scale)

ε_i = the random error term, assumed to follow a standard normal distribution.

The observed adoption level corresponds to threshold values on this latent scale. The model estimates these thresholds along with the regression coefficients to determine how the explanatory variables influence the probability of smart farming adoption.

Results and Discussion

Socio-economic profile of sample farmers

Table 1 revealed that marked socio-economic differences between adopters and non-adopters. Adopters were relatively younger (mean age 45 years) compared to non-adopters (56 years), indicating greater openness to technological change. They also had higher levels of formal education (13 years versus 7 years) and

operated larger farm holdings (4.31 acres compared to 2.72 acres). Technological awareness was substantially higher among adopters, reflecting better exposure to modern practices. In contrast, non-adopters possessed greater farming experience (29 years versus 22 years), suggesting a more conservative approach to innovation. Extension contact was significantly higher among adopters (51 compared to 19), highlighting the critical role of institutional support and information dissemination. Overall, younger age, higher education, larger farm size and stronger extension linkages emerged as key determinants of smart farming adoption.

Descriptive statistics of the input and output variables of data envelopment analysis

Table 2 presented per-acre input costs and output values for 60 smart farming adopters, revealing substantial variability. Fertiliser dominated costs, averaging ₹130970/acre (SD ₹53468) with a wide range (₹32304–₹247741), indicating heterogeneous nutrient management. Labour was the next major expense at ₹32914/acre, while plant protection and machinery costs were relatively modest at ₹16888 and ₹4090, respectively. The average output value stood at ₹449634/acre (SD ₹98502), ranging from ₹325333 to ₹801900 more than a twofold variation. This pronounced dispersion in costs and returns underscores significant efficiency differences across farms, strongly justifying the application of DEA for robust performance benchmarking.

Estimates of technical efficiency: Standard and bootstrapped data envelopment analysis

Table 3 shows that there is a significant overestimation bias in conventional DEA. The mean technical efficiency was reduced from 0.73 to 0.62 after bootstrapping (with 2000 replications), which shows that the farms could only gain 62 % of the potential output which means that there was space to gain savings of 38 % without using more inputs. This level of efficiency is consistent with findings reported in smallholder farming literature, where mean technical efficiency typically ranges between 0.60 and 0.80 (13, 14). In particular, a DEA study of banana cultivation in Karnataka, India reported mean technical efficiencies of 70.30 % and 49.40 % for two crop seasons respectively (15), suggesting that the 62 % efficiency observed in the present study is broadly consistent with banana-specific benchmarks in India. The comparatively higher efficiency in the present study relative to the Karnataka findings

Table 1. Socio-economic characteristics of sample farmers

Variable	Adopters (N = 60)	Non-adopters (N = 60)	Std. Dev.	Overall mean
Age (years)	45	56	12.51	50.09
Education (years of schooling)	13	7	4.68	10.04
Farming experience (years)	22	29	13.24	25.40
Farm size (acres)	4.31	2.72	2.04	3.53
Technological awareness (1–5 Likert)	4.31	2.46	1.39	3.40
Extension/industrial contact (count)	51	19	-	70
Government support (count)	41	13	-	54
Risk orientation (Sujan Singh scale)	3.94	2.72	1.04	3.34
Perceived usefulness (1–5 Likert)	4.08	2.81	1.17	3.46

Table 2. Descriptive statistics of data envelopment analysis (DEA) variables smart farming adopters

(N = 60) (₹/acre)

Variable	Mean	Std. Dev.	Minimum	Maximum
Labour cost	32914.65	4532.02	25680.20	41118.75
Fertiliser cost	130970.22	53468.30	32304.25	247741.00
Plant protection cost	16888.33	1599.16	13500.00	19500.00
Machinery cost	4090.00	497.43	3500.00	4800.00
Output value	449634.16	98502.05	325333.00	801900.00

Table 3. Summary statistics of technical efficiency scores

(N = 60)

Statistics	Standard DEA	Bootstrapped DEA	Bias
Mean efficiency	0.73	0.62	0.1034
Minimum	0.35	0.30	0.0179
Maximum	1.00	0.92	0.2394
Standard deviation	0.23	0.18	0.0708

DEA: data envelopment analysis.

may reflect the positive role of the bundled firm-supported smart farming package - integrating drip irrigation, fertigation and digital advisory - which is absent in conventional banana farming systems. The systematic overestimation of the standard DEA is confirmed by the average bias at 0.1034. The best farm had a farm efficiency after correction, of only 0.92, meaning that no farm was operating efficiently. The decrease of the standard deviation from 0.23 to 0.18 also indicates that the efficiency distribution is more accurate and closer, further strengthening the robustness and reliability of the bootstrapped DEA estimates.

Distribution of the technical efficiency scores

The efficiency distribution showed a dramatic change after bias correction, as seen in Table 4. According to the standard DEA, 45 % of the farms were low efficient, 23.33 % were medium efficient and 31.67 % were highly efficient. When applying the bootstrapped DEA, however, 55 % was classified as low, 43.33 % as medium and just 1.67 % as highly efficient. The significant decline of the number of farms perceived as high efficiency (from 31.67 % to 1.67 %) revealed the positive bias of conventional DEA estimates. This redistribution highlights the need for bias correction to have realistic assessments. The distribution of efficiency scores as shown in Fig. 1 is a more precise one based on the bootstrapped DEA framework.

Input slack analysis

The analysis of input slack can be obtained by using the data of Table 5 which shows the critical sources of technical inefficiency. The inefficiency is mainly due to fertiliser, which has a mean of

₹23182.95 per acre, or 93.30 % of total input slack, reflecting excessive and unbalanced use of fertilisers in intensive banana cultivation. Labour (₹1129.66; 4.50 %), plant protection chemicals (1.80 %) and machinery (0.40 %) are minor sources of inefficiency. This significant fertility imbalance highlights the necessity of precision nutrient management interventions such as sensor-based fertigation, drip-integrated fertigation and nutrient advisory systems based on data to greatly improve input-use efficiency and farm performance. This finding is consistent with horticulture efficiency literature; Ahovi et al. (16) similarly found fertiliser to be the dominant source of input-specific technical inefficiency (22 %) among Dutch vegetable farms using the same bootstrap truncated regression framework, underscoring that fertiliser mismanagement is a persistent inefficiency driver across diverse horticultural systems, regardless of development context.

Determinants of technical inefficiency (Simar-Wilson truncated regression)

The bootstrap truncated regression results presented in Table 6 support the findings that farmers are heterogeneous and that technical inefficiency is determined by some factors. Technology adoption intensity (Technological count) is the most important explanatory variable and it has a negative correlation with inefficiency that is strong and statistically significant. It suggested that for farmers using more technologies, they are closer to the production frontier and thus more technically efficient. This finding is in line with the theoretical prediction that modern technologies boost productivity by using inputs more efficiently and eliminating inefficiencies. Education also shows a significant negative effect on

Table 4. Distribution of technical efficiency scores

(N = 60)

Efficiency Category	DEA (No.)	DEA (%)	Bootstrap DEA (No.)	Bootstrap DEA (%)
Low efficiency (TE < 0.70)	27	45.00	33	55.00
Medium efficiency (0.70 ≤ TE ≤ 0.90)	14	23.33	26	43.33
High efficiency (TE > 0.90)	19	31.67	1	1.67
Total	60	100.00	60	100.00

DEA: data envelopment analysis.

Table 5. Input slack among smart farming adopters

(N = 60)

Input resource	Mean slack (₹/acre)	Percent (%) of total excess input
Fertiliser	23182.95	93.30
Labour	1129.66	4.50
Plant protection chemicals	442.63	1.80
Machinery	91.18	0.40

Table 6. Determinants of technical inefficiency (Simar-Wilson Bootstrap Truncated Regression)

(N = 60)

Variable	Coefficient	Std. Error	95 % CI	Significance
Intercept	3.653	1.044	-	***
Age(years)	0.013	0.016	(-0.084, 0.038)	ns
Experience	-0.024	0.012	(-0.044, 0.002)	ns
Education	-0.099	0.026	(-0.180, -0.049)	***
Farm Size(acres)	-0.044	0.036	(-0.108, 0.024)	ns
Government Support	-0.098	0.179	(-0.471, 0.312)	ns
Perceived Usefulness	-0.013	0.091	(-0.170, 0.187)	ns
Technological Awareness	-0.042	0.091	(-0.191, 0.173)	ns
Extension/Industrial Contact	0.020	0.021	(0.002, 0.111)	ns
Risk Orientation	0.169	0.211	(-0.323, 0.683)	ns
Technology Count	-0.876	0.162	(-1.143, -0.507)	***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, ns: not significant. Negative coefficients indicate reduction in inefficiency (efficiency improvement). Confidence intervals obtained using bootstrap percentile method.

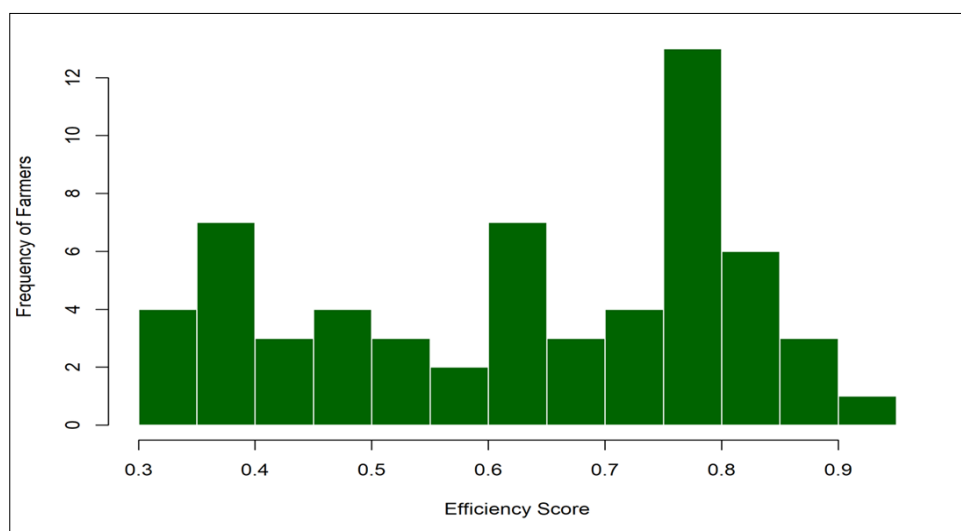


Fig. 1. Distribution of bootstrapped data envelopment analysis (DEA) technical efficiency scores among smart farming adopters (N = 60).

inefficiency, indicating that more educated farmers are better able to utilise available resources efficiently. Education likely enhances managerial ability, access to information and decision-making skills, all of which contribute to improved farm performance. This result is consistent with banana efficiency literature in Bangladesh and India, where education has consistently been identified as a positive determinant of technical efficiency (13, 15). The convergence of findings across geographically diverse banana-producing settings lends theoretical support to the view that human capital accumulation is a robust predictor of farm efficiency, independent of the specific technological environment.

Other factors like age, farm size, government support, perception, risk orientation, extension/industrial contact and individual technology awareness were not statistically significant. This suggests that these factors do not play a decisive role in explaining efficiency differences among farmers in the study area, at least within the current model specification.

Determinants of smart farming technology adoption (Logit model)

The model fit of Binary Logit models is very good: Pseudo $R^2 = 0.87$; LR $\chi^2 = 127.18$, $p < 0.0001$ and the predictive accuracy is high (93.33 %). Table 7 shows that the Binary Logit models used in this study have an excellent model fit with high predictive accuracy (93.33 %). Extension and institutional contact were the most influential driver (OR = 37.17; ME = 0.64), meaning that farmers affiliated with extension systems or Agri-industry networks were 37 times more likely to adopt and had a 64 percentage-point greater likelihood. The other strong and highly significant determinants were perceived usefulness (OR = 11.65, ME = 0.55) and technological awareness (OR = 6.08, ME = 0.40). The positive and meaningful effect of education was (OR = 1.53; ME = 0.09). Age,

farm size, risk orientation and government support, on the other hand, did not show significant differences and underscored the important influence of information access and perception-based factors on the adoption decisions.

Limitations

The study acknowledges several limitations that should be considered when interpreting the findings. First, the sample is restricted to 120 farmers in a single district (Erode), Tamil Nadu, which may limit the generalisability of findings to other districts, states, or agro-climatic zones with different institutional and infrastructural contexts. Second, the cross-sectional design of the study precludes causal inference and does not capture dynamic changes in efficiency over time. Third, the study focuses exclusively on banana cultivation and findings may not be directly applicable to other horticultural or field crops. Future research should employ larger, multi-district longitudinal samples across diverse cropping systems to validate and extend these findings.

Conclusion

Based on the findings of this study, it is concluded that there was a significant scope for improving production potential in smart farming with the adoptive farmers of the Erode district having a mean technical efficiency of 0.62 (bias corrected) and a considerable degree of underutilisation. Fertiliser mismanagement was identified as a potentially important source of inefficiency (based on input slack analysis, accounting for 93.30 % of total input slack). Technology intensity and farmer education were identified as the key drivers of efficiency, while extension contact, perceived usefulness and technological awareness consistently influenced adoption of smart farming technologies.

Table 7. Logit model: Smart farming technology adoption

(N = 120)

Variable	Coeff.	Pr(> z)	Sig.	Odds ratio	Marginal effect
Extension/industrial contact	3.62	0.01	**	37.17	0.64
Perceived usefulness	2.45	0.01	**	11.65	0.55
Technological awareness	1.81	0.01	**	6.08	0.40
Education (years)	0.42	0.03	*	1.53	0.09
Income	0.00	0.08	.	1.00	0.00
Age (years)	0.05	0.28	ns	1.05	0.01
Farm size (acres)	0.25	0.32	ns	1.28	0.06
Risk orientation	-1.34	0.14	ns	0.26	-0.30
Government support	0.31	0.79	ns	1.36	0.07

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.10$; ns: not significant. Model statistics: LR $\chi^2(2) = 127.18$ (df = 9, $p < 0.0001$); Pseudo $R^2(2) = 0.87$; Prediction accuracy = 93.33 %; Log-likelihood = -19.59; AIC = 59.18.

Policy

The findings carry important policy implications at both the state and central government levels. First, the Tamil Nadu Department of Agriculture, in collaboration with agricultural universities, should invest in structured training programmes, farmer field schools and digital literacy initiatives focused specifically on fertigation scheduling, sensor-based nutrient management and mobile advisory use among banana cultivators, directly targeting the identified 38 % efficiency gap. Second, central government schemes such as the Pradhan Mantri Krishi Sinchayee Yojana (PMKSY) and the Rashtriya Krishi Vikas Yojana (RKVY) should be leveraged to provide subsidised access to integrated precision irrigation and fertigation infrastructure at the farm level. Third, the strong and consistent effect of extension contact across all adoption models (OR = 37.17) provides a clear empirical basis for formalising public-private partnerships between state Agricultural Extension Departments and agri-technology firms such as Mobitech Wireless Solutions. Fourth, subsidy and credit schemes must be structured to incentivise the adoption of integrated technology bundles rather than individual technologies, given the empirical evidence that combined adoption yields significantly higher efficiency and net revenue returns.

Acknowledgements

The authors are extremely grateful to Mobitech Wireless Solutions Private Limited, Erode, for their assistance in identifying and facilitating access to the participating farmers. The authors also express their sincere gratitude to the banana farmers of Erode district for generously sharing their time and valuable information. Financial support provided by the Tamil Nadu Agricultural University is gratefully acknowledged.

Authors' contributions

DT conceived the study, developed the survey instrument, collected the field data, performed the DEA and bootstrapped DEA analyses and drafted the manuscript. SS contributed to data collection and logit model estimation. PM assisted with data collection and conducted the bootstrapped truncated regression analysis. MD contributed to the study design, provided methodological guidance and critically revised the manuscript for important intellectual content. KM contributed to the statistical analysis and manuscript organisation. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

References

1. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming: a review. *Agric Syst.* 2017;153:69–80. <https://doi.org/10.1016/j.agry.2017.01.023>
2. Zhang N, Wang M, Wang N. Precision agriculture: a worldwide overview. *Comput Electron Agric.* 2002;36(2–3):113–32. [https://doi.org/10.1016/S0168-1699\(02\)00096-0](https://doi.org/10.1016/S0168-1699(02)00096-0)
3. Klerkx L, Jakku E, Labarthe P. A review of social science on digital agriculture, smart farming and agriculture 4.0: new contributions and a future research agenda. *NJAS Wageningen J Life Sci.* 2019;90–91:100315. <https://doi.org/10.1016/j.njas.2019.100315>
4. Feder G, Just RE, Zilberman D. Adoption of agricultural innovations in developing countries: a survey. *Econ Dev Cult Change.* 1985;33(2):255–98. <https://doi.org/10.1086/451461>
5. Department of Economics and Statistics. District Statistical Handbook, Erode District 2023–24. Chennai: Government of Tamil Nadu; 2024.
6. Farrell MJ. The measurement of productive efficiency. *J R Stat Soc Ser A Gen.* 1957;120(3):253–81. <https://doi.org/10.2307/2343100>
7. Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision-making units. *Eur J Oper Res.* 1978;2(6):429–44. [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
8. Banker RD, Charnes A, Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manage Sci.* 1984;30(9):1078–92. <https://doi.org/10.1287/mnsc.30.9.1078>
9. Coelli TJ, Rao DSP, O'Donnell CJ, Battese GE. An introduction to efficiency and productivity analysis. 2nd ed. New York: Springer; 2005.
10. Simar L, Wilson PW. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Manage Sci.* 1998;44(1):49–61. <https://doi.org/10.1287/mnsc.44.1.49>
11. Simar L, Wilson PW. Estimation and inference in two-stage, semi-parametric models of production processes. *J Econom.* 2007;136(1):31–64. <https://doi.org/10.1016/j.jeconom.2005.07.009>
12. Singh S. Risk orientation of farmers in relation to adoption of farm practices. Ludhiana: Punjab Agricultural University; 1977.
13. Bravo-Ureta BE, Pinheiro AE. Technical, economic and allocative efficiency in peasant farming: evidence from the Dominican Republic. *Dev Econ.* 1997;35(1):48–98. <https://doi.org/10.1111/j.1746-1049.1997.tb01186.x>
14. Binam JN, Tonye J, Wandji N, Nyambi G, Akoa M. Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. *Food Policy.* 2004;29(5):531–45. <https://doi.org/10.1016/j.foodpol.2004.07.013>
15. Naik AK, Moolimane CB, Madhu DM, Sri KK, Hanumanthappa R, Hithaishree M. Economic efficiency of banana production in Uttara Kannada district of Karnataka, India. *Asian Res J Agric.* 2024;17(2):106–15. <https://doi.org/10.9734/arja/2024/v17i2427>
16. Ahovi E, Schneider K, Oude Lansink A. Technical inefficiency of Dutch vegetable farms: specific-input analyses. *PLoS One.* 2021;16(4):e0250494. <https://doi.org/10.1371/journal.pone.0250494>

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

Reprints & permissions information is available at https://horizonpublishing.com/journals/index.php/PST/open_access_policy

Publisher's Note: Horizon e-Publishing Group remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc
See https://horizonpublishing.com/journals/index.php/PST/indexing_abstracting

Copyright: © The Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution and reproduction in any medium, provided the original author and source are credited (<https://creativecommons.org/licenses/by/4.0/>)

Publisher information: Plant Science Today is published by HORIZON e-Publishing Group with support from Empirion Publishers Private Limited, Thiruvananthapuram, India.