



## Technical and Economic Efficiency in Farming: A Literature Study Using the DEA and Frontier Production Approaches

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### ABSTRACT

*Technical and economic efficiency are key indicators in evaluating farm performance, particularly in the context of limited land resources, input constraints, and the challenges posed by climate change. This study aims to systematically review existing literature that employs Data Envelopment Analysis (DEA) and Frontier Production Function approaches particularly Stochastic Frontier Analysis (SFA) to measure farm efficiency in Indonesia and other developing countries. DEA provides a non-parametric means of assessing technical efficiency without assuming a specific production function, whereas frontier approaches offer parametric analysis by incorporating random disturbances in the production process. Based on a review of 20 selected articles, the findings reveal that farmers' technical efficiency generally ranges from 60% to 85%, while economic efficiency tends to be lower due to input-output price imbalances and limited access to market information. Key factors influencing efficiency include farmers' education level, farm size, technology adoption, and participation in farmer groups. This study highlights the strengths of these quantitative approaches as data-driven tools for agricultural policy formulation at both micro (farm) and macro (national policy) levels. The findings underscore the importance of integrating DEA and SFA methods to provide a more comprehensive picture of farm performance. Enhancing efficiency thus requires a combination of technical training, agricultural digitalization, and the development of inclusive policies that support smallholder farmers in a sustainable manner.*

**Keywords:** *Technical Efficiency, Economic Efficiency, Farming, DEA, Frontier Production, Agricultural Productivity*

## INTRODUCTION

Efficiency in farming has become a central focus in the pursuit of sustainable agricultural development, particularly in developing countries facing challenges such as limited land availability, restricted access to inputs, and the growing impact of climate change. According to Prasetyo and Yuliana (2022) technical efficiency in the agricultural sector serves as a key indicator in evaluating the effectiveness of resource management at the farm level. This aligns with the Indonesian government's broader efforts to improve agricultural productivity without significantly increasing production costs. Efficiency in this context extends beyond the proper use of inputs and includes farmers' ability to optimize outputs through improved managerial practices and technological adoption.

Across different regions, farm efficiency remains highly variable, depending on the type of crops cultivated, geographical conditions, and the socio-economic characteristics of the farmers. A study by Dewi et al. (2023) on maize farmers in South Sulawesi reported an average technical efficiency level of approximately 70%, indicating significant room for improvement. Key factors contributing to this inefficiency include limited access to production technologies, inadequate technical training, and weak integration between agricultural extension services and farmer groups.

Advancements in quantitative methods for measuring efficiency have accelerated, with Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) emerging as widely adopted approaches. As noted by Kurniawan and Safitri (2021), DEA offers analytical flexibility by accommodating multiple inputs and outputs without requiring a predefined functional form of the production process. Conversely, SFA incorporates random errors into the production model, making it more realistic, especially in agriculture where uncertainty and variability are prevalent.

The application of DEA and SFA has led to several key findings regarding efficiency patterns in agriculture. Research by Rohmah and Hidayat (2022) found DEA to be particularly effective in evaluating efficiency across horticultural farmer groups, while SFA was more suitable for identifying the influence of external factors such as rainfall variability, market prices, and seed distribution. Hence, a complementary use of both approaches can provide a more comprehensive and objective evaluation of farm performance.

Beyond technical considerations, farm efficiency is also shaped by social and

institutional factors. According to Wahyuni et al. (2023) variables such as farmers' education levels, access to credit, and participation in farmer groups have shown a positive correlation with technical efficiency. This indicates that efficiency-oriented interventions must also incorporate social and policy dimensions aimed at enhancing farmer capacity. In this regard, the role of agricultural extension agents and local institutions becomes increasingly vital.

Additionally, global market dynamics and climate variability significantly affect farm efficiency outcomes. A study by Hartati and Anwar (2024) demonstrated that farmers who have access to market information and adopt digital agricultural technologies tend to achieve higher economic efficiency. Digital innovations such as land management applications and climate prediction systems are emerging as data-driven tools for enhancing farm performance. This underscores the necessity of digital transformation in agriculture not as a luxury, but as an imperative for future resilience.

Given these developments, assessing farm efficiency through DEA and frontier production models becomes crucial for evidence-based policymaking and strategic planning aimed at strengthening rural economies. Quantitative, field-based efficiency analyses serve as diagnostic tools for identifying weaknesses and potential improvements in farming systems. It is essential that governments, researchers, and agricultural stakeholders collaborate in translating such findings into actionable, technically sound policies.

Therefore, this literature review aims to synthesize recent studies on the measurement of technical and economic efficiency in farming using DEA and frontier production approaches. The review focuses on methodological frameworks, efficiency outcomes, and key contributing factors. In doing so, it seeks to provide relevant scientific recommendations for advancing sustainable agricultural productivity.

## **METHODS**

This study employed a systematic literature review (SLR) approach to examine relevant research findings on technical and economic efficiency in farming systems. The review focused on scientific sources published between 2019 and 2024, ensuring the novelty and relevance of the data. Articles were retrieved from reputable academic databases including Google Scholar, ScienceDirect, DOAJ, and Garuda. The keywords used in the search included:

technical efficiency, economic efficiency, Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), and frontier production function. Selected articles were limited to those that analyzed farm efficiency, specifically within Indonesia and other developing countries.

The article selection process consisted of several stages. First, a preliminary screening was conducted based on titles and abstracts to determine topic relevance. Second, full-text screening was applied using the following inclusion criteria: (1) the study must involve an analysis of farm efficiency; (2) it must apply DEA or SFA methods; and (3) it must present empirical data or quantitative analysis. Articles in the form of opinions, commentaries, or those not meeting methodological standards were excluded. From this process, 20 articles were selected for in-depth analysis.

Data analysis was carried out qualitatively, through summarization and comparison of methodological approaches, efficiency measurement outcomes, and the key variables used in each study. The review also examined the strengths and limitations of each analytical approach and assessed their relevance to the agricultural context in Indonesia. Through this approach, the study aims to provide a comprehensive understanding of the trends in DEA and SFA application in farm efficiency research, along with their implications for the development of evidence-based agricultural policy and sustainable farming practices.

## **RESULTS AND DISCUSSION**

### **1. Trends in the Use of DEA and SFA Methods**

The Data Envelopment Analysis (DEA) method has emerged as one of the most widely used non-parametric approaches for measuring technical efficiency in farming systems. Based on the review of 20 selected articles in this study, approximately 60% employed the DEA approach, primarily focusing on strategic agricultural commodities such as rice, horticulture, and smallholder plantation crops. DEA is favored for its ability to evaluate relative efficiency among production units (decision-making units) without requiring a specific functional form. For example, Kurniawan and Safitri (2021) examined organic rice farming in West Java and demonstrated that DEA could identify efficient and inefficient farmers, while also offering input improvement recommendations through benchmarking against best-performing peers. A major advantage of DEA lies in its ability to handle multiple input-output combinations simultaneously, making it particularly suitable for the complex and diverse agricultural

landscape of countries like Indonesia. Moreover, DEA has been widely applied in evaluating government programs, such as subsidized fertilizer distribution, technical training

, and agricultural technology adoption. Dewi et al. (2023), in their study on maize farmers in South Sulawesi, revealed that DEA is not only useful in measuring technical efficiency but also effective in assessing the success of program-based agricultural interventions. DEA is considered flexible, as it does not rely on statistical assumptions about data distribution, making it well-suited for primary survey data collected from farmers. However, DEA also has limitations, particularly its inability to separate statistical noise from technical inefficiency, which may lead to biased results in the presence of outliers or uncontrolled external factors. To address this, some researchers have started integrating DEA with other methods such as the Analytic Hierarchy Process (AHP) or Tobit regression to enhance the robustness of their findings (Wahyuni et al., 2023).

On the other hand, frontier production approaches such as Stochastic Frontier Analysis (SFA) are increasingly used in studies that consider uncertainty in the production process, including climate variability, access to technology, and variations in input quality. SFA is a parametric method that requires a specific functional form commonly Cobb-Douglas or translog and includes two components in the error term: technical inefficiency and statistical noise. In their study on horticultural farmers, Hartati and Anwar (2024) demonstrated that SFA could capture the effects of climate factors and digital information access on farming efficiency factors that DEA alone could not explain. SFA allows researchers to control for external random effects, making the efficiency estimation more robust and better suited to the dynamic, multifactorial nature of agricultural production.

SFA is also widely used to analyze the relationship between socioeconomic variables and technical efficiency, such as farmers' age, education level, land ownership, and extension service intensity. Rohmah and Hidayat (2022), in their study of chili farmers in East Java, found that technical efficiency was strongly influenced by farmer group participation and the use of appropriate technologies, such as drip irrigation and pest-resistant seeds. Compared to DEA, SFA's key strength lies in its ability to distinguish between inefficiency caused by managerial shortcomings and output variations driven by exogenous factors beyond farmers' control. Nonetheless, a major limitation of SFA is its dependence on assumptions regarding the functional form and error distribution, which, if misspecified, can result in biased efficiency

estimates. Consequently, recent studies have begun adopting combined approaches, such as metafrontier analysis and panel data SFA models, to improve the accuracy and generalizability of findings across different farming contexts (Prasetyo & Yuliana, 2022).

## **2. Technical and Economic Efficiency Results**

Most of the reviewed literature on technical efficiency in farming indicates that farmers' technical efficiency across various commodities remains within the range of 60% to 80%. This suggests considerable potential for improving production output without increasing input use simply through more efficient resource utilization. For instance, Santosa, Mulyani, and Prasetyo (2023) found that rice farmers in Central Java achieved an average technical efficiency of 68.4%, implying that farmers could increase their output by 31.6% with the same level of input. Similarly, a study by Rahayu et al. (2022) on horticultural farms in West Sumatra reported an average technical efficiency of 72.1%, highlighting the importance of farm management and technical training in enhancing efficiency.

Disparities in technical efficiency are particularly evident in smallholder plantation crops, where farmers with access to extension services and modern technology tend to perform more efficiently. Halim and Surya (2024) in their study on coffee farmers in South Sulawesi, reported an average technical efficiency of 61.5%, largely attributed to limited access to improved seeds and modern cultivation practices. This finding aligns with Harahap and Dewi (2023) who identified poor agricultural literacy and lack of input diversification as primary causes of technical inefficiency. To boost productivity, policy interventions should prioritize technical capacity-building through continuous training and the equitable distribution of high-quality agricultural inputs.

In contrast, economic efficiency which combines technical and allocative efficiency tends to be lower, particularly among smallholder farmers who face constraints in accessing quality inputs and market information. According to Yuliana and Mardiana (2023) the average economic efficiency of bird's eye chili farmers in Sleman Regency was only 54.3%, compared to a technical efficiency of 70.6%. This gap was primarily due to suboptimal input use in relation to input and output prices. Furthermore, the dominance of middlemen in agricultural marketing has distorted price signals and hindered fair value capture by farmers, reflecting the oligopsonistic structure of local markets.

Other contributing factors to low economic efficiency include limited access to credit,

price volatility of inputs, and a lack of cost-based farm management strategies. Setiawan and Lestari (2024) in their study on maize farmers in East Nusa Tenggara, reported an average economic efficiency of 48.7%, indicating a strong reliance on informal credit and weak bargaining power in purchasing inputs like fertilizers and seeds. They emphasized the need for institutional support such as farmer cooperatives and low-interest microcredit schemes as a means to enhance economic efficiency. Therefore, improving access to efficient production factors and reliable market price information is essential for sustainably increasing economic efficiency among smallholder farmers.

### 3. DEA and SFA Comparison

**Table 1.** DEA and SFA Comparison

Aspect	DEA (Data Envelopment Analysis)	SFA (Stochastic Frontier Analysis)
<b>Approach Type</b>	Non-parametric	Parametric
<b>Production Function</b>	Does not require a specific production function	Requires specification of a production function (e.g., Cobb-Douglas or Translog)
<b>Handling of Error/Noise</b>	Does not account for statistical error or noise	Accounts for two error components: inefficiency and random noise
<b>Sensitivity to Outliers</b>	Highly sensitive to outliers	More robust to outliers due to inclusion of statistical noise
<b>Computational Complexity</b>	Relatively simple; uses linear programming	More complex; requires statistical parameter estimation
<b>Interpretability</b>	Easy to interpret visually (relative efficiency scores)	Stronger in statistical inference and absolute efficiency estimation
<b>Data Requirements</b>	Requires large sets of input-output data	Can be applied to panel data and allows for dynamic inference
<b>Typical Applications</b>	Commonly used for benchmarking and assessing relative efficiency among units	Applied in efficiency studies involving unobserved variables like weather uncertainty, policies, etc.
<b>Main Strength</b>	No need for a specific production function; suitable for multiple input and output variables	Capable of distinguishing technical inefficiency from random error
<b>Main Limitation</b>	Vulnerable to noise and outliers; unable to capture stochastic fluctuations	Results are highly dependent on correct model specification and error distribution assumptions

### 4. Factors Influencing Efficiency

One of the key determinants of both technical and economic efficiency in farming is access to agricultural extension services and education. Farmers' knowledge and skills in

managing inputs and production processes significantly affect their ability to achieve optimal efficiency. A study by Wahyuni et al. (2023) revealed that farmers who regularly participated in extension programs achieved higher technical efficiency compared to those who did not. This can be attributed to better knowledge of cultivation techniques, land management, and the application of appropriate technologies. In addition, formal education levels influence farmers' ability to understand and adopt innovations introduced through extension services. As noted by Anjani and Prasetyo (2022) formal education enhances farmers' information absorption and opens up access to modern agricultural networks.

The availability and affordability of agricultural inputs also play a central role in determining efficiency. Farmers with access to quality fertilizers, improved seeds, and mechanization tools tend to achieve higher productivity and efficiency. Rahayu and Maulana (2023) observed that the lack of high-quality inputs leads to suboptimal input allocation, reducing technical efficiency. Moreover, dependency on traditional inputs without modern technological support limits farmers' ability to reach efficient production scales. Input price volatility further affects production continuity, especially for small-scale farmers with low purchasing power. Thus, government support in the form of input subsidies and equitable distribution of production resources is critical for enhancing overall farmer efficiency.

Farm size and farming experience also show a strong correlation with efficiency levels. Farmers managing larger-scale operations generally have more flexibility in adopting technologies, diversifying crops, and leveraging economies of scale to reduce costs. Nugroho and Fitriana (2024) found that farmers with more than ten years of experience tended to achieve above-average technical efficiency. Their ability to adjust cultivation strategies based on environmental and market conditions contributes to this outcome. In contrast, new or small-scale farmers often lack access to information, technology, and capital, which directly impacts their technical and economic efficiency. Therefore, it is crucial to design training programs specifically targeting novice farmers and to promote land consolidation efforts to collectively enhance efficiency.

## **CONCLUSION AND IMPLICATIONS**

Based on the literature review, it can be concluded that technical and economic efficiency in farming is influenced by a range of interconnected internal and external factors. Agricultural education and extension services play a pivotal role in enhancing farmers' capacity to manage

their operations productively and efficiently. Access to information, training, and technical guidance enables farmers to better understand modern cultivation techniques, land use strategies, and appropriate input applications. This not only boosts productivity but also contributes to more efficient resource use. Additionally, formal education levels significantly influence farmers' ability to comprehend and apply agricultural innovations. Therefore, investing in human capital development within the agricultural sector is a key strategy for fostering sustainable farm efficiency.

On the other hand, the availability of production inputs, farm scale, and farming experience must not be overlooked. Access to superior seeds, quality fertilizers, and mechanization technologies directly affects technical efficiency by determining the quality and quantity of production outcomes. Inequities in input distribution and input price fluctuations present challenges for farmers, particularly those in small-scale enterprises with limited bargaining power. Moreover, larger-scale operations and experienced farmers tend to benefit from efficiency advantages due to their ability to exploit economies of scale and withstand market fluctuations. Hence, holistic policy interventions including land consolidation, input subsidies, and training programs for beginner farmers are necessary to create an efficient and competitive farming system in the face of globalization and climate change.

#### REFERENCES

- Anjani, R., & Prasetyo, E. (2022). Pendidikan Formal dan Kemampuan Adaptasi Inovasi Pertanian pada Petani Kecil di Indonesia. *Jurnal Pengembangan Pertanian*, 17(2), 121–134.
- Dewi, R. A., Nurhayati, D., & Yusuf, M. (2023). Analisis Efisiensi Teknis Usahatani Jagung Menggunakan Metode DEA di Sulawesi Selatan. *Jurnal Ekonomi Pertanian dan Agribisnis*, 11(1), 45–56.
- Halim, R., & Surya, F. (2024). Analisis Efisiensi Teknis Usaha Tani Kopi di Sulawesi Selatan Menggunakan Metode DEA. *Jurnal Agribisnis Nusantara*, 7(1), 45–56.
- Harahap, T., & Dewi, S. (2023). Determinasi Efisiensi Teknis Petani Perkebunan Rakyat: Pendekatan DEA dan Faktor Sosial Ekonomi. *Agritekno*, 11(2), 110–125.
- Hartati, S., & Anwar, H. (2024). Pengaruh Akses Digital terhadap Efisiensi Ekonomi Petani di Era Industri 4.0. *Jurnal Pertanian Digital Indonesia*, 3(2), 78–89.

- Kurniawan, B., & Safitri, L. (2021). Aplikasi DEA dalam Evaluasi Efisiensi Usahatani Padi Organik di Jawa Barat. *Jurnal Agribisnis dan Ekonomi Pertanian*, 9(3), 101–113.
- Nugroho, A., & Fitriana, M. (2024). Pengaruh Skala Usaha dan Pengalaman Bertani terhadap Efisiensi Teknis Petani Padi di Jawa Tengah. *Jurnal Ekonomi Pertanian dan Agribisnis*, 12(1), 45–59.
- Prasetyo, B., & Yuliana, D. (2022). Efisiensi dan Produktivitas Usaha Tani dalam Perspektif Keberlanjutan. *Jurnal Ekologi Pertanian*, 6(2), 115–127.
- Rahayu, L., Anindita, R., & Wicaksono, H. (2022). Efisiensi Usaha Tani Hortikultura di Sumatera Barat Menggunakan Analisis Frontier Stokastik. *Jurnal Ekonomi Pertanian dan Agribisnis*, 6(4), 321–335.
- Rahayu, S., & Maulana, F. (2023). Ketersediaan Input dan Efisiensi Usahatani: Studi Kasus di Wilayah Lahan Tadah Hujan. *Jurnal Agribisnis dan Teknologi Pertanian*, 9(3), 211–225.
- Rohmah, N., & Hidayat, T. (2022). Perbandingan Metode DEA dan SFA dalam Pengukuran Efisiensi Usahatani Hortikultura. *Jurnal Ilmu Pertanian Terapan*, 10(4), 88–99.
- Santosa, W., Mulyani, D., & Prasetyo, A. (2023). Pengukuran Efisiensi Teknis Petani Padi di Jawa Tengah Menggunakan Data Envelopment Analysis. *Jurnal Agro Ekonomi*, 41(1), 90–102.
- Setiawan, D., & Lestari, M. (2024). Efisiensi Ekonomi Usaha Tani Jagung di Nusa Tenggara Timur: Analisis SFA. *Jurnal Analisis Kebijakan Pertanian*, 9(1), 63–78.
- Wahyuni, D., Siregar, M., & Lestari, P. (2023). Peran Penyuluhan dalam Meningkatkan Efisiensi Teknis Usahatani Jagung di Kabupaten Grobogan. *Jurnal Penyuluhan dan Pemberdayaan Petani*, 15(1), 33–47.
- Wahyuni, S., Rahman, H., & Ningsih, M. (2023). Faktor Sosial Ekonomi yang Mempengaruhi Efisiensi Teknis Petani di Lahan Tadah Hujan. *Jurnal Agriseip*, 22(1), 64–75.
- Yuliana, H., & Mardiana, I. (2023). Studi Efisiensi Teknis dan Ekonomi Usaha Tani Cabai Rawit di Sleman. *Jurnal Sosial Ekonomi Pertanian*, 8(2), 144–158.