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FINANCIAL EFFICIENCY ANALYSIS OF SMALLHOLDER FARMING SYSTEMS USING DATA ENVELOPMENT ANALYSIS (DEA) AND PROFITABILITY INDICATORS

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Abstract
Smallholder farming systems play a pivotal role in global food security, yet they remain economically vulnerable due to structural constraints, limited resource access, and market inefficiencies. This study evaluates the financial efficiency of smallholder farms by integrating Data Envelopment Analysis (DEA) with profitability indicators, providing a comprehensive framework that captures technical, allocative, scale, and economic efficiency dimensions. DEA is employed as a non-parametric frontier approach to measure relative efficiency in transforming inputs into outputs, while profitability measures such as gross margin, net return, and benefit-cost ratio complement the analysis by capturing actual financial performance. The study further decomposes efficiency using CCR and BCC models to distinguish constant and variable returns to scale, enabling identification of managerial inefficiencies and structural constraints. In addition, the role of slacks is examined to highlight specific input redundancies, offering actionable insights for resource optimization. Comparative discussion with Stochastic Frontier Analysis (SFA) underscores the robustness of DEA in handling multiple inputs and outputs, despite its sensitivity to noise. The framework also incorporates socio-economic determinants such as education, credit access, gender disparities, and labor dynamics, alongside emerging challenges including climate change, environmental degradation, and digital transformation in agriculture. Findings from global case studies indicate that while many smallholders operate near technical efficiency frontiers, their financial inefficiency is largely driven by scale limitations, poor market integration, and institutional barriers. The integration of eco-efficiency and climate-smart agriculture further highlights the need for sustainable productivity improvements. Overall, the study demonstrates that combining DEA with profitability and contextual indicators offers a powerful analytical tool for policy design aimed at

improving smallholder viability, promoting resource efficiency, and ensuring sustainable agricultural development.

1. Introduction

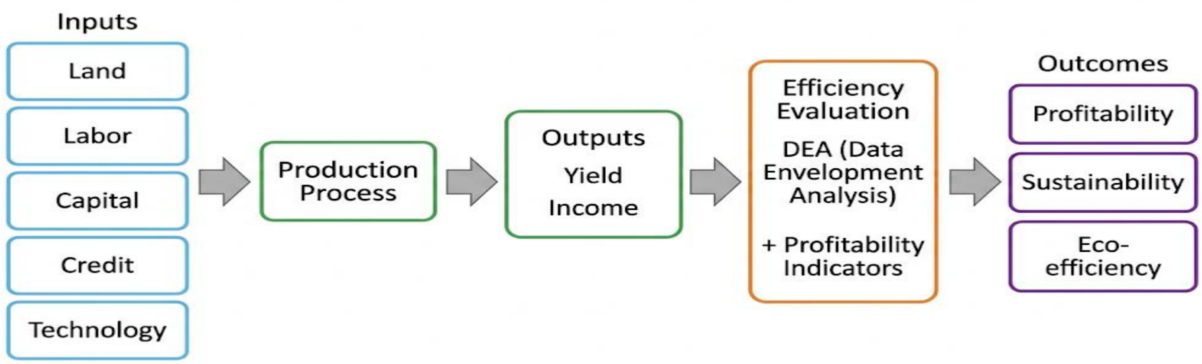
The global agricultural sector is currently navigated through a complex matrix of increasing population pressure, climate-induced resource scarcity, and a fundamental shift toward sustainable intensification (Matta et al., 2026). Within this landscape, smallholder farming systems typically defined as operations managing less than five hectares of land occupy a position of critical importance, yet they are simultaneously characterized by extreme vulnerability (Raymond et al., 2020). These systems produce approximately 46% of the world's food supply using roughly one-third of the global agricultural land, underscoring a productivity-per-hectare ratio that often surpasses that of larger commercial enterprises (Fuglie et al., 2024). Despite this output, the financial efficiency and long-term economic viability of smallholder units remain precarious, often hampered by limited access to technology, high transaction costs, and a lack of integrated market participation (Langyintuo, 2020).

The analytical focus on financial efficiency within these systems has increasingly turned toward the integration of non-parametric frontier techniques, specifically Data Envelopment Analysis (DEA), alongside traditional profitability indicators (Moradi-Motlagh et al., 2022 This dual approach allows for a more nuanced understanding of how farmers allocate scarce resources and the degree to which they can improve their livelihoods by moving toward a best-practice frontier without necessarily requiring entirely new technological inputs (Bhaduri et al., 2018). By decomposing efficiency into its technical, allocative, and scale components, researchers can identify whether the primary constraints to farm success are managerial, structural, or related to market pricing (Şirikçi, 2026).

2. Theoretical Foundations of Agricultural Efficiency

The conceptualization of efficiency in agricultural production stems from a neoclassical economic framework that distinguishes between the physical transformations of inputs into (Van der Ploeg, 2019). Outputs and the economic optimization of resource allocation based on prevailing market prices. This distinction, pioneered by Farrell in the mid-20th century, provides the basis for measuring technical efficiency (TE), allocative efficiency (AE), and overall economic efficiency (EE) (Özelli, 2021). Technical efficiency is fundamentally a measure of a farm's success in producing the maximum possible output from a given set of inputs, or conversely, achieving a specific output level with the minimum possible input set. This relationship is non-monetary and focuses on the mastery of the production process itself (Tenaye, 2020). To better understand how financial efficiency is structured in smallholder farming systems, a conceptual framework is presented in Figure 1.

Figure 1: Conceptual Framework of Financial Efficiency in Smallholder Farming Systems



This framework integrates both production inputs and economic outputs, linking traditional efficiency theory with modern DEA-based evaluation. Allocative efficiency introduces the dimension of price, reflecting the ability of a farm to use inputs in optimal proportions given their respective costs (Mivumbi & Yuan, 2023). A farm may be technically efficient by operating on its production frontier but allocatively inefficient if it utilizes expensive inputs where cheaper substitutes would suffice for the same technological outcome (Orinda et al., 2018). The product of TE and AE yields the economic efficiency of the firm, representing the total capacity to minimize costs or maximize profits within the constraints of the available technology (Ketokivi & Mahoney, 2020). In the context of smallholder systems, where market imperfections are rampant and credit is often constrained, the gap between technical and allocative efficiency reveals significant insights into the structural barriers preventing farmers from achieving financial sustainability (Arora, 2025).

Scale efficiency (SE) represents a further refinement of the efficiency concept, addressing the question of whether a farm is operating at its most productive. In smallholder agriculture, many units are "sub-optimal" not because of poor management, but because (Tsikada, 2025). They are too small to exploit economies of scale or too large to be managed effectively with family labor alone (Foster & Rosenzweig, 2022). The relationship between farm size and efficiency is frequently debated, with some studies suggesting a U-shaped relationship where both very small and very large farms exhibit higher efficiency levels than medium-sized counterparts (Rada & Fuglie, 2019).

Table 1. Dimensions and Determinants of Efficiency in Smallholder Agriculture

Efficiency Type	Component Analysis	Determinant Factors
Technical (TE)	Output/Input transformation	Managerial skill, technology adoption, soil quality (Begum et al., 2010; Muzekenyi et al., 2021).
Allocative (AE)	Cost minimization/Price optimization	Market access, credit availability, information symmetry (Begum et al., 2010; Muzekenyi et al., 2021).
Scale (SE)	Optimal size of operation	Land tenure, capital investment, labor availability (Mahamadou, 2026; Muzekenyi et al., 2021).
Economic (EE)	Combined TE and AE	Policy environment, infrastructure, systemic resilience (Begum et al., 2010; Gadanakis, 2015).

3. Data Envelopment Analysis (DEA) Methodology in Farming Systems

Data Envelopment Analysis has emerged as the preferred non-parametric tool for assessing efficiency in heterogeneous systems like smallholder agriculture due to its ability to handle multiple inputs and outputs without requiring a pre-specified functional form (Adamie et al., 2019). Unlike parametric methods such as Stochastic Frontier Analysis (SFA), which assume a specific distribution for inefficiency and error terms, DEA uses linear programming to construct a piecewise linear surface (or frontier) that "envelopes" the data (Petridis & Dey, 2018). Any unit falling on this frontier is assigned an efficiency score of 1.0, while those below the frontier are considered inefficient, with their score representing the radial distance to the best-practice boundary (Inana, 2025).

The flexibility of DEA allows researchers to choose between input-oriented models which focus on how much inputs can be reduced while maintaining a constant output level and output-oriented models, which seek to maximize production from a fixed set of resources (Zubir et al., 2024). For smallholders facing severe resource constraints and high input costs, the input-oriented approach is often more relevant, as it provides a direct measure of potential cost savings (Saravia-Matus et al., 2021).

3.1 CCR vs. BCC Models and Returns to Scale

The initial Data Envelopment Analysis (DEA) model developed by Charnes, Cooper, and Rhodes (CCR) is based on the assumption of constant returns to scale (CRS), meaning that output changes proportionally with input regardless of the scale of operation (Benicio & Mello, 2019). However, this assumption is often unrealistic in real-world contexts such as rural agriculture, where constraints like land fragmentation, labor limitations, and resource heterogeneity frequently lead to variable and often diminishing returns (Ntihinyurwa & de Vries, 2021). To address this limitation, the Banker, Charnes, and Cooper (BCC) model introduced a convexity constraint that allows for variable returns to scale (VRS), enabling a decomposition of overall efficiency into pure technical efficiency and scale efficiency (Cooper et al., 2022). This distinction is particularly important in empirical studies; for example, research on pineapple farmers in Ghana showed a mean technical efficiency of 0.505 under CRS, but under VRS assumptions many farmers were found to be technically efficient while still operating at suboptimal scale levels (Boakye et al., 2024). Mathematically, the input-oriented VRS DEA model for a decision-making unit (DMU) $i$is formulated as $\min_{\theta,\lambda} \theta$subject to $-y_i + Y\lambda \geq 0$, $\theta x_i - X\lambda \geq 0$, $N_1'\lambda = 1$, and $\lambda \geq 0$, where θrepresents the efficiency score, $x_i$and $y_i$are the input and output vectors, and λdenotes the intensity variables defining the reference frontier (Khoveyni & Eslami, 2025; Pearse et al., 2025). The convexity constraint $N_1'\lambda = 1$ensures that each DMU is benchmarked only against comparably sized peers, thereby capturing variable returns to scale and improving the realism of efficiency estimation (Avilés-Sacoto et al., 2020).

3.2 The Role of Slacks and Benchmarking

Beyond the radial efficiency score, DEA provides information on "slacks," which represent the non-radial reductions in specific inputs required to reach the frontier (Miran, 2024). This is particularly actionable for extension services. For example, in rice production in the Mekong Delta, DEA identified that even after the general reduction in inputs suggested by the efficiency score, farmers still overused seeds by 28 USD/ha and fertilizers by 155 kg/ha (Tu et al., 2021). By identifying these specific "input slacks," policymakers can move beyond general advice and provide targeted recommendations for resource conservation (Kyshakevych et al., 2025). Beyond radial efficiency scores, DEA also identifies specific input inefficiencies known as slacks, as illustrated in Figure 2. These slacks provide practical guidance for reducing overuse of inputs in farming systems.

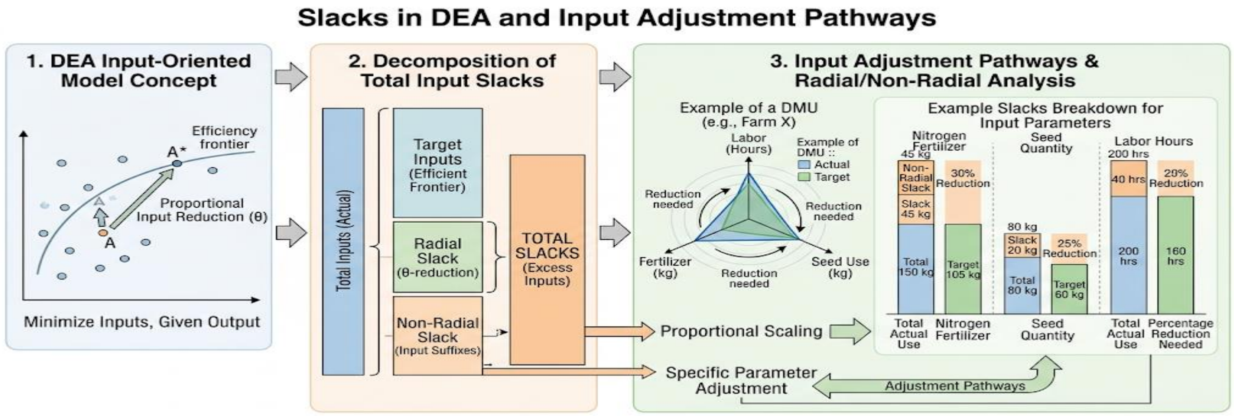


Figure 2: Slacks in DEA and Input Adjustment Pathways. Visualizing the breakdown of inefficiencies and target reduction levels for input parameters.

4. Comparative Analysis: DEA vs. Stochastic Frontier Analysis (SFA)

While DEA is a powerful non-parametric tool, the agricultural domain also heavily utilizes Stochastic Frontier Analysis (SFA), a parametric approach that uses econometric techniques to estimate the frontier (Asmare & Begashaw, 2018). The fundamental difference lies in how each method treats deviations from the frontier. DEA is deterministic, meaning it assumes all deviations are the result of inefficiency (Letti et al., 2022). SFA, conversely, decomposes the error term into two parts: one representing technical inefficiency and the other representing random noise, such as weather variability, pests, or measurement errors (Aparicio et al., 2023).

Studies comparing the two methods often find that SFA yields higher efficiency scores because it attributes some of the distance to the frontier to "luck" or external factors (Arsad et al., 2018). In a comparative study of potato farming in Bangladesh, the SFA mean efficiency score was 85.3%, while the DEA VRS score was significantly lower at 52.7% (Ghahremanloo et al., 2020). This suggests that while DEA is useful for benchmarking against absolute best-performers, it may overstate inefficiency by failing to account for the inherent stochasticity of biological production systems (Pavão, 2023). However, DEA remains more robust when dealing with multiple outputs and when the researcher lacks a definitive functional form for the production technology (Nepomuceno et al., 2023).

Table 2. Methodological Comparison of Frontier Estimation Techniques

Method	Characteristics	Pros	Cons
DEA	Non-parametric, Linear Programming	No functional form needed; handles multi-outputs easily (Begum et al., 2010).	Sensitive to outliers; assumes no random noise (Uddin & Khan, 2023).
SFA	Parametric, Econometric	Accounts for weather/shocks; statistical hypothesis testing (Mahamadou, 2026; Uddin & Khan, 2023).	Requires specific functional form; sensitive to specification errors (Uddin & Khan, 2023).

5. Profitability Indicators as Complements to Efficiency

Technical efficiency is a necessary but insufficient condition for the economic survival of a smallholder farm. A farmer could be 100% technically efficient at producing a crop that has no market value or whose input costs exceed its revenue (Zewdie et al., 2021). Therefore, the analysis of financial efficiency must integrate profitability indicators such as Gross Margin, Net

Return, and Benefit-Cost Ratio (BCR) (Rashid, 2021).

5.1 Profit Efficiency and Market Orientation

Profit efficiency measures the ability of a farm to achieve the maximum possible profit given the prices of inputs and outputs. In the vegetable farming sector of Nepal, profit inefficiency was found to be high, primarily driven by sub-optimal input combinations and high transaction costs associated with reaching distant markets (Shrestha et al., 2021). Profitability in these systems is significantly explained by labor, land, seeds, fertilizer, and capital, but the *inefficiency* of profit generation is often a social and institutional issue, linked to a lack of access to credit, extension services, and information on market prices (Tadele, 2021).

Net return and BCR serve as straightforward indicators of the financial health of the farming unit. In Bangladesh, poultry farms achieved an average net return of 1,386.53 USD per 1,000 birds with a BCR of 1.38, indicating that for every dollar invested, the farmer received 1.38 dollars in return (AKTAR, 2018). While this indicates a profitable enterprise, the integration of DEA reveals that even these profitable farms could save 10% of their total resources by following the input package of the most efficient producers in the sample (Reig-Martínez & Picazo-Tadeo, 2004).

5.2 The Policy Analysis Matrix (PAM) and DEA Integration

A more advanced integration involves the Policy Analysis Matrix (PAM), which allows for the comparison of private and social profitability (Badem & Hurma, 2025). Private profitability is calculated at observed market prices, reflecting the actual returns to the farmer under the current policy regime, including taxes and subsidies. Social profitability is calculated at "shadow prices," which reflect the true opportunity cost to the economy, removing the effects of policy interventions (Chintapalli & Tang, 2022).

Integrating DEA with PAM allows researchers to define a "profit-efficient" benchmark (Ceylan, 2022). In Ghana, this combination demonstrated that while "average" maize and rice farmers appeared unviable at social prices, "efficient" farmers identified through DEA were highly competitive and socially profitable (Akromah et al., 2024). This suggests that policy should not necessarily focus on moving farmers *out* of certain crops, but rather on bridging the efficiency gap through the dissemination of best practices (Kleijn et al., 2019).

6. Socio-Economic Determinants of Smallholder Inefficiency

Efficiency is not merely a product of physical inputs; it is deeply embedded in the socio-economic and institutional context of the farming household. Identifying these determinants is a critical step in turning a DEA score into actionable policy (Akhtar et al., 2023).

6.1 Human Capital and Experience

Education consistently emerges as a primary driver of technical efficiency (Morales-Piñero et al., 2024). Higher educational attainment enhances a farmer's "allocative capacity" the ability to process information about new technologies, weather forecasts, and market trends (Molua et al., 2020). In South Africa's Eastern Cape, technical efficiency among maize farmers was significantly boosted by education, which facilitated the adoption of Improved Maize Varieties (IMVs) (Sigigaba et al., 2021). Similarly, farming experience provides tacit knowledge that allows for better management of shocks, although this can sometimes lead to rigid, "old-style" agronomic practices that resist new, more efficient technologies (Mangani, 2021).

6.2 Access to Credit and Institutional Support

Market failures in rural credit are a major source of allocative inefficiency (Khan et al., 2024). Smallholders often face a trade-off between purchasing high-quality inputs (like hybrid seeds) and meeting immediate household consumption needs (de Brauw & Bulte, 2021). Credit access allows for the timely purchase of inputs, which is critical in rain-fed systems where planting windows are narrow (ADEMOLA, 2021). Extension services also play a pivotal role; they serve as the primary channel for technology transfer and information dissemination. However, the quality of these services varies greatly; in Ethiopia, poor extension services were cited as a primary reason for a mean technical efficiency of only 44.33% among certain irrigation users (Atinaf et al., 2023).

6.3 Gender and Labor Dynamics

Smallholder farming is heavily reliant on family labor, yet significant gender disparities exist in efficiency and resource access (Ankrah et al., 2020). Women, who make up a substantial portion of the smallholder workforce, often have less access to land rights, credit, and extension services than men. In many systems, male-headed households exhibit higher technical efficiency simply because they possess more secure land tenure and better links to formal markets (Mulungu & Kabwela, 2025). Furthermore, the reliance on family labor introduces a negative correlation with technical efficiency in some commercialized contexts, as family labor is often used less intensively or with less specialized skill than hired wage labor (Mizik et al., 2025).

7. The Challenge of Family Labor and Shadow Wages

Valuing family labor is one of the most significant hurdles in smallholder financial analysis (Eshetu et al., 2018). Because family members are not typically paid a wage, their contribution is often excluded from cost-benefit analyses, which can lead to an overestimation of net returns (Flyvbjerg & Bester, 2021). Conversely, valuing family labor at the prevailing market wage often makes smallholder farming look like a losing proposition (Baglioni, 2022).

7.1 Endogenous Shadow Prices

Economic theory posits that households face an endogenous "shadow wage" that reflects the marginal productivity of their labor on the farm and their personal preferences for leisure (Hill et al., 2021). This shadow wage is typically lower than the market wage, particularly in areas with high unemployment or where farming provides "non-market values" like social status or food security (Frey et al., 2020). DEA-based distance functions can be used to calculate these shadow prices, showing that smallholders often act rationally by working on their farms for a return that is lower than the wage they would receive in a distant city, once transaction and relocation costs are considered (Garriga et al., 2023).

7.2 Subsistence vs. Market Orientation

The "separability" of production and consumption decisions is a key concept here. For large commercial farms, these decisions are separate: they maximize profit and then use that profit to buy food (Camara et al., 2023). For many smallholders, however, production and consumption are "non-separable" they grow what they eat, and their consumption needs dictate their production choices (Knigge et al., 2022). This often leads to a "safety-first" strategy rather than a profit-maximizing one, which traditional efficiency measures may categorize as "inefficiency" even if it is a rational response to market risk (Barra & Zotti, 2019).

8. Environmental Efficiency and the Eco-Efficiency Paradigm

In the 21st century, the definition of efficiency has expanded to include environmental sustainability (Petrakopoulou & Corcuera, 2022). "Eco-efficiency" assesses the ability of a farm to produce economic value while minimizing its ecological footprint, such as greenhouse gas emissions, nutrient runoff, and pesticide leaching (Acevedo-Ramos et al., 2023).

8.1 Sustainable Land Management (SLM)

Adopting Sustainable Land Management practices, such as stone bunds, cover cropping, and minimum tillage, has been shown to improve technical efficiency in the long run by preserving soil fertility (Bhattacharyya et al., 2023). In Ghana, adopters of SLM were found to be 7.5% more technically efficient than non-adopters, while also achieving higher yields under climate uncertainty (Adjiba et al., 2023). However, the transition to SLM can be difficult for the poorest farmers, as it often requires an initial investment in labor and capital that only pays off after several seasons (Emerton & Snyder, 2018).

8.2 Pollution as an "Undesirable Output"

DEA models can be adapted to treat environmental degradation as an "undesirable output" (Halkos & Petrou, 2018). This allows for the calculation of environmental efficiency scores. For example, a study of Indian farmers found that their average environmental efficiency was 46%, suggesting they could reduce their use of polluting inputs (like chemical fertilizers and pesticides) by 54% without decreasing their total output (Nayak et al., 2023). Interestingly, non-farm income was found to *increase* environmental efficiency, suggesting that as farmers become less desperate for immediate yield at any cost, they adopt more environmentally friendly practices (Mustafa et al., 2021).

9. Impact of Climate Change on Production Efficiency

Climate change is no longer a future threat; it is an active driver of inefficiency in smallholder systems (Abegunde et al., 2019). Smallholder systems are particularly vulnerable due to their reliance on rain-fed crops and limited adaptive capacity (Borona, 2021).

9.1 Diminishing Factor Productivity

Research in Sub-Saharan Africa (SSA) shows that climate change proxies, such as CO2 and methane emissions, significantly diminish the productivity of land, labor, and fertilizers (Omotoso & Omotayo, 2024). For every degree of increase in mean annual temperature, rice yields can drop by as much as 5.8%. Furthermore, heat stress impairs the physical ability of farm laborers to work effectively, creating a direct link between environmental change and reduced technical efficiency (Hossain et al., 2024).

9.2 Adaptation Strategies and Efficiency

Climate-smart agriculture (CSA) practices, such as the use of weather-resistant seed varieties and improved water management, are essential for maintaining efficiency in the face of these shocks (Shahbaz et al., 2022). In South Africa, the adoption of Improved Maize Varieties (IMVs) has been promoted as a primary strategy to boost both yields and technical efficiency, with adopters showing significantly higher resilience to climatic variability than traditional farmers (Chivasa et al., 2022). However, the high initial cost of these technologies remains a barrier for the most vulnerable smallholders (Vasavi et al., 2025).

Table 3. Climate Impacts and Smallholder Adaptation Responses

Climate Stressor	Direct Impact on Efficiency	Adaptation Response
Increased Temp	Reduced labor productivity; higher evaporation (PLOS ONE, 2024).	Heat-tolerant seeds; improved irrigation (PLOS ONE, 2024).
Rainfall Variability	Timing of fertilizer application disrupted (PLOS ONE, 2024).	Shifting planting dates; water harvesting (PLOS ONE, 2024).
CO2 Emissions	Lower nutrient density in some staples (PLOS ONE, 2024).	Diversification into high-value crops (SSA Climate Study, 2023).
Pest/Disease Outbreak	Increased crop loss (Technical inefficiency) (SSA Climate Study, 2023).	Integrated Pest Management (IPM); resistant varieties (South Africa IMV Study, 2025).

10. Digital Agriculture and the Future of Efficiency Estimation

The integration of Information and Communication Technologies (ICT) is revolutionizing how efficiency is measured and managed in smallholder systems (Mapiye et al., 2023).

10.1 Machine Learning and Hybrid DEA

The frontier of efficiency analysis is shifting toward hybrid models that combine DEA with Machine Learning (ML) (Mirmozaffari et al., 2021). Recent studies, such as those conducted in the Gaya region of Niger (2025), use Random Forest algorithms to identify the non-linear determinants of technical efficiency (Idolor et al., 2026). These hybrid approaches are far more accurate than traditional Tobit models at predicting which farmers are likely to be efficient and why, allowing for highly localized and specific policy interventions (Li et al., 2020). In addition, advanced biosensing technologies are being deployed for rapid pathogen detection in food and environmental samples, further protecting farm outputs (Ali et al., 2021).

10.2 Data Governance and Power Imbalances

However, the "datafication" of smallholder agriculture raises serious ethical questions (Garwe et al., 2025). Smallholders are often required to share business-sensitive data with service providers to receive advice or subsidies, leading to an "excessive transparency" of the farmer to the public and private sectors, while the providers' own data remains a black box (Garg, 2025). This "data power imbalance" can disempower farmers, as technology providers may use this data to engage in price discrimination or commodity market speculation that could ultimately undermine food security (Gautier et al., 2020).

Ensuring that data-driven efficiency improvements benefit the farmer requires a robust framework for data governance (Oyeboade & Olagoke-Komolafe, 2023). This includes the development of digital agriculture codes of conduct that prioritize data ownership, privacy, and informed consent for smallholder producers (Wilgenbusch et al., 2022).

11. Synthesis of Global Case Studies

The application of DEA and profitability indicators across diverse regions reveals common themes and localized variations in smallholder efficiency (Boakye et al., 2024).

11.1 Sub-Saharan Africa: The Yield Gap and Structural Barriers

In Ghana, pineapple farmers face a mean technical efficiency of 0.505, implying a potential for a 49.5% reduction in inputs while maintaining current output (Ntiamoah et al., 2025). This is largely due to the inability of farmers to fully exploit available technologies. In Ethiopia, wheat productivity remains low (3.0 t/ha rainfed vs 4.0 t/ha irrigated) despite the country becoming the largest producer in SSA (Tadesse & Asefa, 2025). Here, technical efficiency is heavily influenced by the type of irrigation system used, with small-scale users proving more efficient than large-scale, centrally managed schemes (Morais et al., 2021).

11.2 Asia: Intensification and Organic Transitions

Vietnam's Mekong Delta serves as a model for both intensive and sustainable rice production. DEA analysis of organic vs. conventional systems shows that conventional farmers operate closer to the meta-frontier, but organic systems are catching up, driven by female-headed households and higher price expectations for sustainable products (Tran et al., 2024). In Nepal, the transition to high-value vegetable farming is hampered by a "subsistence-oriented" mindset and poor market infrastructure, which keeps profit efficiency low despite high potential (Diao et al., 2023).

11.3 Latin America: Dairy Efficiency and Macro Shocks

In Ecuador and the Andean region, technical efficiency in smallholder dairy farming is influenced by labor and forage management (Torres-Inga et al., 2025). These systems showed a steady increase in efficiency until the COVID-19 pandemic in 2021, which caused an "atypically low" efficiency score (0.20) due to supply chain disruptions and input price spikes. This highlights that even technically skilled smallholders are highly vulnerable to macro-economic volatility (Gatti et al., 2021).

Conclusion

The synthesis of methodological frameworks, empirical evidence, and case study analyses presented in this paper demonstrates that Data Envelopment Analysis (DEA), when integrated with profitability indicators and contextual socio-economic variables, provides a robust and nuanced framework for assessing financial efficiency in smallholder farming systems. While technical efficiency alone is insufficient for economic viability, the decomposition into allocative, scale, and environmental components reveals that many smallholders exhibit reasonable pure technical efficiency under variable returns to scale yet suffer from sub-optimal scale economies, structural barriers such as limited credit access, poor extension services, gender disparities, and market imperfections. The valuation of family labor through endogenous shadow wages typically lower than market wages in high-unemployment contexts explains the rational non-separability of production and consumption decisions, where apparently inefficient "safety-first" strategies represent logical risk management rather than managerial failure. Furthermore, environmental efficiency and climate adaptation are inseparable from financial performance; eco-efficiency models demonstrate substantial potential for input reduction without output loss, while climate-smart agriculture practices enhance resilience against temperature increases and rainfall variability. Methodological advancements through machine learning integration offer enhanced predictive accuracy, though ethical concerns regarding data governance, ownership, and power imbalances must be addressed through robust frameworks prioritizing farmer-centric rights and informed consent. Ultimately, cross-regional evidence from Sub-Saharan Africa, Asia, and Latin America confirms that policy interventions should focus not on transitioning farmers out of agriculture but on bridging efficiency gaps through targeted dissemination of best practices, improved market access, institutional support, and context-appropriate interventions that recognize the heterogeneity of smallholder systems and their vulnerability to macroeconomic volatility.

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