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Research Article

Profit Efficiency Determinants and Implications for Household Food Security Among Smallholder Wheat Farmers in Ada'a District of Central Ethiopia

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Abstract: *Wheat is a central focus of the Ethiopian government's policy framework for achieving food self-sufficiency and food security. Improving wheat profitability is therefore essential for sustainable rural livelihoods and food system resilience. While much research has examined technical inefficiency, little is known about profit efficiency and its nexus with food security, particularly in high-potential locations like Ada'a District. Applying a concurrent, embedded mixed-methods design, this critical case study estimates farm-level profit efficiency, identifies its determinants, and examines implications for household food security among 414 smallholder wheat farmers using a translog stochastic frontier profit function, beta regression, and propensity score matching (PSM). The results reveal substantial profit inefficiency (γ = 0.6003), with an average efficiency score of 0.737, ranging from 0.13 to 0.90, implying that farmers could increase profits by 26.32% without additional inputs. Profit efficiency varied widely across households, with 44% operating below the mean and even the most efficient farms falling short of the frontier by 9.58%. Land, fertilizer, and pesticide use significantly enhanced profitability, while labor, farm capital, and seed costs reduced margins, reflecting input misallocation. Interaction effects revealed both complementarities (e.g., fertilizer × land, pesticide × land, seed × capital) and inefficiencies (e.g., labor × land, seed × land, fertilizer × capital), accounting for 18–22% of variation in profit efficiency. Beta regression identified improved seeds, irrigation, frequent extension contacts, and farming experience as efficiency enhancers, whereas pest incidence and land fragmentation increased inefficiency. PSM analysis showed that profit efficiency had a positive and statistically significant relationship with food security. Households in the lowest efficiency quartile experienced 7.23–8.47-point reductions in food consumption scores, while those in the highest quartile gained 6.88–8.91 points, highlighting efficiency's role as a channel for transmitting welfare gains. Policies should promote equitable irrigation access, improved seed adoption, timely pest management, responsive extension services, cooperative approaches to land fragmentation, and rural infrastructure development. Targeted support for low-efficiency households, promotion of input complementarities, and improved access to labor-saving technologies and farm capital are critical strategies to enhance wheat profit efficiency as well as the food security of households in Ada'a District. These strategies can enhance profitability, food security, and resilience to climatic and market shocks.*

. **Keywords:** Beta regression; Food security; Profit efficiency; Propensity score matching; Stochastic frontier profit analysis; Wheat farming

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1. Introduction

Rapid urbanization and dietary shifts have driven a sustained 9% annual increase in Africa's wheat (*Triticum aestivum*) imports over the past two decades, exposing systemic vulnerabilities rooted in economic inefficiencies, suboptimal resource allocation, and imperfect markets (van Dijk et al., 2017; Noort et al., 2022; Silva et al., 2023). Despite production gains, Africa remains dependent on imports for nearly 60% of wheat consumption, reflecting persistent structural inefficiencies (Baffes & Etienne, 2024; Geffersa & Agbola, 2025). Ethiopia, producing roughly 22% of Africa's wheat, has experienced a decline in self-sufficiency from 99% in 1960 to 70% in 2023, with deficits met through imports and food aid (Senbeta & Worku, 2023; USDA, 2025). However, increased production has not consistently translated into improved household welfare, as high input costs, price distortions; limited irrigation, land degradation, and weak policy coordination constrain welfare transmission (Shikur, 2022; Hodjo et al., 2024; Zidouemba et al., 2025). Despite potential yields exceeding 10 t/ha, national averages remain near 3.05 t/ha, highlighting substantial unrealized efficiency gains (Darkaoui et al., 2023; USDA, 2025).

Ada'a District, a major wheat-producing area in central Oromia, exemplifies this paradox. It contributes nearly 15% of Oromia's output, yet average yields of 1.8 t/ha remain below the national average (Birhanu et al., 2022; USDA, 2025). This gap reflects not only technological constraints but also economic inefficiencies, including suboptimal input allocation and market imperfections (van Dijk et al., 2017). From an efficiency perspective, distinguishing technical and profit efficiency is critical. Technical efficiency indicates the extent to which a farmer can achieve maximum output from a specified set of inputs (Farrell, 1957; Coelli et al., 2005), whereas profit efficiency captures both technical and allocative performance under prevailing prices and thus provides a more policy-relevant measure of economic performance (Kumbhakar & Lovell, 2003).

This study applies a welfare transmission approach to connect farm-level efficiency with household outcomes. Household production theory (Becker, 1965) frames households as decision-making units that allocate time and market purchases alongside home production to maximize utility. The agricultural household model (Singh et al., 1986) demonstrates the non-separability of production and consumption choices, while the efficiency literature (Farrell, 1957; Aigner et al., 1977; Kumbhakar & Lovell, 2000; Coelli et al., 2005) offers the empirical foundation for efficiency measurement. Instead of examining these perspectives in isolation, the study integrates them to explore how efficiency improvements translate into welfare gains through increased income and stronger resilience to shocks. This integration reframes profit efficiency as a transmission mechanism rather than a purely technical indicator, explaining why production gains do not automatically result in improved food security. Although prior studies estimate technical efficiency of wheat production and its influencing factors in smallholder agriculture (Endalew et al., 2023; Girma et al., 2024; Tleubayev & Syzdykov, 2025; Zhou, W. et al., 2025), they largely prioritize technical efficiency and production outcomes, with limited attention to welfare implications.

Evidence on the profit efficiency–food security nexus remains scarce, particularly in relatively high-potential areas such as Ada'a (Mulusew & Hong, 2023). The fact that 39.3% of Ada'a households experience moderate or severe food insecurity despite favorable production conditions (Shumiye et al., 2025) reveals a critical disconnect between production potential and welfare outcomes. Accordingly, this study aims to: (i) measure wheat farmers' profit efficiency and its distribution, (ii) identify key determinants of efficiency and inefficiency, and (iii) analyze the linkage between profit efficiency and household food security. By linking farm-level efficiency with household welfare outcomes, specifically food security, using an integrated econometric framework, this study extends efficiency analysis beyond production outcomes to welfare effects in smallholder systems and addresses the persistent disconnect between high-potential wheat yields and improved household welfare, referred to as the "efficiency–food security paradox". The study contributes theoretically by positioning profit efficiency as the bridge between production and welfare, empirically by providing farm-level evidence from Ada'a District, methodologically by integrating Stochastic Frontier Analysis, Beta Regression, and Propensity Score Matching, and practically by enhancing policy relevance, informing evidence-based decisions for Ada'a District under Ethiopia's National Wheat Development Strategy (2021), which covers the wheat-belt zones.

2. Literature Review

2.1. Review of theoretical literature

Linkages between farm profit efficiency and household food security are most effectively interpreted through integrated theoretical frameworks. Production economics defines profit efficiency as the optimal allocation of land, labor, and capital to maximize output and profit (Coelli et al., 2005). The farm-household model emphasizes the link between production and consumption, showing that market imperfections, labor constraints, and limited credit can prevent efficiency from improving welfare (Singh et al., 1986). Efficiency theory, operationalized through stochastic frontier analysis, quantifies deviations from the profit frontier, distinguishing true inefficiency from random shocks (Aigner et al., 1977).

Efficiency alone does not guarantee improved food or nutrition. The welfare transmission framework clarifies how farm profits affect household food security via income used for food purchases or direct consumption of self-produced foods (Herforth & Harris, 2014; Ruel et al., 2018). The Sustainable Livelihood Framework situates efficiency within households' broader asset base, natural, social, financial, human, and physical capital, which mediates resilience and sustained access to food (DFID, 1999). The food entitlements perspective challenges the assumption that welfare relies solely on food supply, emphasizing households' capacity to secure food via production, markets, labor, or transfers (Sen, 1981). Under this lens, efficiency improves dietary diversity and caloric intake only if entitlements are strengthened. Collectively, these frameworks show a non-linear pathway: efficient input use raises potential profits, but household decisions and institutional contexts determine whether gains are reinvested, consumed, or lost. Social norms, rights, and structural conditions further mediate outcomes. Thus, profit efficiency by itself cannot ensure food security. Interventions must simultaneously enhance productivity, entitlement structures, and livelihood assets to translate efficiency gains into nutritional improvements.

2.2. Empirical literature review

2.2.1. Determinants of agricultural efficiency

Empirical evidence highlights an intricate interaction of farm-level, socio-economic, environmental, and institutional determinants shaping efficiency. Global and Ethiopian studies consistently underscore education, extension support, credit access, and farm management as key drivers, while subsidies may undermine efficiency (Ruzhani & Mushunje, 2025). African studies emphasize irrigation and adoption of resilient, locally adapted varieties (Ongoma et al., 2025; Isong et al., 2026). However, efficiency gains do not consistently translate into food security, with welfare effects varying by context (Ogundari, 2014).

In Ethiopia, stochastic frontier analyses show inefficiency gaps often exceeding 55%, with small-scale irrigation users outperforming larger farms. Major constraints include poor extension services, outdated practices, land fragmentation, and limited education (Tenaye, 2020; Zewdie et al., 2021). Spatial and social effects, such as information spillovers, indicate efficiency is partly socially embedded (Fikadu & Gebre, 2024). Overall, access to inputs, knowledge, and infrastructure supports efficiency, but the influence of specific drivers varies, highlighting the need for integrated technological, institutional, and social interventions (Harudin, 2025).

2.2.2. Approaches for measuring profit efficiency

Agricultural efficiency is measured via two main approaches: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). SFA estimates a stochastic production frontier, decomposing deviations into inefficiency and noise, and can be extended to profit frontiers (Aigner et al., 1977; Battese & Corra, 1977). DEA constructs a deterministic frontier, measuring relative efficiency without functional assumptions (Farrell, 1957; Charnes et al., 1978). DEA may overstate inefficiency in noisy environments, whereas SFA isolates managerial and allocative performance from stochastic shocks, making it more suitable for welfare analysis (Coelli et al., 2005).

2.2.3. Comparison of methodological approaches

The choice between SFA and DEA shapes how efficiency is interpreted. SFA separates inefficiency from stochastic shocks under explicit functional assumptions, while DEA uses non-parametric linear programming without imposing a production structure (Rella & Dipierro, 2025). SFA is preferable in stochastic agricultural environments, while DEA serves as a benchmarking tool under high-quality data. Divergences in findings illustrate this: Afghanistan shows high technical but lower economic efficiency (Radmand & Rezaei, 2025), while Ethiopia reports allocative inefficiencies from market and institutional constraints (Tesema, 2021). This underscores the importance of profit- and welfare-oriented measures over purely technical ones.

Within this context, SFA provides a theoretically consistent framework for welfare analysis, separating noise from inefficiency and supporting hypothesis testing (Aigner et al., 1977; Kumbhakar & Lovell, 2000). DEA remains useful for benchmarking, but for this study, SFA's robustness in stochastic settings and relevance to welfare-linked efficiency make it preferable. Using translog functional forms allows flexible modelling of non-linear input–output relationships, generating efficiency scores for welfare analysis that link inputs to output, income, and food security, consistent with welfare transmission and food entitlement frameworks.

2.2.4. Efficiency–welfare linkages in smallholder agriculture

Profit efficiency integrates technical and allocative dimensions, offering a more comprehensive measure of welfare potential than technical efficiency alone (Becker, 1965; Singh et al., 1986). Efficiency gains can raise real income, lower shadow prices, and strengthen resilience, facilitating food security. Empirical evidence supports this, though findings vary by context (Ali & Flinn, 1989; Battese & Coelli, 1995; Kumbhakar & Lovell, 2000; Nano, 2023; Argaw et al., 2025). Market volatility, infrastructure deficits, and institutional barriers may block translation of efficiency into welfare (Hakim et al., 2021). Synthesizing studies, profit efficiency emerges as the critical intermediary between farm performance and household welfare, capturing households' ability to convert production into income under prevailing prices and constraints. In wheat systems like Ada'a, measured efficiency mediates food security, consumption stability, and resilience to shocks, shifting the analytical focus from a "yield gap" to a "welfare gap."

2.3. Conceptual framework of the study

A synthesis of existing theoretical and empirical studies culminates in the study's conceptual framework (Figure 1). In the diagram, solid arrows denote empirically tested relationships, while dotted arrows represent hypothesized or conceptual links not yet empirically established.

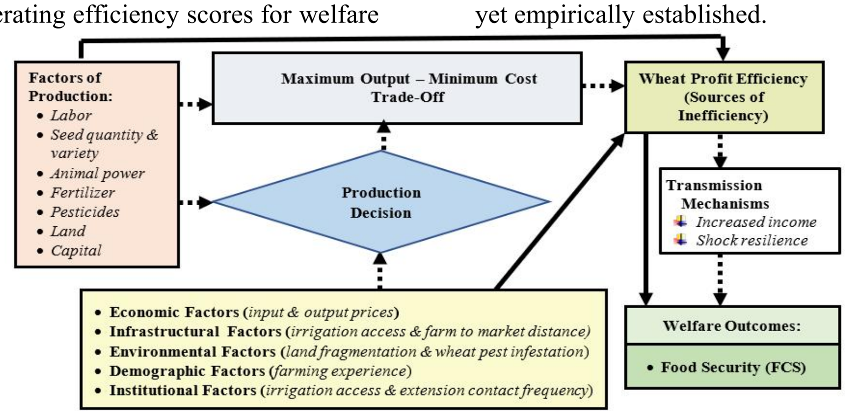

Figure 1: Conceptual framework of profit efficiency–food security linkages.
Source: Author's own construction based on literature review.

The conceptual framework (Figure 1) illustrates smallholder wheat production as a multi-stage transformation process linking farm-level decisions and resource use to household welfare outcomes, particularly food security. It is grounded in household production theory (Becker, 1965), which views households as utility-maximizing units combining market and non-market inputs, and the agricultural household framework (Singh et al., 1986), highlighting the interdependence of production and consumption decisions in rural settings. At the decision-making stage, economic, infrastructural, institutional, environmental, and demographic factors shape production choices. Inputs such as labor (hired and family), seed, animal power, fertilizer, pesticides, land, and capital serve dual roles, as household decision variables and as physical drivers of output and costs. The combination of output maximization and cost minimization generates wheat profit efficiency, integrating technical and allocative efficiency under prevailing market conditions. Profit efficiency functions both as the outcome of farm-level decisions and as the intermediary transmitting efficiency gains into household welfare. As illustrated by the red dotted box, profit efficiency translates into welfare improvements including higher income, labor reallocation, and reduced vulnerability to shocks. These mechanisms explain how efficiency gains extend beyond the farm gate to household well-being. The final stage captures welfare outcomes, household food security, income stability, and reduced vulnerability. The framework posits profit efficiency as the critical intermediary, determining whether production gains are converted into sustained welfare improvements. In light of this, we propose the testable hypothesis (H1): higher profit efficiency has a positive relationship with household food security.

3. Materials and Methods

3.1. The study area

The study was conducted in Ada'a District (Figure 2), located 45 km southeast of Addis Ababa in East Shoa Zone, Oromia Region, Central Ethiopia. The district covers 708.49 km² with a subtropical climate and elevations ranging from 1,600 to over 3,100 m above sea level (Ada'a District Finance Office, 2023). Average annual rainfall is about 839 mm (Birhanu et al., 2022), concentrated in two rainy seasons, spring (April–May) and summer (June–August), with short rains in February and March (Belay, 2018; Ethiopian Meteorological Institute, 2025). Geographically, Ada'a lies between 8°34′00″–8°58′00″ N latitude and 38°48′00″–39°12′00″ E longitude. Based on 2024 projections, the district's population is 188,181, with women comprising 48% (ESS, 2024). Administratively, Ada'a includes 24 rural and four urban kebeles, with Bishoftu as its center. The dominant livelihood is mixed farming, combining crops and livestock, with subsistence production meeting most household food needs (Belay, 2018).

Ada'a was purposively selected as a representative high-potential wheat-producing district. Wheat is grown under rain-fed (80%) and irrigated (20%) systems, generating variation in technology adoption, input use, and farm management (ESS, 2023; Tadesse & Asefa, 2025). Despite contributing 15% of Oromia's wheat output, yields average only 1.8 t/ha, well below the national mean of 3.05 t/ha (Birhanu et al., 2022; Tariku et al., 2022; USDA, 2025). This gap reflects economic inefficiencies as farmers struggle to achieve profit-maximizing production under technical and market constraints (van Dijk et al., 2017). Although Ada'a is considered relatively food secure, local data reveal hidden vulnerabilities: 32.8% of households produce below subsistence needs, 43.4% cultivate less than one hectare, and 39.3% face moderate or severe food insecurity (Ada'a District Agriculture Office, 2024; Shumiye et al., 2025). This productivity–food security paradox underscores the importance of examining profit efficiency in high-potential regions often assumed to be secure.

Consequently, the district provides a suitable empirical setting to test whether profit efficiency improvements translate into household food security. Ethiopia's current agricultural policy, particularly the 2021 National Wheat Development Strategy, aims at national self-sufficiency, making Ada'a a timely focus. If a high-potential region like Ada'a faces structural bottlenecks that prevent efficiency gains from improving welfare, it becomes a stress test for the local wheat development policy as well as the national strategy. Such findings would likely imply the need for "course correction" in areas such as input pricing or market stabilization. This "early warning system" logic aligns with Flyvbjerg's (2006) rationale for critical cases and Yin's (2018) emphasis on mechanism-based generalization. It provides a robust justification for purposive sampling, highlighting that lessons from Ada'a serve as prognostic indicators for the success of Ethiopia's wheat initiative in similar regions.

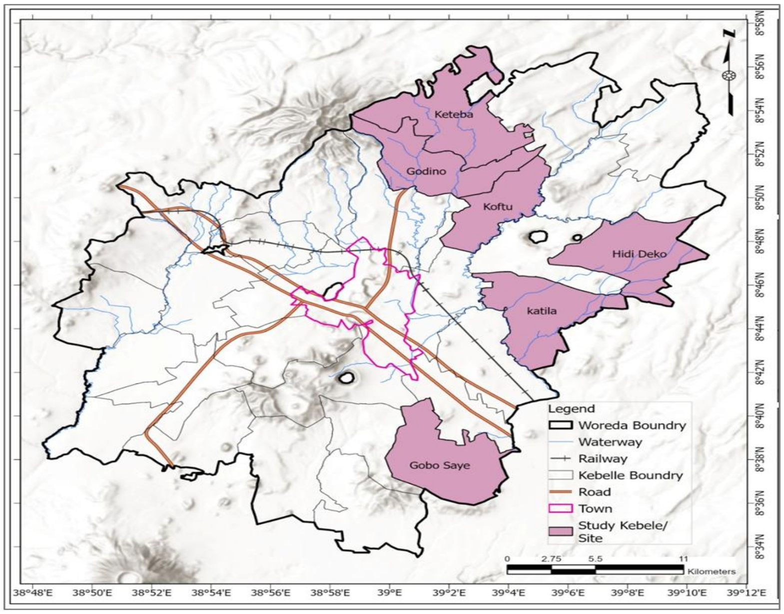

Figure 2: Location of Ada'a district
Source: Adapted from CSA (2007) and the Humanitarian Data Exchange (HDX) (2024).

3.2. Study Design

This study is guided by the pragmatic research paradigm, which prioritizes methods best suited to answering research questions rather than adhering to a single epistemological stance (Tashakkori & Teddlie, 2010). A concurrent embedded mixed-methods design was utilized, combining quantitative and qualitative approaches within a single framework. While the analysis is primarily quantitative, a qualitative strand was embedded to provide contextual depth and support for statistical results. The choice of this design follows established recommendations that mixed methods capitalize on the complementary strengths of quantitative breadth and qualitative depth while mitigating their limitations (Creswell & Plano Clark, 2018). Moreover, Greene et al. (1989) emphasize that embedding qualitative insights within quantitative analysis enhances triangulation, complementarity, and development, thereby strengthening validity and interpretive richness. In this study, qualitative evidence ensures that numerical findings are not only statistically robust but also grounded in the lived realities of smallholder households, providing a deeper understanding of the efficiency and household food security relationship.

3.3. Determination of sample size and sampling strategy

The research used a three-stage sampling approach combining probability and non-probability techniques. First, the study purposively selected Ada'a District as a critical case study (see Section 3.1). As a high-potential wheat-producing area assumed to be food secure, it provides an appropriate setting to examine the profit efficiency–food security nexus. Second, the study adopted stratification of the kebeles following the Ada'a District Agriculture Bureau, which classified the district's 22 rural Kebeles into high-, medium-, and low-productivity categories. From each stratum, two Kebeles were randomly selected, yielding six in total. This ensured representation across productivity levels while maintaining randomness within strata, allowing for a balanced assessment of wheat profit efficiency and household food security. Finally, households were drawn through probability-proportional-to-size random sampling based on Kebele household lists. The target population consisted of rural households engaged in mixed farming. Determination of sample size followed Yamane's (1967) formula:

$$n = N/(1 + Ne^2)$$

where N=5,563 households and a 5% allowable error, the required minimum sample size was determined to be 374. To account for potential nonresponse and missing values, a 15% contingency was added, increasing the final sample size to 430.

A qualitative component was incorporated to support explanatory objectives using purposive sampling. A maximum variation approach captured diverse perspectives across institutional actors and farming households, aiming to explain quantitative patterns rather than achieve statistical representativeness. Sample size was determined by analytical sufficiency, where diversity and explanatory depth outweighed numerical representation (Ritchie & Spencer, 1994). Accordingly, six KIIs and six FGDs took place, consistent with methodological guidance for embedded mixed-methods designs (Creswell & Plano Clark, 2018). Selection of key informants relied on their institutional positions, experience, and active participation in cereal production value chains, using snowball sampling. Criteria included at least three years of professional experience and familiarity with input systems, extension services, and local markets. The final sample included representatives from the district agriculture office, extension workers, a cooperative leader, and an input supplier/trader, ensuring institutional triangulation.

FGDs employed stratified purposive sampling guided by quantitative results. Farmers were grouped by wheat production levels (high, medium, low) as classified by the Ada'a District Agriculture Office. Six FGDs (two per category) were held, each with 6–10 participants drawn from the survey sample, ensuring direct linkage between qualitative and quantitative data. Groups were internally homogeneous but varied across categories to capture differences in production, socioeconomic conditions, land fragmentation, and market access. Recruitment was facilitated through local contacts and community leaders, with voluntary informed consent obtained.

3.4. Data collection instruments and procedures

The development of instruments and procedures was guided by the concurrent embedded mixed-methods design. A cross-sectional, structured in-person survey was conducted with 430 randomly selected households by trained enumerators under close supervision. A pre-test with 30 respondents assessed reliability and refined clarity. The survey questionnaire was primarily developed for this study, with selected FCS questions adapted from the WFP (2008). Secondary data from government reports and credible publications contextualized and validated primary findings, particularly on wheat inputs, outputs, and farming systems. Measurement of household food security employed the FCS, a standardized WFP methodology that integrates dietary diversity, frequency of consumption, and the nutritional value of food groups. Data were gathered through a seven-day recall of household consumption. Frequencies (0–7 days) for eight food groups were multiplied by nutritional weights ranging from 0.5 for staples (fats, sugars) to 4 for protein-rich foods (meat, dairy). Summed scores yielded a continuous variable classifying households as having poor, borderline, or acceptable consumption patterns (WFP, 2008).

Qualitative data collection was conducted using standardized semi-structured guides to ensure thematic consistency. Interviews and discussions were carried out in Afan Oromo and Amharic, with participants' consent to record their responses via audio, and complemented by field notes. Recordings were transcribed and translated into English with attention to contextual meaning. Data of both quantitative and qualitative types were gathered concurrently from April to May 2024, covering the 2023/24 agricultural season.

3.5. Data cleaning and preparation

The dataset was subjected to rigorous cleaning prior to analysis. For the quantitative survey, systematic checks identified data entry errors, implausible values, and logical inconsistencies (e.g., negative or unrealistic input/output values). Missing data were assessed: observations lacking critical variables (e.g., output, key inputs, or food security indicators) were excluded, while minor gaps were addressed through imputation or listwise deletion depending on their pattern. Continuous variables were standardized for unit consistency, and transformations such as per-hectare normalization ensured comparability across households. Only observations with complete and consistent data were retained for final analysis.

For qualitative data (KIIs and FGDs), cleaning involved verbatim transcription, translation where necessary, and systematic familiarization. Transcripts were cross-checked against field notes and audio recordings to ensure accuracy and minimize errors. Inconsistencies or unclear responses were resolved through iterative review of original recordings, and all data were anonymized to protect confidentiality. Using the Framework Analysis approach (Ritchie & Spencer, 1994), transcripts were cleaned, organized, indexed, and coded to facilitate qualitative analysis.

3.6. Measurement, data quality, and analytical diagnostics

Key variables were derived from participant-reported survey responses, potentially affected by recall bias, measurement error, and strategic misreporting. To mitigate these risks, procedural validation and econometric strategies were applied. Internal consistency checks and systematic outlier screening were conducted. Outliers were identified through graphical inspection (boxplots, scatterplots) and standardized residuals from preliminary ordinary least squares (OLS) regressions. Observations exceeding three standard deviations or falling outside agronomically plausible ranges were treated as reporting errors and excluded. In line with the translog functional specification, continuous variables were log-transformed to reduce extreme-value influence and convert multiplicative disturbances into an additive structure. Continuous regressors were mean-centered to mitigate multicollinearity from interaction and squared terms. Within the stochastic frontier analysis (SFA) framework, measurement error was accommodated through the composite error structure: the symmetric noise component (v_i) captured random shocks and reporting inaccuracies, while the one-sided component (u_i) represented inefficiency. This decomposition enabled separation of statistical noise from inefficiency in estimating profit efficiency scores.

Multicollinearity was assessed for both SFA and beta regression models using Variance Inflation Factors (VIF). Anticipated collinearity among higher-order terms in the translog specification was reduced through mean-centering while retaining flexibility. VIF diagnostics were also computed for the beta regression model to ensure coefficient stability. The study employed a propensity score matching (PSM) framework to construct a comparison group with similar observable characteristics, strengthening the assessment of profit efficiency's association with household food security. Matching quality was evaluated using standardized mean differences, and sensitivity to hidden bias was tested with Rosenbaum bounds. All quantitative analyses were conducted in Stata 17. Cleaned datasets and annotated do-files can be obtained from the authors upon a justified request to facilitate reproducibility.

3.7. Data Analysis

The quantitative dataset was examined using descriptive statistics, stochastic frontier analysis (SFA), beta regression, and propensity score matching (PSM). Summary statistics (frequencies, percentages, means, standard deviations, and coefficients of variation) were used to describe household and farm characteristics, profit efficiency scores, and food security indicators. Independent t-tests compared mean profit efficiency between households with and without specific characteristics (coded 1 = yes, 0 = no), while Spearman's correlation assessed associations between continuous variables and profit efficiency. Likelihood ratio tests evaluated model specifications and tested hypotheses. Profit efficiency distributions were visualized using bar graphs. Beyond descriptive analysis, SFA estimated farm-level profit efficiency, beta regression examined determinants of inefficiency, and PSM assessed the association between profit efficiency and household food security while controlling for selection bias. This framework integrates efficiency measurement with its determinants and outcomes, offering a comprehensive view of the efficiency–food security nexus.

The qualitative analysis was carried out using a deductive thematic approach based on Ritchie and Spencer's (1994) framework analysis, aligned with the findings of the econometric models. The process involved familiarization, development of a coding framework based on key variables (input use, pest infestation, land fragmentation, extension services, market access, and the profit–food security linkage), systematic coding of transcripts, and organization into thematic matrices. The emphasis was on identifying explanatory mechanisms and contextual factors rather than generating independent qualitative theory.

3.7.1. Covariate selection and validation

Potential predictors for the econometric models (SFA, beta regression, and PSM) were identified through a comprehensive literature review, with inclusion guided by theoretical relevance and empirical support. Variables lacking justification or showing limited variability were excluded to maintain parsimony, interpretability, and parameter stability. This approach aligns with best practices in regression modelling, where indiscriminate inclusion undermines inference and stability (Wallisch et al., 2020), while careful selection enhances accuracy and interpretability (Ullmann et al., 2024). Harrell (2015) similarly emphasizes theory-driven covariate selection. By excluding weak predictors, the final models focus on variables most likely to influence profit inefficiency. To ensure robustness, likelihood ratio and Wald tests were applied in SFA and beta regression to examine joint and individual significance of covariates. Nested model comparisons and fit metrics (pseudo-R^2, AIC, BIC) assessed the influence of excluded variables. For PSM, covariate balance tests and Rosenbaum bounds sensitivity analyses evaluated whether selected covariates adequately controlled for inherent differences across treatment versus control groups and assessed vulnerability to unobserved confounders.

3.7.2. Stochastic frontier profit analysis (SFPA)

The stochastic profit frontier, which separates inefficiency from random shocks, is widely regarded as a robust method for measuring profit efficiency in cross-sectional data (Battese & Coelli, 1995; Ali et al., 1996). Stochastic frontier analysis can be implemented using either single-stage (joint maximum likelihood) or two-stage procedures, each with trade-offs. The two-stage approach first estimates the frontier to obtain inefficiency scores, which are then regressed on explanatory variables, offering interpretive clarity but potentially introducing bias since the first stage assumes inefficiency is independently distributed while the second allows dependence on covariates. The two-stage approach, despite the indicated limitations, continues to be widely employed in agricultural efficiency research owing to its adaptability and simplicity (Jondrow et al., 1982; Kumbhakar & Lovell, 2000; Amena & Mulatu, 2020; Shrestha et al., 2022; Agazhi et al., 2024). Following this approach, the present study estimated farm-level wheat profit efficiency using a stochastic frontier function, generated efficiency scores, and subsequently examined determinants of inefficiency with a beta regression model. This procedure quantifies inefficiency while identifying key drivers of farmer performance, providing a robust empirical foundation for policy interventions (Jondorw et al., 1982; Kumbhakar & Lovell, 2000).

This study adopted the translog specification for its theoretical flexibility and empirical relevance. Unlike the restrictive Cobb–Douglas, the translog allows variable output elasticities and captures nonlinear input interactions (Christensen et al., 1973). Such flexibility is critical in cereal production, where complementarities and substitutabilities among inputs (labor, land, capital, seed, fertilizer) are common. The translog's second-order approximation models these interactions without rigid assumptions, while effectively separating inefficiency from random shocks, yielding robust and consistent estimates of profit efficiency (Battese & Coelli, 1995; Ali et al., 1996). Statistical tests comparing Cobb–Douglas and translog forms supported the empirical specification, which was used to estimate profit efficiency and examine links to household food security.

The stochastic wheat profit function was defined in terms of gross margin (GM), calculated as total wheat revenue (TR) minus total variable costs (TVC).

$$\mathrm{GM} = \pi = \mathrm{TR} - \mathrm{TVC} = \mathrm{P_i Q_i} - \sum \mathrm{w_i X_i} \;\ldots\ldots\ldots(1)$$

To normalize the profit function, the gross margin (π) is divided on both sides of equation (1) by the market price of wheat output (P_i). That is,

$$\pi_i^* = \frac{\pi}{P_i} = \frac{P_i Q_i - \sum w_i X_i}{P_i} = Q_i - \frac{\sum w_i X_i}{P_i} = f(X_i, Z) - \sum p_i X_i \text{ ……………(2)}$$

where Z represents a vector of fixed factor input prices and where $p_i = \frac{w_i}{P_i}$ represents the vector of normalized variable input prices for wheat production. The function $f(X_i, Z)$ represents the wheat production function. The normalized profit function is theoretically and econometrically appropriate, treating input prices and fixed factors as exogenous for price-taking farmers (Christensen et al., 1973; Diewert, 1974). The normalized wheat profit efficiency model is specified as follows:

$$\pi_i^* = \frac{\pi}{P_i} = f(X_i, Z) * \exp(v_i - u_i) \text{………………..…(3)}$$

where π_i^* represents the normalized profit of the i^{th} farmer, calculated as gross revenue minus total variable costs divided by the farm-specific wheat price; X_i denotes a vector of variable inputs; Z represents the vector of fixed inputs; P_i is the wheat output price; and ϵ_i is the composite stochastic error term, consisting of two independent elements of v_i and u_i. The stochastic profit function in this study is defined as a function of variable input prices, fixed factors, and error terms.

$$\pi_i = f(p_i, Z_i) * e^{\epsilon_i}$$

$$\epsilon_i = v_i - u_i$$

where p_i represents the vector of variable input prices for the wheat farm, standardized by the market price of wheat output (P_i); Z_i denotes the vector of the fixed factor of the i^{th} farm; and ϵ_i is the farm error term. Random profit variations beyond the farmer's control are captured by v_i, which is assumed to be independently and identically distributed with $N(0, \sigma_v^2)$, remaining independent of u_i. Profit inefficiency is represented by u_i, which is assumed to follow a nonnegative half-normal distribution $N(\mu_i, \sigma_u^2)$. Among the distributions most frequently applied in stochastic frontier analysis are the truncated normal distribution (Stevenson, 1980) and the gamma distribution (Greene, 2003).

Thus, u_i captures inefficiencies in the production process and is modelled with mean $\mu_i = \delta_0 + \sum_k \delta_k V_{ki}$ and variance $N(\mu_i, \sigma_u^2)$. In efficiency analysis, the specification of an appropriate distribution for the non-negative error term u_i is critical. Although stochastic frontier analysis commonly employs distributions such as the truncated normal, gamma, half-normal, and exponential, no definitive theoretical criterion exists for choosing one over another; the selection depends on data characteristics and empirical fit in specific contexts (Kumbhakar & Lovell, 2000). The profit inefficiency effect model is defined as follows:

$$u_i = \delta_0 + \sum_{k=1}^{K} \delta_k V_{ki} + \omega_i \text{ …………………….(4)}$$

where V_{ki} indicates the k^{th} variable, which explains i^{th} farm inefficiencies, δ_0 is the intercept, and δ_k is the coefficient for unknown parameters to be estimated. A farmer's profit efficiency (PE) for wheat is determined by comparing actual profit to frontier profit, accounting for variable input prices and fixed production factors. This relationship is expressed mathematically as follows:

$$PE_i = \frac{Actual\ Farm\ Profit}{Frontier\ Farm\ Profit} = \frac{f(X_i, Z)\ exp\ (v_i - u_i)}{f(X_i, Z)\ exp\ (v_i)} = exp\ (-u_i)$$

A unidirectional $u_i \geq 0$ indicates a farm's profit efficiency relative to the frontier. When $u_i = 0$, the farm operates on the efficiency frontier, achieving 100% profit efficiency by maximizing returns under the prevailing price and fixed inputs. If $u_i > 0$, the farm is inefficient, with profit falling below the frontier due to suboptimal performance (Ali et al., 1996). Farm-specific profit efficiency, denoted as PE_i, is defined as the mean of the conditional distribution of u_i as follows:

$$PE_i = E[e^{u_i} | \epsilon_i] = E\left[e^{\left(-\delta_0 - \sum_{k=1}^{K} \delta_k V_{ki}\right)} \middle| \epsilon_i\right] \text{ ………(5)}$$

We computed the conditional expectation u_i from the observed error term ϵ_i and then applied maximum likelihood estimation in Stata 17.0 to estimate the stochastic profit frontier model as outlined below.

$$\ln(\pi^*) = \alpha_0 + \sum_{j=1}^{5}\alpha_j \ln p_j^* + \frac{1}{2}\sum_{j=1}^{5}\sum_{k=1}^{5}\gamma_{jk}\ln p_j^* \ln p_k^* + \sum_{j=1}^{5}\sum_{l=1}^{2}\delta_{jl}\ln p_j^* \ln Z_l + \sum_{l=1}^{2}\varphi \quad \frac{1}{2}\sum_{l=1}^{2}\sum_{t=1}^{2}\eta_{lt}\ln Z_l \ln Z_t + v - u \text{ ……………… (6)}$$

where π^* represents normalized profit, calculated as total revenue minus variable costs, divided by the market price of wheat output. p_j^* denotes the price of the j^{th} input normalized by the wheat output price. Z_l represents the quantity of the l^{th} fixed input. Equation (6) lists the costs of capital and farmland used for wheat production as fixed inputs. The rental value for farmers who did not own land was calculated using the prevailing rates for land rentals. The costs for animal traction power, seeds, fertilizer, and pesticides used in the production of wheat during the 2023/24 season are among the variable expenses, as are labor costs, which comprise both hired and family labor, assuming that there is no productivity difference between the two. The value of wheat output was calculated via the farm gate price. The coefficients α_0, α_j, γ_{jk}, δ_{jl}, φ_l, η_{lt} are unknown parameters to be estimated. *ln* refers to the natural logarithm. The first term in equation (6) represents the intercept; the second term shows how each variable input drives normalized profit; the third and fourth terms capture interaction effects among variable inputs and between inputs and fixed factors. The fifth term shows the direct effects of fixed factors, the sixth captures their interactions, and the seventh includes the composite error term ($\epsilon = v - u$).

The variance parameters, $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \frac{\sigma_u^2}{\sigma^2}$, were estimated to assess sources of deviation in wheat farm profit from the efficiency frontier. Here, σ_v^2 captures the symmetric random error (v_i), and σ_u^2 reflects inefficiency (u_i). The total variance (σ^2) measures overall deviation, whereas gamma (γ), ranging from 0-1, represents the share due to inefficiency. Therefore, a $\gamma = 0$ suggests that profit variation is purely random, indicating full efficiency. In contrast, $\gamma > 0$ implies that inefficiency (i.e., technical, allocative, or scale) is present. If $\gamma = 1$, all deviation stems from inefficiency. The generalized likelihood ratio (LR) test is used to test the following hypotheses:

$$LR_\lambda = -2\{\ln[L(H_0)] - \ln[(L(H_1)]\} \text{……………..(7)}$$

where Equation (7), which represents the likelihood ratio (LR) test, evaluates hypotheses by comparing the log-likelihoods under the null ($L(H_0)$) and alternative ($L(H_1)$) scenarios. The LR_λ statistic follows a chi-square (χ^2) distribution, with degrees of freedom corresponding to the number of restrictions imposed by the null. The null hypothesis is not rejected when the LR_λ value falls below the critical threshold at a specified significance level. The analysis involves testing three distinct hypotheses:

$$H_0: \gamma_{jk} = \delta_{jl} = \eta_{lt} = 0$$

The coefficients of the cross terms in the translog model (Equation (6)) are zero, so the Cobb–Douglas model fits.

H_0: $\gamma = 0$. There are no profit inefficiency effects, so the inefficiency model is not needed

$$H_0: \delta_0 = \delta_1 = \delta_2 \ldots = \delta_8 \text{ ………………………(8)}$$

Profit inefficiency effects are absent in the beta regression model (Equation 8); the combined impact of these variables on inefficiency is statistically insignificant.

Researchers have used a variety of econometric approaches to study the determinants of profit inefficiency, including quantile regression (Kelemu & Negatu, 2016), Heckman's two-stage approach (Leta, 2018), ordinary least squares (Amena & Mulatu, 2020), the double-hurdle model (Gidelew et al., 2022), and, the Tobit model (Agazhi et al., 2024). Each method captures different aspects of farm-level efficiency. In this study, the average wheat profit inefficiency score was 0.2632, ranging from 0.0958 to 0.8663. Because these scores are fractional and bounded, selecting an appropriate estimation technique is critical. Models such as Heckman, Tobit, or double-hurdle are generally suitable when the data include zero values. However, all observations in this study are strictly positive, making these models inappropriate. The Tobit model may introduce bias by treating nonzero inefficiency scores as censored and assuming they stem from a single latent process. The double-hurdle model assumes a two-stage decision process, which does not match the nature of fractional inefficiency scores and could lead to incorrect conclusions. Heckman's two-stage approach requires valid exclusion restrictions and assumes normally distributed errors, leaving estimates highly sensitive to assumption violations. Quantile regression does not consider the bounded range of the outcome variable and may produce infeasible predictions, while ordinary least squares is unsuitable for fractional data because it can generate inconsistent estimates and values outside the (0,1) interval. Even censored models like Tobit may fail when observations cluster near boundaries, underscoring the need for a method tailored to fractional outcomes.

Fractional response models, such as beta regression, provide a robust alternative for continuous, bounded dependent variables representing rates, proportions, or probabilities, including profit inefficiency (Francis, 2017). The fractional response probit model is particularly appropriate when the outcome variable takes values bounded between zero (full efficiency) and one (complete inefficiency) (Papke & Wooldridge, 2008; Francis, 2017). In this study, the minimum and maximum wheat profit inefficiency scores do not reach the absolute bounds of 0 or 1. Model comparison shows that beta regression (AIC = -878.86, BIC = -846.65) outperforms the two-limit Tobit model (AIC = -846.70, BIC = -814.49). Empirical evidence also supports beta regression as suitable for continuous dependent variables confined within, but not including, the limits (Ferrari, 2013). Although rarely applied to profit inefficiency, beta regression has been widely used to address non-normality and heteroscedasticity in bounded data. It models outcomes restricted to the unit interval while accommodating skewness and varying variance structures (Usuga Manco et al., 2025). Its application aligns with recent efficiency studies (Endalew et al., 2023; Degfachew et al., 2025). In this study, the profit inefficiency variable is modelled as following a beta distribution, allowing for the analysis of demographic, socioeconomic, institutional, environmental, and infrastructural determinants.

$$f(y; m, \varphi) = \frac{\Gamma\varphi}{\Gamma(m\varphi)\Gamma\big((1-m)\varphi\big)} y^{m\varphi-1}(1-y)^{(1-m)\varphi-1}, 0 < y < 1$$

where m represents the expected value of y, that is, $E(y) = m$. The parameter φ, known as the precision parameter, controls the dispersion of the dependent variable, with higher values of φ resulting in a smaller variance and tighter clustering around the mean. Specifically, $Var(y) = \frac{V(m)}{1+\varphi}$, where $V(m) = m(1-m)$. In standard beta regression, the mean m is linked to covariates, while the precision φ is considered a nuisance parameter. Therefore, $E(y_i|x_i)$, where x_i represents the vector of covariates and y_i is the outcome variable.

In beta regression, selection of the link function determines how covariates affect the mean of the outcome variable, constrained between 0 and 1, shaping the overall regression model. Accordingly, we specified three links: logit, probit, and complementary log-log (cloglog). The logit link models the dependent variable on a log-odds scale and is widely used for its symmetry and interpretability. The probit link is similar but assumes a standard normal latent distribution, giving slightly different tail behavior. The cloglog link is asymmetric, stretching the upper tail, and is particularly suitable when the dependent variable is skewed toward higher values. Choosing the appropriate link ensures the model accurately captures the outcome's distribution. The link functions are defined below:

Logit: $g(m_i) = \ln\left(\frac{m_i}{1-m_i}\right)$ ……………………….(8)

Probit: $g(m_i) = \varphi^{-1}(m_i)$………………………..(9)

Cloglog: $g(m_i) = \log(-\log(1-m_i))$………..(10)

The best link function was determined using the lowest AIC and BIC values, with the corresponding specification chosen for the final estimation. Predictors were incorporated into the beta regression framework according to theoretical justification and empirical validation (see Section 3.7.1), with their hypothesized effects summarized as follows: Seed type (1 = improved variety, 0 = local variety), where improved seeds are expected to reduce inefficiency by increasing yields and resource-use efficiency. Access to irrigation (1 = yes, 0 = no) is also expected to lower by stabilizing production under varying climatic conditions. Distance between the wheat farm and the main road, expressed in minutes of travel, may influence efficiency, as greater distances can limit market access, delay input delivery, and increase transportation costs, potentially raising farm inefficiency. Wheat pest infestations (1 = yes, 0 = no) are likely to increase inefficiency due to yield loss. More frequent extension contact (number of visits) and greater farming experience (in years) are both expected to reduce inefficiency by improving farm management. Among the factors influencing farm efficiency, information plays a crucial role. Access to wheat price information (1 = yes, 0 = no) is expected to improve efficiency by enabling more informed marketing and sales choices. Land fragmentation, defined as the division of a farm into several scattered, noncontiguous plots of varying size and quality, is expected to increase inefficiency because such plots are more difficult to manage (1 = yes, 0 = no).

3.7.3. Application of the propensity score matching (PSM) method

Propensity Score Matching (PSM) was applied to assess the relationship between wheat profit efficiency (PE) and household food security, as measured by the FCS. PSM constructs a counterfactual by matching households in the treatment groups (*high_PE* or *low_PE*) with observationally similar households in the comparison group based on their propensity scores, thereby balancing observable covariates and reducing selection bias. This allows estimation of the average treatment effect on the treated (ATET), interpreted as the conditional difference in food security outcomes for households classified within a specific efficiency group. However, the validity of PSM relies on the conditional independence assumption and the presence of common support; as a result, it cannot control for unobserved heterogeneity or provide definitive causal inference.

Profit efficiency (PE), estimated from the stochastic frontier model, is inherently a continuous and relative measure rather than an absolute benchmark. To construct analytically meaningful treatment groups, the study adopts a distribution-based classification by partitioning households into quartiles. The bottom quartile (*low_PE*) represents the most inefficient 25 percent of producers operating far from the empirical profit frontier, while the top quartile (*high_PE*) captures the most efficient 25 percent, approximating near-frontier performance. Each of these groups is compared with the remaining households. Focusing on the extreme quartiles is methodologically deliberate. First, it maximizes contrast in underlying production behavior and resource allocation, thereby strengthening the empirical signal when examining welfare outcomes. By concentrating on the tails of the distribution, the approach reduces overlap in the outcome-generating process and approximates a stronger counterfactual contrast between groups, improving the interpretability of estimated effects relative to marginal differences in efficiency. Second, the use of quartile-based thresholds avoids imposing arbitrary absolute cut-offs on a relative metric. Instead, it relies on non-parametric, data-driven classification that is robust to the typically skewed distribution of efficiency scores, consistent with the interpretation of efficiency as a relative performance measure in frontier analysis (Kumbhakar & Lovell, 2000; Coelli et al., 2005).

Within this framework, "treatment" is defined as exposure to distinct production regimes rather than a purely statistical classification. Households in the *high_PE* group reflect near-optimal input allocation and market-oriented decision-making consistent with frontier behavior, whereas those in the *low_PE* group capture binding inefficiency constraints, including suboptimal input use and limited access to productivity-enhancing resources. Accordingly, the two comparisons, "*Efficient vs. Rest*" and "*Inefficient vs. Rest*", enable estimation of the ATET, interpreted as the conditional welfare differential associated with residing in the upper or lower tail of the efficiency distribution, rather than implying a strictly causal effect in the absence of strong identification assumptions. The construction of the treatment variable and the interpretation of the findings follow an approach similar to that used in prior empirical studies, including Karki et al. (2015), which documented a positive relationship between technical efficiency and household welfare outcomes, such as income and food security.

Propensity scores were obtained through logistic modelling, where treatment status was specified as a function of selected covariates. Covariates comprised household head's education and age, farm size, household size, access to extension services, livestock holdings (measured in tropical livestock units, TLU), and cooperative membership, following the procedures described in Section 3.7.1. To reduce potential confounding and create comparable groups, propensity score matching (PSM) was performed using multiple algorithms: nearest-neighbor matching with one and five neighbors, and radius matching with a calliper of 0.01.

Covariate balance between treated and control households was evaluated using standardized mean differences (SMDs), and robustness to potential unobserved confounding was assessed using Rosenbaum sensitivity bounds (see Section 3.6 for details of the matching procedure and diagnostics). Once satisfactory balance was achieved, the ATET was computed (Equation 11) with robust standard errors that adjust for the matching procedure:

$$\mathrm{ATET} = \mathrm{E}[\mathrm{F}_1|\mathrm{T}=1,\mathrm{X}] - \mathrm{E}[\mathrm{F}_0|\mathrm{T}=0,\mathrm{X}] \ldots\ldots\ldots(11)$$

Where F_0 indicates the FCS, a household would achieve if it were a member of the control group, F_1 reflects the FCS if it were a member of the treatment group (low or high profit efficiency), T is the treatment indicator ($T = 1$) for treated, ($T = 0$) otherwise), and the vector of observed covariates used in the propensity score estimation is represented by X. Accordingly, this estimate of ATET captures the predicted difference in FCS between treated and matched households, conditional on X.

The reliability of the estimated relationship between profit efficiency and the FCS was further evaluated using a Rosenbaum sensitivity test, conducted after estimating the ATET. The results indicate that the positive effect of profit efficiency remains significant at the 5% threshold up to a critical Γ (Gamma) value of 1.4. This implies that an unobserved confounder would need to increase the odds of being profit-efficient by 40% while being strongly correlated with food security to invalidate the findings (Rosenbaum, 2005). Beyond $\Gamma = 1.4$, the upper-bound p-value rises to 0.090 at $\Gamma = 1.5$, suggesting moderate sensitivity to extreme hidden bias. Within agricultural economics and food security studies, a Γ (gamma) threshold of 1.4 is generally considered sufficient to provide credible treatment effect estimates when combined with high-quality covariate balance (Caliendo & Kopeinig, 2008). Taken together, these diagnostics indicate that, although unobserved bias cannot be entirely excluded, it is unlikely to be strong enough to overturn the estimated effect. Accordingly, the analysis provides robust empirical evidence that higher profit efficiency is associated with improved household food security.

4. Results

4.1. Wheat farm profit efficiency scores and their distribution across households

Figure 3 illustrates the distribution of profit efficiency scores for the sampled wheat farms, with a mean score of 0.7368, spanning values between 0.1337 and 0.9042. This finding suggests that, on average, 26.32% of the inefficient farms could improve their performance by overcoming existing constraints. Such a gap implies significant unrealized productivity potential, highlighting that improvements in management practices and resource allocation could yield meaningful gains in profitability without necessarily increasing input use.

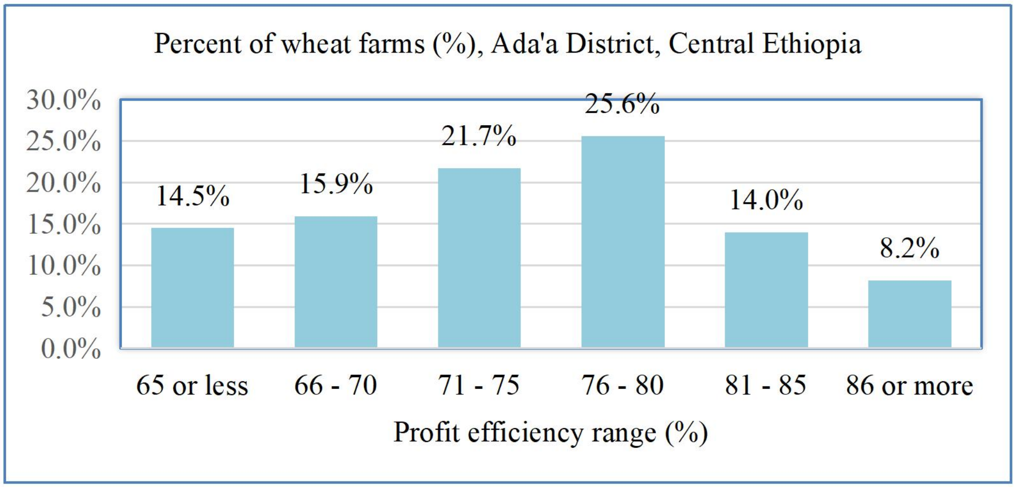

Figure 3: Profit efficiency score distribution of wheat farms
Source: Authors' construction via own survey data (2024)

Approximately 44% (182) of households operated below the mean efficiency score, whereas 56% (232) operated above it, indicating substantial room for improving efficiency among a significant share of farmers. Approximately 15% of the households had efficiency scores of 65% or lower, whereas approximately 16% scored between 66% and 70%. No farms achieved a profit efficiency score higher than 0.9042, indicating that even the most efficient farms have the potential for further improvement. The least profit-efficient wheat farmer would need a 95.81% improvement to match the most efficient farmer in the study area. On average, farmers require a 29.11% efficiency gain to reach this benchmark. Even the most efficient farmers fall short of the production frontier by 9.58%.

Wheat farm profit efficiency scores show clear stratification across quartiles (Table 1). Q1 farms have the lowest mean efficiency (0.61) and high variability (CV ≈ 13.4%), indicating substantial performance gaps. Efficiency rises through Q2 (0.72) and Q3 (0.77), with variability narrowing (CVs 2.47% and 1.74%), reflecting more consistent performance. Q4 achieves the highest mean efficiency (0.84) with slightly higher dispersion (CV ≈ 3.3%) than Q2 and Q3. The overall mean efficiency is 0.74, ranging from 0.13 to 0.90, highlighting the coexistence of underperforming and highly efficient farms.

Table 1**:** Distribution of wheat farm profit efficiency scores by quartiles

Quartile	**Observations**	**Minimum value**	**Maximum value**	**Mean value**	**Standard deviation**	**CV † (%)**
Q1	104	0.1337	0.6880	0.6128	0.0821	13.3975
Q2	103	0.6886	0.7470	0.7205	0.0178	2.4705
Q3	105	0.7478	0.7974	0.7739	0.0135	1.7444
Q4	102	0.7990	0.9042	0.8414	0.0277	3.2921
Total	414	0.1337	0.9042	0.7368	0.09477	12.8624

Source: Author's computation; † = coefficient of variation

4.2. Comparison of profit efficiency scores by farm characteristics

Table 2 presents a mean comparison of profit efficiency scores by selected binary farm characteristics. Approximately 52% of households reported access to irrigation. Farms with irrigation recorded a greater mean profit efficiency (0.7490) relative to non-irrigated farms (0.7235). The mean difference in profit efficiency between irrigated and non-irrigated farms was -0.0255 (significant at the 1% level), suggesting a significant relationship between irrigation access and higher profit efficiency in this sample. This may reflect the role of irrigation in reducing moisture stress, improving input utilization, and enabling more stable production outcomes. Similarly, about 73% of farmers using improved seeds had higher profit efficiency (0.754) than those using local seeds (0.690), with the difference (-0.064, $p < 0.01$). This finding indicates that adoption of improved agricultural technologies may play an important role in enhancing farm-level profit efficiency through better yields, resilience, and market returns. Households with access to wheat price information exhibited slightly higher profit efficiency (0.7459 vs. 0.7292), and the difference in group means (-0.0167) is marginally significant at the 10% threshold. This finding likely suggests that access to market information may contribute to better production and marketing decisions, although the effect appears relatively modest in this sample. Improved price awareness can help farmers time sales, negotiate better prices, and allocate resources more efficiently.

Table 2**:** Comparison of mean profit efficiency across selected binary farm characteristics

Variables	**Observations (percentages)**	**Mean profit efficiency score**	**Mean difference**	**Standard error of the mean difference**
Access to irrigation				
Access	215 (51.9)	0.7490	-0.0255***	0.0092
No access	199 (48.1)	0.7235		
Seed type				
Improved seed	301 (72.7)	0.7542	-0.0639***	0.0100
Local seed	113 (27.3)	0.6903		
Access to wheat price information				
Access	187 (45.2)	0.7459	-0.0167*	0.0093
No access	227 (54.8)	0.7292		
Land fragmentation				
Yes	103 (24.9)	0.7067	0.0400**	0.0106
No	311 (75.1)	0.7467		
Wheat farm pest infestation				
Yes	152 (36.7)	0.7318	0.0078^{NS}	0.0097
No	262 (63.3)	0.7396		

Source: Authors' calculation using own survey data 2024; NS= not significant
*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Similarly, as depicted in Table 2, approximately 25% of households reported land fragmentation as a key constraint, and those experiencing fragmentation had lower mean profit efficiency (0.7067) than households without fragmentation (0.7467), with the mean difference (0.0400) statistically significant at the 5% level. Table 3 summarizes the correlations between continuous covariates and profit efficiency. Farming experience showed a modest positive association with profit efficiency ($r = 0.1955$, $p < 0.01$). Frequent extension contact was also positively correlated ($r = 0.1688$, $p < 0.01$). Proximity of the farm to the main road showed a weak positive relationship ($r = 0.106$, $p < 0.05$).

Table 3: Correlation of continuous farm characteristics with profit efficiency

Variable	Mean ± SD	Correlation with profit efficiency (r)
Farming experience (years)	13.2 ± 8.71	0.1955***
Frequency of extension contact	1.90 ± 1.80	0.1688***
Distance from the farm to the main road (minutes)	47.72 ± 24.00	0.1064**

Source: Authors' calculation using own survey data 2024; SD= Standard Deviation

** and *** denote statistical significance at the 5% and 1% levels, respectively.

4.3. Functional specification tests of the stochastic frontier profit model

A fundamental step in frontier modelling involves selecting an appropriate functional form to capture the complexities of agricultural production. The empirical validity of the profit frontier analysis was assessed using several diagnostic tests. The likelihood ratio test did not support the restricted Cobb–Douglas specification, favouring the translog model (χ^2 = 129.93, $p < 0.01$). Evidence also contradicted the hypothesis of no inefficiency effects (χ^2 = 8.53, $p < 0.01$), indicating the presence of non-random deviations from the frontier. Additionally, the explanatory variables in the beta regression were jointly significant (χ^2 = 82.00, $p < 0.01$), confirming the collective explanatory power of the selected determinants.

4.4. Stochastic translog profit function estimates of the determinants of wheat profit efficiency

The stochastic frontier analysis (Table 4) reveals important insights into the determinants of wheat profit efficiency. Land, fertilizer, and pesticide costs have significant positive effects on wheat profit, with 1% increases in these inputs increasing profits by 8.63%, 2.03%, and 1.96%, respectively ($p<0.01$). In contrast, holding other factors constant, labor (both family and hired), farm capital, and seed costs negatively affect profits, with 1% increases in these inputs reducing profits by 2.26%, 4.27%, and 3.82%, respectively; these effects are significant at the 10%, 1%, and 1% levels.

Wheat profit efficiency is also influenced by several significant interaction terms identified through stochastic frontier analysis (Table 4). Negative interactions include: labor × land (WL: –0.619, $p < 0.01$) and seed × land (SL: –0.379, $p < 0.05$); land × capital (LC: –0.506, $p < 0.01$) and fertilizer × capital (FC: –0.110, $p < 0.01$); and animal power × fertilizer (AF: –0.086, $p < 0.10$) and animal power × pesticides (AP: –0.195, $p < 0.10$). The interaction between fertilizer and pesticides (FP: –0.080, $p < 0.10$) is also negative. Positive interactions are seed × capital (SC: 0.189), fertilizer × land (FL: 0.210), and pesticide × land (PL: 0.309); these effects are significant at the 1%, 1%, and 5% levels, respectively. These positive interactions imply complementarities among certain inputs, where combining resources in balanced proportions enhances profitability more than using them independently. Quadratic terms show: pesticides × pesticides (PP: 0.065, $p < 0.05$) and fertilizer × fertilizer (FF: 0.060, $p < 0.01$) with diminishing marginal returns, and land × land (LL: 1.197, $p < 0.01$) exhibiting increasing returns. Collectively, the significant interaction terms account for approximately 18–22% of the total variation in profit efficiency.

The translog model demonstrates strong overall fit (Wald χ^2 (35) = 1,322.56, $p < 0.001$) and confirms significant profit inefficiency (σ^2 = 0.42, LR test p = 0.002), with the inefficiency component dominating random noise (γ = 0.6003, explaining about 60% of total variance). The Breusch–Pagan/Cook–Weisberg test (χ^2 = 0.08, p = 0.7765) indicates homoskedasticity, supporting model reliability. Overall, these diagnostic results strengthen confidence in the robustness and policy relevance of the estimated model. Therefore, interventions focused on extension support, input-use efficiency, and farm management skills may generate larger gains than input expansion alone.

Table 4: Estimates from the translog profit frontier model using the maximum likelihood method

Variables	Coefficient	Std. Error
Constant	32.2288***	8.1790
lnW(Labor, W)	-2.2624*	1.3715
lnA(Animal power, A)	0.8698	1.1473
lnS(Seed, S)	-3.8190***	1.0693
lnF(Fertilizer, F)	2.0267***	0.5331
lnP(Pesticides, P)	1.9596***	0.7033
lnL(Land, L)	8.6308***	1.8800
lnC(Capital, C)	-4.2672***	0.9306
0.5lnWxlnW	-0.1838	0.1715
0.5lnAxlnA	-0.1982*	0.1126
0.5lnSxlnS	0.0574	0.0884
0.5lnFxlnF	0.0603***	0.0205
0.5lnPxlnP	0.0654**	0.0253
lnWxlnA	0.3248***	0.1185
lnWxlnS	0.0399	0.1097
lnWxlnF	-0.0486	0.0597
lnWxlnP	-0.0719	0.0638
lnAxlnS	0.0737	0.1062
lnAxlnF	-0.0856*	0.0518
lnAxlnP	-0.1953*	0.1026
lnSxlnF	0.0578	0.0397
lnSxlnP	0.0617	0.0394
lnFxlnP	-0.0797*	0.0476
lnWxlnL	-0.6186***	0.1831
lnWxlnC	0.1716	0.1053
lnAxlnL	0.1185	0.1680
lnAxlnC	-0.0612	0.1013
lnSxlnL	-0.3789**	0.1497
lnSxlnC	0.1890***	0.0622
lnFxlnL	0.2096***	0.0784
lnFxlnC	-0.1103***	0.0298
lnPxlnL	0.3086**	0.1227
lnPxlnC	-0.0090	0.0322
0.5lnLxlnL	1.1970***	0.2295
0.5lnCxlnC	0.3303***	0.0854
lnLxlnC	-0.5062***	0.1138
Diagnostic statistics		
Sigma square ($\sigma^2 = \sigma_u^2 + \sigma_v^2$)	0.2953	0.0408
Gamma ($\gamma = \sigma_u^2/\sigma^2$)	0.6003	
Log likelihood function	-232.8507	
Wald χ^2 (35)	1,322.56	
Breusch Pagan/Cook-Weisberg test (χ^2)	0.0800	
Sample size	414	

Source: Authors' calculation via survey data from 2024

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.5. Beta regression analysis of factors affecting wheat profit inefficiency

A comparative assessment of alternative link functions was conducted using robust standard errors, evaluating logit, probit, and complementary log-log (cloglog) specifications based on AIC and BIC. The cloglog link showed the lowest AIC (−878.86) and BIC (−846.65), indicating the best fit, and was selected as the final model, reflecting the positive skew of profit inefficiency scores. Wheat profit inefficiency ranged from 0.096 to 0.866, satisfying the open (0,1) interval for beta regression. Comparison with the two-limit Tobit model confirmed that beta regression provided a more parsimonious fit (AIC = −874.59, BIC = −834.33) than Tobit (AIC = −842.70, BIC = −802.44). As shown in Table 5, the beta regression ($\chi^2 = 81.73$, $p < 0.01$) significantly outperformed the null, confirming that predictors explained inefficiency effectively.

Table 5: Determinants of wheat profit inefficiency in Ada'a District estimated using beta regression

Variables	Coefficients	Robust Std. Err.	Average marginal effect (dy/dx)
Irrigation access (1=yes)	-0.073 *	0.038	-0.0165
Farm-to-main road distance (minutes)	-0.002*	0.001	-0.0004
Wheat pest infestation (1=yes)	0.093 **	0.042	0.0210
Seed type (1=improved variety)	-0. 258***	0.046	-0.0580
Frequency of extension contact	-0.021 *	0.010	-0.0046
Household access to wheat price info (1=yes)	-0.063	0.038	-0.0142
Land fragmentation (1=yes)	0.123***	0.045	0.0277
Number of years of farming experience	-0.006 **	0.002	-0.0014
Constant	-0.807***	0.069	-
Model fit information			
Log pseudolikelihood value: 447.4303			
Likelihood ratio χ^2-value (8): 88.87 ***			

Source: Authors' calculation via survey data from 2024
NS=Not significant; *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

As indicated in Table 5, beta regression analysis reveals that, controlling for other factors, the use of improved wheat seed reduced inefficiency by 5.8 percentage points ($p < 0.01$). Land fragmentation increased inefficiency by 2.77 points ($p < 0.01$), and pest infestation raised it by 2.10 points ($p < 0.05$). Access to irrigation lowered inefficiency by 1.65 points ($p < 0.10$), and each additional extension contact reduced inefficiency by 0.46 points ($p < 0.05$). Farming experience decreased inefficiency by 0.14 points per year ($p < 0.05$), while distance to the main road increased it by 0.04 points per additional minute of walking ($p < 0.10$). Access to wheat price information was not significant. The overall fit was confirmed by a log pseudolikelihood of 447.43 and a likelihood ratio $\chi^2(8) = 88.87$ ($p < 0.01$).

4.6. Implications of wheat profit efficiency for household food security

Understanding how wheat profit efficiency affects household food security is critical, as higher efficiency can enhance income stability, resource use, and food access. We examined this relationship using propensity score matching across households with different efficiency levels. Before matching, standardized mean differences (SMDs) indicated moderate imbalances for education (−0.229), household size (−0.237), and tropical livestock units (TLU, −0.217). After matching, balance improved substantially, with all SMDs below 0.1, except farm size (SMD = 0.097), which remained acceptable. Matching used nearest-neighbor algorithms with one and five neighbors, and radius matching with a 0.01 caliper. Sensitivity analysis using the Rosenbaum bounds test indicated that higher profit efficiency continued to have a significant impact on household food security at the 5% level up to a critical Γ of 1.4; at Γ = 1.5, the upper-bound p-value rose to 0.090.

Table 6 summarizes the average treatment effects of wheat profit efficiency on household food security, proxied by FCS. Households in the bottom 25% of efficiency had significantly lower FCS scores. The ATET via nearest-neighbor matching with one neighbor was −8.47 points (z = −2.04, p < 0.05), with five neighbors −7.90 points (z = −2.60, p < 0.01), and radius matching (0.01) −7.23 points (z = −2.40, p < 0.05). Households in the top 25% of efficiency had positive and significant effects: ATET via one neighbor 8.91 (z = 3.21, p < 0.01), five neighbors 6.88 (z = 2.79, p < 0.01), and radius matching 7.12 (z = 2.39, p < 0.05).

Table 6: Average treatment effect using neighborhood matching and the radius matching algorithm.

Category	**NNM (1)**		**NNM (5)**		**Radius (0.01)**	
	ATT	**AI† robust S.E.**	**ATT**	**AI† robust S.E.**	**ATT**	**S.E.**
Inefficient vs. The Rest - *Households with profit efficiency(pe): PE* ≤ 0.69 *vs. PE* > 0.69						
FCS	-8.47**	4.14	-7.90***	3.04	-7.23**	3.01
Efficient vs. The Rest - *Households with profit efficiency (pe): PE* ≥ 0.80 *vs. PE* <0.80						
FCS	8.91***	2.77	6.88***	2.46	7.12**	2.97

Source: Calculated by the author. Statistical significance is indicated as follows: * p < 0.10, ** p < 0.05, *** p < 0.01.
† = Abadie–Imbens robust standard errors

5. Discussion

The mean wheat profit efficiency was 0.737, ranging from 0.134 to 0.904. Stochastic frontier results showed that land, fertilizer, and pesticide costs increased profits, while labor, capital, and seed costs reduced them. Beta regression indicated that improved seed use, irrigation access, frequent extension contacts, and farming experience reduced inefficiency, whereas land fragmentation, pest infestation, and distance to main roads increased it. Propensity score matching showed that households in the bottom 25% of efficiency had food consumption scores 7.23–8.47 points lower, while those in the top 25% had scores 6.88–8.91 points higher across methods. Post-matching diagnostics confirmed covariate balance, with standardized mean differences below 0.1. Sensitivity analysis using Rosenbaum bounds showed that effects remained significant at the 5% level up to Γ = 1.4, indicating robustness to moderate unobserved bias.

5.1. Wheat profit efficiency levels

Our analysis shows that wheat profit efficiency among smallholder farmers is highly variable and below potential. The mean score of 0.737 (range 0.134–0.904) indicates that most farmers operate beneath the production frontier, with even top performers falling 9.6% short. On average, farmers could raise profits by about 29% if they matched best performers, while the least efficient would require nearly a 96% improvement. Approximately 44% of households fall below the mean, highlighting widespread losses from suboptimal input use and management. The lowest quartile (Q1) shows the greatest variability (CV = 13.40%), compared to Q2 (2.47%), Q3 (1.74%), and Q4 (3.29%), indicating higher exposure to risk and managerial inefficiency. This pattern aligns with farm management and efficiency theory, which emphasize heterogeneity, resource constraints, and allocative inefficiency. Overall, the wide efficiency gaps point to substantial untapped potential, where improved input allocation and management could stabilize incomes, smooth consumption, and strengthen household food security.

5.2. Determinants of wheat profit efficiency

Our stochastic frontier analysis (SFA) shows that land, fertilizer, and pesticide use significantly enhance wheat profitability. While other factors held constant, a 1% increase in land area increased profits by 8.63%, while equivalent increases in fertilizer and pesticide use raised profits by 2.03% and 1.96%, respectively. This demonstrates that land contributed far more to profit growth than chemical inputs. Economically, farmers could achieve larger gains by expanding or better utilizing farmland, whereas chemical inputs, though beneficial, offered smaller improvements. These findings were supported by agricultural extension workers, who observed that farmers with larger plots applied inputs more efficiently and scheduled operations more effectively, boosting yields per hectare. Smaller plots often faced challenges in coordinated input application. A district agriculture office expert noted that timely, balanced fertilizer and pesticide use increased yield, but effectiveness depended on farmers' knowledge and management skills, underscoring that input efficiency was contingent on technical capacity. Farmers in FGDs, particularly those with smaller or fragmented plots, revealed that some underutilized fertilizers due to labor and cost constraints, highlighting a trade-off between plot size and input efficiency.

Our results on land, fertilizer, and pesticide use align with Shrestha et al. (2022), Ngeno (2024), and Mohamed (2025), who find that larger landholdings and well-managed inputs improve wheat profit efficiency in Nepal, Kenya, and Iraq, respectively. In contrast, Asefa and Ayalew (2024) report higher efficiency among smaller farms in Ethiopia, reflecting fragmentation, labor, and input access constraints. Ferreira and Féres (2020) identify a U-shaped, scale-dependent pattern in how farm size affects efficiency, while Arbelo Pérez et al. (2023) stress the role of farm heterogeneity. The positive effects of fertilizer and pesticide use found in the current analysis align with Shrestha et al. (2022) and Endalew et al. (2023), but contrast with Ngeno (2024) and Mohamed (2025), where mismanagement or environmental pressures lowered profitability. Collectively, these studies converge on the principle that efficiency gains depend on coordinated input use and farm management, but diverge due to context-specific agronomic, institutional, and socio-economic conditions. The evidence on land highlights an ongoing debate: whether larger farms consistently enhance efficiency or whether fragmentation and management capacity allow smaller farms to perform equally or better, underscoring the context-dependent nature of land–efficiency relationships.

The interaction effects in our SFA model show how inputs combine to shape profit efficiency. Negative interactions, such as labor × land or seed × land, suggest diminishing returns when inputs increase simultaneously without productivity gains. Positive interactions between fertilizer × land or pesticide × land indicate synergies when inputs are well coordinated. The qualitative study reveals a shared recognition of the importance of coordination, though differences emerge across production levels. Extension workers noted that delays in labor-intensive operations and uneven seed sowing on larger farms amplified inefficiencies, reinforcing the observed negative interactions. District agriculture experts emphasized that coordinated fertilizer application and proper land management increased yields, although variable soil fertility and inconsistent irrigation weakened these synergies. Farmers in FGDs in high-production areas reported that careful coordination of labor and seed improved outcomes, whereas FGDs in low-production areas highlighted that fragmented plots and limited labor capacity exacerbated inefficiencies.

Collectively, these findings underscore that efficiency depends not only on input levels but also on their coordination within institutional, labor, and market contexts, with effectiveness varying by farm size, management skill, and local constraints. Theoretically, our findings align with production economics models emphasizing input complementarity and marginal productivity interdependence, where efficiency is shaped as much by input combinations and management as by input quantities.

5.3. Beta regression analysis of factors affecting wheat profit inefficiency

The beta regression results indicate that wheat profit inefficiency in Ada'a District is significantly influenced by improved seed use, pest infestation, land fragmentation, extension contact, farming experience, irrigation access, and farm proximity to roads. Access to irrigation was associated with a small but statistically marginal reduction in inefficiency, lowering it by 1.65 percentage points. This suggests that water availability stabilizes yields and enhances input use, consistent with production frontier theory, which posits that easing key constraints reduces both technical and allocative inefficiencies. Qualitative evidence corroborated the quantitative finding, though perspectives varied. District agriculture experts noted that irrigation enabled timely fertilizer use and reduced reliance on erratic rainfall, while cooperative leaders observed that access was uneven, favoring better-connected farmers. Farmers with irrigation reported more stable yields, whereas those in rainfed areas highlighted vulnerability to rainfall variability and challenges in planning inputs. Collectively, these perspectives confirm the econometric result while emphasizing that irrigation's efficiency gains depend on infrastructure quality, equitable access, and effective management. This aligns with Ajay et al. (2025), who identified costly irrigation as a source of inefficiency, but contrasts with Mohamed (2025), where mismanagement increased inefficiency.

Farm proximity to main roads slightly reduced inefficiency, as remote farmers adapted input timing and labor allocation. Qualitative insights showed nuanced views. District agricultural experts emphasized that all-weather roads enabled timely input delivery and market access, while cooperative leaders noted improved coordination, though benefits varied. Farmers reported that road access eased transport and planning, whereas remoteness required adaptive strategies. These findings indicate that road access shapes efficiency directly, by lowering costs, and indirectly, by enabling adaptive management. Prior studies report inconclusive evidence on the role of distance. Endalew et al. (2022) found that greater farm-to-road distance increased inefficiency, while Ebrahim et al. (2020) showed that remoteness mainly constrained market participation. These mixed findings suggest that distance acts less as a direct driver of profit efficiency and more as a proxy for market integration and institutional access, with its impact contingent on the strength of rural infrastructure and support systems.

Pest infestation increased profit inefficiency by about 2 percentage points, raising production costs and reducing input productivity. Qualitative evidence supported this: farmers reported repeated or mistimed pesticide applications with limited effectiveness, while extension workers highlighted delayed responses that increased costs without improving yields. The primary mechanism appears twofold: inefficiency arises from higher expenditures and reduced yield response due to poor timing and management. Our finding aligns with Langridge et al. (2022), who highlighted growing pest management challenges under ecological variability, as well as Taddesse et al. (2020) and Singh and Joshi (2025), both of which document pest-induced yield and output losses in the field and during storage.

Switching from local to improved seed varieties reduced wheat profit inefficiency by approximately 6 percentage points, underscoring the economic importance of input quality in enhancing productivity. While seed quantity was negatively associated with profit efficiency in the SFA, suggesting diminishing returns or misallocation, the use of improved seed varieties significantly reduced inefficiency, indicating gains from technology adoption and input quality. This finding is consistent with production frontier theory, which posits that efficiency improves as inputs are used closer to their optimal combination. Qualitative evidence from an extension worker corroborated this finding, noting that improved seeds enhanced yield stability, reduced vulnerability to pests, and enabled better allocation of complementary inputs, including fertilizer and labor.

> *Farmers using improved seeds achieved higher yields and more resilient crops, even under suboptimal rainfall, though access remained constrained by limited availability and affordability, often leading to delayed planting and reduced benefits.*

Empirically, our finding aligns with Shrestha et al. (2022) and Ngeno (2024), who found that the use of improved or high-yield seed varieties significantly lowered profit inefficiency by enhancing returns to inputs and reducing both technical and allocative inefficiencies.

Frequency of extension visits reduced profit inefficiency by 0.46 percentage points per unit, and farming experience reduced it by 0.14 percentage points per unit, emphasizing the role of human capital in improving input allocation, timing, and decision-making. Qualitative evidence provides mixed but largely supportive insights. Extension workers emphasized that frequent contact enabled farmers to adopt improved practices, apply inputs at the right time, and respond more effectively to production challenges. More experienced farmers were also observed to make better agronomic decisions based on accumulated knowledge. However, some farmers in FGDs across low, medium, and high production categories noted that the effectiveness of extension support depended on its quality and consistency, with irregular visits, limited adaptation to indigenous knowledge, and generic advice constraining its impact. These findings suggest that while experience and extension access enhance efficiency, their effectiveness depends on the relevance, timing, and practical applicability of the support provided. Our findings align with Mdoda et al. (2022) and Shrestha et al. (2022), indicating that frequent extension contact enhances profit efficiency by promoting optimal input use and effective farm management. Farming experience also positively affected efficiency, consistent with Mirza et al. (2015) and Mohamed (2025), reflecting the benefits of accumulated tacit knowledge. Convergence highlights the role of human capital, while contextual differences suggest its impact is stronger where services are accessible, tailored, and responsive to local conditions.

Lastly, land fragmentation was associated with a slight increase in profit inefficiency, increasing it by about three percentage points. This reflects the structural limitations of small, scattered plots, which constrain optimal input use and reduce economies of scale in Ada'a district. Wheat farmers with low- and medium-production levels in FGDs noted the following:

> *Under our customary practice, we, as parents, divided already small landholdings among multiple heirs due to increasing family size and limited wage employment opportunities for youth, resulting in ever-smaller and scattered plots. As a result, this fragmentation had become a 'silent thief' of farm income. When our holdings were split into several tiny parcels across the Kebele, we lost significant time and incurred additional costs in moving oxen, transporting inputs, and collecting harvests. Although we worked harder, the scattered nature of our land constrained productivity and eroded expected profits long before produce reached the market.*

Discussants emphasized that "oxen drain," input waste, and labor fatigue were direct consequences of land fragmentation. Theoretically, our finding aligns with production theory on economies of scale and portfolio theory in agricultural economics, both emphasizing the trade-off between maximizing returns and mitigating risk through diversification. Empirically, our finding corresponds with Zhou, C et al. (2024), who reported that land fragmentation generally lowered technical efficiency, though farmers could offset this through crop diversification or part-time activities. Similar evidence from Ciaian et al. (2018), Ntihinyurwa et al. (2019), and Aslam and Fazal (2025) showed that fragmentation reduced productivity yet provided risk management benefits by spreading labor and production across multiple crops. These results underscore the dual role of fragmentation, reflecting trade-offs between efficiency and economic resilience.

5.4. Implications of wheat profit efficiency for rural household food security

The Propensity Score Matching results revealed a significant relationship between wheat profit efficiency and household food security. Households in the lowest efficiency quartile recorded a 7.23–8.47-point reduction in FCS, while those in the highest quartile recorded gains of 6.88–8.91 points. This demonstrates that profit efficiency is both a production outcome and a critical welfare transmission channel, directly influencing households' ability to access and consume diverse and sufficient food. The robustness of the results (Γ = 1.4) further suggests that this relationship remained stable even in the presence of moderate unobserved heterogeneity.

Qualitative evidence reinforced the quantitative findings. Agricultural extension workers noted that households with better input coordination and higher yields sustained food consumption throughout the year, particularly during lean periods. Cooperative leaders emphasized that more efficient farmers generated larger marketable surpluses, translating into improved purchasing power and dietary diversity. These insights converge with our empirical results, indicating that efficiency affects food security through both own-production consumption and market-mediated income effects. However, the relationship appeared conditional rather than linear. District agricultural experts pointed out that even highly efficient farmers did not always achieve improved food security if income was diverted to debt repayment, input costs, or non-food expenditures. Input suppliers and traders highlighted that price volatility and the timing of sales eroded efficiency benefits, showing that market conditions mediated how efficiency translated into food consumption. This underscores that efficiency alone is essential but insufficient for enhanced food security without supportive institutional and market environments. Our findings align with the agricultural household model, which posits the interdependence of production and consumption decisions. In this framework, improvements in profit efficiency raise net farm income, transmitting to food security through three channels: (i) enhanced market-based food access, (ii) increased own-production for consumption, and (iii) relaxation of liquidity constraints enabling consumption smoothing during shocks. However, as our findings show, this transmission is context-dependent: in settings of price volatility, climate variability, and imperfect markets, income gains may be diverted to debt servicing, asset building, or precautionary savings, reducing immediate consumption effects.

Empirical evidence partially converges with our findings. Argaw et al. (2025) reported that improvements in technical, allocative, and economic efficiency enhanced food availability and access, supporting the observed link between efficiency and household caloric intake. Adeniyi and Dinbabo (2020) similarly found positive effects on household income and food security, though benefits varied across socio-economic strata, echoing our observation that efficiency gains translate into differential welfare outcomes. In contrast, Hakim et al. (2021) reported no significant effect of technical efficiency on household food security, emphasizing how contextual factors, including baseline efficiency, livelihood diversification, and socio-economic structures, moderate the efficiency–food security relationship.

6. Conclusion and Recommendation

This study examined the determinants of wheat profit efficiency among smallholder farmers in Ada'a District and its implications for household food security. The mean profit efficiency was 0.737, indicating substantial unrealized profit potential and considerable variation across households. This finding suggests widespread inefficiency in resource use rather than limited production potential. Land, fertilizer, and pesticide use increased profitability, while labor, farm capital, and seed costs reduced profit margins. Efficiency was improved by improved seed adoption, irrigation access, extension contacts, and farming experience, whereas it was reduced by land fragmentation, pest infestation, and distance to roads. These results indicate that both input quality and access to services and infrastructure are critical determinants of efficiency. Profit efficiency was strongly associated with welfare outcomes, as higher-efficiency households achieved better food consumption scores, while low-efficiency households were food insecure. This finding indicates profit efficiency is a key channel linking production performance to household welfare. The study shifts focus from technical to profit efficiency, emphasizing input cost structure and complementarities in farm performance. It further shows that efficiency outcomes are shaped by both economic and institutional constraints. Empirical results provide evidence that improving efficiency has direct implications for food security in the study area.

Policy priorities should focus on expanding irrigation and rural infrastructure, strengthening extension services, and improving access to quality seeds and pest management systems. Addressing land fragmentation and improving road connectivity are also important for reducing structural inefficiencies. Interventions should also emphasize how inputs are combined, not only their availability. Targeted support is needed for the lowest efficiency households, who face the greatest food insecurity risk. Promoting efficient input combinations and facilitating access to labor-saving technologies and capital can further enhance profitability. The study is limited by its cross-sectional design, single-crop scope, and reliance on self-reported data. Future research should use panel data, multiple crops, and regions, and further explore institutional and climate-related factors. Despite these limitations, the findings provide robust and policy-relevant evidence for improving farm profit efficiency and food security in similar contexts.

Conflicts of interest

The authors declared that there is no conflict of interest.

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