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Technical efficiency analysis of bread wheat (*Triticum aestivum*) production and its determinants in central and southern Oromia region, Ethiopia: stochastic frontiers analysis approach

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Background: Enhancing technical efficiency (TE) is a cost-effective pathway to increasing agricultural productivity, particularly in settings where access to modern technologies is limited. This study assesses the level of technical efficiency among wheat producers in central and southern Oromia, Ethiopia, identifies key sources of inefficiency, and quantifies the associated yield gap.
Methods: Using cross-sectional data from 345 wheat-growing households in the Arsi, West Arsi, and Bale zones, the analysis combines descriptive statistics with stochastic frontier techniques to estimate farm-level efficiency and its determinants.
Results: The results show that agrochemicals, animal traction, and machinery use are major contributors to wheat output, with evidence that better coordination of traditional and modern inputs can enhance productivity. The mean technical efficiency is 0.62, indicating that wheat output could increase by about 38% if farmers operated at the production frontier. On average, actual yields of 3.40 t ha^{-1} fall well below the potential frontier yield of 5.45 t ha^{-1}, implying substantial production losses due to inefficiency. Tractor ownership and cooperative membership significantly improve efficiency, while larger household size and cultivated area are associated with lower efficiency.
Conclusion: These findings underscore the importance of promoting scale-appropriate mechanization, improving access to complementary inputs, and strengthening farmer organizations to narrow yield gaps and enhance wheat productivity in Ethiopia.

KEYWORDS
Ethiopia, stochastic frontier analysis, technical efficiency, translog, wheat

1 Introduction

In Ethiopia's sedentary mixed farming system, smallholder farmers predominantly engage in crop production, with wheat standing out as one of the most widely cultivated cereals (Azeze et al., 2024). Wheat functions both as a staple food and a key cash crop: it contributes to employment, food security, income generation, and national GDP growth, and serves as the primary staple for approximately 36% of the population (Anteneh and Asrat, 2020). In terms of production volume and productivity, wheat is the second most important cereal after maize, although it ranks fourth in area cultivated. According to the Central Statistical Agency (CSA, 2021) maize recorded a yield of over 9.6 million metric tons at 4.24 t ha^{-1}, whereas wheat produced more than 5.3 million metric tons at an average yield of 2.97 t ha^{-1}, underscoring its central yet relatively less productive role in Ethiopia's cereal economy.

Recent trends indicate that Ethiopia has strengthened its position in African wheat markets. The country is the largest wheat consumer in Africa and produced about 7 million metric tons (MMT) in 2022/23, up from 5.5 MMT in 2021/22, making it the largest producer in Sub-Saharan Africa and the second largest on the continent after Egypt (FAOSTAT, 2025). Yet, despite this expansion in both area and output, wheat productivity in Ethiopia remains among the lowest in Africa (Ritchie et al., 2022). Wheat is produced by both large-scale commercial farms and small-scale farms (Minot et al., 2019), but around 96% of total production comes from smallholder, largely subsistence-oriented farms (Taffesse et al., 2013). Aside from a few government-owned large-scale commercial farms, wheat cultivation is predominantly rainfed (Demeke and Di Marcantonio, 2013), making production highly vulnerable to droughts, frosts, and other climatic shocks. Of the 2.1 M ha under wheat, only about 19% (0.4 M ha) is irrigated, and total wheat production is estimated at 6.7 million metric tons, with yields of about 3.0 t ha^{-1} on rainfed farms and 4.0 t ha^{-1} under irrigation (Tadesse et al., 2022). These figures point to substantial productivity differentials between production systems and highlight untapped potential.

In Ethiopia, unlike other staple grains, wheat has historically been the most heavily imported cereal in terms of volume. The share of domestic wheat consumption met through imports has fluctuated between 25 and 35%, depending on harvest size and other influencing factors. According to FAO (2024), wheat imports accounted for more than 60% of the country's total grain imports. In 2023, Ethiopia imported approximately 449,579 metric tons of wheat, primarily from the United States and Ukraine. This represents a notable decline compared to previous years, reflecting the government's efforts to increase domestic wheat production and reduce dependency on imports (WITS, 2023). To achieve greater self-sufficiency, the country has implemented several initiatives, including the expansion of irrigated wheat farming, the use of improved seed varieties, and the adoption of modern agricultural practices. These efforts aim not only to meet domestic demand but also to position Ethiopia as a potential wheat exporter in the region (Effa et al., 2025; Senbeta and Worku, 2023). Despite these advances, significant yield gaps remain at the national level, estimated at 44% for rainfed wheat and 55% for irrigated wheat, indicating considerable room for improving productivity (Tadesse et al., 2022).

In broad terms, two main strategies can be pursued to increase agricultural output. The first is to intensify production through the adoption of improved technologies, such as high-yielding varieties, chemical fertilizers, and other agrochemicals, often requiring higher investment and scaling up operations. The second focuses on moving producers closer to the existing production frontier, that is, maximizing output given current levels of input and technology by using available resources more efficiently. While both strategies are important, the latter is particularly relevant where capital and access to new technologies are constrained, as is often the case for smallholder farmers in Ethiopia. Accordingly, this study emphasizes the second pathway and investigates whether improvements in production efficiency can enhance wheat productivity.

Efficiency analysis is a core aspect of production economics and is especially critical in developing countries, where production resources are scarce, and the pace of technological innovation is relatively slow. Following Farrell (1957), economic efficiency can be decomposed into technical and allocative efficiency. Technical efficiency (TE) refers to the ability of a producer to obtain the maximum feasible output from a given set of inputs, or equivalently, to use the minimum amount of inputs required to produce a given level of output, given the existing technology (Farrell, 1957; Fethi and Pasiouras, 2010; Sharma and Sekhon, 2021). Allocative efficiency reflects the ability to choose the cost-minimizing combination of inputs, given their relative prices, so that inputs are used in the most economically efficient proportions (Farrell, 1957).

Although both technical and allocative efficiencies jointly determine overall economic efficiency, TE tends to be of particular concern in developing-country agriculture for at least two reasons. First, Schultz's "poor-but-allocatively efficient" hypothesis, widely discussed and endorsed by economists and policymakers, argues that small farmers in traditional agricultural settings are generally efficient in allocating resources and respond rationally to price incentives, despite their low-income levels (Falcon, 1988). Second, in many rural markets characterized by imperfections, farmers have limited influence over both input and output prices and typically behave as price takers, which constrains their ability to perform at their frontiers (Sauer and Mendoza-Escalante, 2007). Under such conditions, enhancing technical efficiency becomes a more realistic and immediate avenue for raising output and farm incomes.

The technical efficiency (TE) of Ethiopian wheat growers has been the subject of much empirical research over the past 20 years, primarily due to the predominance of smallholder production and the ongoing output discrepancies. A pooled mean TE of about 71.6% is reported in a recent systematic review and meta-regression of 31 wheat TE studies (covering the period 2011–2022 and encompassing more than 12,000 farm observations). This suggests that, on average, wheat output could be increased by about 28% if farms operated on the frontier using current technologies. Wide variations in TE estimates (about 0.48–0.86) are documented in the same review, which relates this variability to variations in sample size, estimation method (stochastic versus deterministic frontiers), publication type, study location, and the range of efficiency scores (Mulusew and Hong, 2023).

Larger samples have been used in national and multi-regional studies to quantify wheat TE. calculated a mean TE of around 0.77 and a yield gap of 659 kg/ha attributed to technical inefficiency after analyzing 1,616 wheat plots and 946 families under the SARD SC experiment. Hailu (2020) discovered a reduced average TE of 0.62 using data from 1,611 farmers in significant wheat-growing regions. More recently, Diro et al. (2024) used a panel stochastic frontier model to analyze national wheat data from 2011 and 2014, demonstrating that factors under farmers' control accounted for more than 95% of production variation, supporting the claim that increasing management and efficiency can significantly increase yields.

The drivers of inefficiency found in the literature are very consistent, despite variations in location and methodology (Bakhsh et al., 2006; Dessale, 2019; Ruzhani and Mushunje, 2025; Sharma and Sekhon, 2021; Tenaye, 2020). Technical inefficiency is generally decreased by farmer and household characteristics like age, education, agricultural experience, and family labor (Coelli and Battese, 1996; Dessale, 2019; Sharma and Sekhon, 2021; Tenaye, 2020). By reducing liquidity constraints and enhancing access to agronomic advice and inputs, institutional and informational factors like training, credit, extension services, and cooperative membership consistently show up as important drivers of higher TE (Gebrehiwot, 2017; Gemechu et al., 2025; Martey et al., 2019; Nkegbe, 2018; Olagunju et al., 2021; Shamebo et al., 2021; Tenaye, 2020).

Adoption of technology and input use are crucial in determining efficiency. Land, fertilizer, improved seed, and labor are all positively correlated with wheat production, with declining returns at increasing levels, according to numerous studies. Crop rotation, improved varieties, and suggested fertilizer rates are examples of climate-smart agriculture technology that tend to increase TE. In northwest Ethiopia, for instance, Alemayehu et al. (2024) find a mean TE of 0.845, with farmers adopting all three methods concurrently achieving the highest TE. However, since they restrict economies of scale, raise transaction costs, and make timely operations more difficult, several structural limitations, including land fragmentation, insecure tenure, distance to markets, and plot remoteness, are linked to lower TE (Ashrit, 2023). These results are consistent with larger research on cereals that link persisting inefficiencies in Ethiopian agriculture to gender-based limitations, technological adoption gaps, and climatic concerns.

An increasing number of studies emphasize the importance of mechanization and certain husbandry techniques. For example, Alemu et al. (2014) observed a mean TE of approximately 0.83 under row planting versus 0.58 under broadcasting at the plot level in their comparative study in southern Ethiopia, highlighting the significance of improved planting techniques for reducing efficiency disparities. Furthermore, mechanization is expressly mentioned as a factor influencing efficiency in several stochastic frontier studies. Together with other factors, Mamo et al. (2018) find that tractor use considerably increases TE for smallholder wheat growers in the key wheat-growing regions.

According to the latest Arsi Zone study, the use of machinery in production significantly boosts both allocative and economic efficiency, with average technical, allocative, and economic efficiency scores of 80.8, 88.1, and 71.3%, respectively (Agazhi et al., 2024). Beyond investigations specific to wheat, more extensive research on mechanization in Ethiopia reveals that wheat has the greatest mechanization index in terms of operations carried out by tractors and combines, although overall mechanization is still low and unevenly distributed (Berhane et al., 2020; Deribe et al., 2021; Tesema et al., 2023). Even after adjusting for selection into mechanization use, farm-level impact assessments in central and southern Oromia show that automation has a favorable and significant influence on wheat productivity and economic efficiency (Gebiso et al., 2024). Despite these advancements, mechanization is still frequently viewed as a binary variable (tractor use vs. none, mechanized vs. non-mechanized) or as a component of a larger technology package rather than as a multifaceted process (e.g., intensity of mechanization across land preparation, planting, weeding, harvesting, and threshing) (Gebiso et al., 2024).

Several studies have examined TE in wheat production in Ethiopia too, using diverse analytical approaches and datasets (Alemu et al., 2014; Dessale, 2019; Gelaw and Emana, 2008; Mamo et al., 2018; Silva et al., 2021; Tiruneh and Geta, 2016)While these contributions provide useful benchmarks on efficiency levels and associated factors, they often omit potentially important determinants of inefficiency, most notably, the level of farm mechanization and related technological and management practices. Given the sizable national yield gaps and the dominance of smallholder production, a more comprehensive understanding of both the magnitude and the source of technical inefficiency is needed to inform concrete policy interventions aimed at narrowing the gap between actual and potential yields.

In conclusion, three important points are established by the body of current literature. First, TE in Ethiopian wheat production is constantly below unity, with mean estimates usually ranging from 0.6 to 0.85 and a meta-analytic mean of about 0.72. This suggests that there is a significant opportunity to increase output with current resources and technologies. Second, while structural limitations like land fragmentation and, market remoteness reduce efficiency, a variety of socio-economic, institutional, and agronomic factors, particularly education, extension, credit, improved seed use, and good agronomic practices, have been repeatedly identified as drivers of higher TE. Third, there is growing evidence that mechanization, improved planting techniques, and climate-smart practice packages can greatly increase TE and economic efficiency; however, the mainstream wheat TE research has not thoroughly and methodically examined these factors.

Against this backdrop, the present study has three main objectives: (i) provides updated estimates of the technical efficiency of wheat farmers; (ii) explicitly examines the role of farm mechanization as a source of technical inefficiency, along with other socio-economic and agronomic factors; and (iii) quantifies the portion of the yield gap that can be attributed to technical inefficiency. Doing this will create stronger connection between the efficiency literature and Ethiopia's current policy objective, which includes lowering reliance on wheat imports, promoting mechanization, and closing yield gaps.

2 Research methodology

2.1 Description of study area

The Arsi, West Arsi, and Bale zones in the southeast of Ethiopia's Oromia regional state are the focus of this study. Due to extremely favorable weather conditions, the Oromia region is the nation's largest wheat-producing region, accounting for around 53% of the country's total wheat-grown area and around 57-58% of its total production volume (Senbeta and Worku, 2023). With a mean value of 3.18 t ha^{-1}, Oromia had the highest land productivity of wheat (CSA, 2021). Moreover, around 55% of the wheat produced in the Oromia region and 32.50% of the wheat produced nationwide are produced in the three zones alone (Table A1).

2.2 Sampling procedure and data collection

The respondents were chosen using multi-stage sampling approaches. First, three administrative zones were purposefully chosen based on their potential for wheat production and degree of mechanization. Hetosa, Gedeb-Asasa, and Sinana districts were then purposefully chosen from the Arsi, West Arsi, and Bale zones, respectively, using comparable criteria as shown in Figure 1. While minor variations in altitude and micro-climate exist across districts, these differences do not imply distinct production technologies but rather represent within-system variability. Based on Probability Proportionality to Size (PPS), fourteen (14) kebeles, the lowest administrative unit in Ethiopia, were chosen at random from each district to make up the third level. As a result, four kebeles from the Bale zones and five kebeles each from Arsi and West Arsi were chosen. Lastly, depending on PPS, 345 farmer households in total were chosen at random from those random kebeles. The three districts are considered representative of wheat-producing areas in the respective zones, allowing the results to be extrapolated to other regions with comparable agro-ecological conditions and wheat production systems. Structured questionnaires were used to gather quantitative information on the households' socioeconomic status and wheat production. Data collected includes wheat yield, quantity of inputs used like seed, agrochemicals, labor, oxen-days, and others. As data on actual machinery-hours used were not available, due to machinery being hired on a quantity basis, expenditures on machinery (tillage expenses per hectare and harvesting expenses per quintal) were employed as proxy variables for machinery usage.

Machinery input is measured using machinery expenditure (Birr), which proxies the flow of mechanized capital services utilized during the production season. In the study area, smallholder farmers rarely own farm machinery and instead rely on hired tractor and harvesting services with relatively uniform rental rates usually fixed in discussion with government bodies, machinery owners and farmers. Consequently, variation in machinery expenditure largely reflects differences in the intensity of machinery service use rather than price variation. The translog production frontier is particularly suitable for capturing the potentially nonlinear and interactive effects of mechanized services with other production inputs.

2.3 Method of data analysis

The data was analyzed using both econometric model analysis techniques and descriptive statistics. The socioeconomic, institutional, and demographic characteristics of the wheat growers were described using descriptive statistics. Frontier techniques, which push the average response functions to the maximum output or to the efficient business, were essentially used to quantify technical efficiency.

2.3.1 Methodological approaches of technical efficiency analysis

Two competing approaches to TE analysis, parametric (stochastic or econometric) and non-parametric (mathematical programming or data envelopment analysis, also known as deterministic), are widely used in the wake of Farrell's groundbreaking work in the field (Farrell, 1957). Since it acknowledges the impact of random errors and data noise on agricultural output and makes the assumption that producers may not have complete control over deviations from the production frontier, the stochastic frontier model is the one that is recommended (Huang et al., 2014; Meeusen and van Broeck, 1977; Parmeter et al., 2017). This technique's primary benefit is its ability to differentiate between the effects of various inefficiency drivers and random noise. This method also makes it possible to evaluate hypotheses on the efficiency and structure of production. However, its primary constraint is the application of a distributional assumption on the inefficiency term and on the frontier's technology.

The DEA, or non-parametric approach, does not impose such restrictions. However, its main drawback is that it assumes no measurement or sampling errors and that any deviation from the production frontier is fully under the control of the production unit, making it a deterministic method. In reality, farmers have limited control over various climatic and environmental factors, and agricultural production takes place under constant uncertainty. Moreover, DEA overlooks measurement errors, which are common in smallholder farming systems where the use of non-marketed inputs such as family labor and manure is widespread, but accurate record-keeping is rare, if not impossible (Coelli and Battese, 1996). As a result, the stochastic frontier production function (SFPF) has been widely adopted by agricultural researchers (Eshete and Alamirew, 2023; Ji et al., 2023; Mamo et al., 2018; Wassie, 2014).

As discussed above, the translog model is a parametric functional form (typically used for production or cost functions) that can be viewed as a second-order Taylor expansion in logarithms. It is highly flexible and can locally approximate any twice-differentiable production or cost function, while allowing substitution elasticities to vary with input levels (Christensen et al., 1973). In contrast, the FDH (Free Disposal Hull) model and related nonparametric approaches, such as Data Envelopment Analysis (DEA), are deterministic frontier methods that assume only free disposability of inputs and outputs. These models are primarily used for measuring the efficiency of decision-making units (DMUs), rather than for estimating a smooth underlying production function (Papaioannou and Podinovski, 2025). In such settings, every deviation from the frontier hull is interpreted as inefficiency, making the estimates very sensitive to outliers and data errors and likely to overstate inefficiency in the presence of substantial noise (De Borger et al., 1994).

In practice, agricultural production data are affected by measurement error, shocks, and specification noise. For this reason, a translog stochastic frontier model, which explicitly employs a two-part composite error term (statistical noise and inefficiency), is preferred in this analysis.

The two methods used to examine the factors influencing inefficiency are one-stage and two-stage. Nevertheless, a one-stage approach is used, where technical inefficiency outcomes are assumed as a function of various observable factors affecting producers' efficiency (Battese and Coelli, 1995; Battese and Corra, 1977), because the two-stage has been criticized for violating the "identically independently distributed (iid) technical inefficiency effects in the stochastic frontier" (Battese and Coelli, 1995; Johnson and Kuosmanen, 2011; Preciado Arreola et al., 2020; Schmidt, 2011; Zha et al., 2016).

2.3.2 Model specification for one-stage

Both TE and inefficiency-causing variables were evaluated using the SFPF, which simultaneously examines both (Battese and Coelli, 1995). The two production functions most frequently used in agricultural domains to express the frontier production function are the transcendental logarithmic (translog) and Cobb–Douglas functions. According to the authors, unless the researcher is interested in examining the production function's overall structure, the functional form has no bearing on the TE measure (Banik, 1994; Kopp and Smith, 1980; Krishna and Sahota, 1991). To ascertain which functional forms will most closely fit our data, this study used a generalized likelihood ratio test.

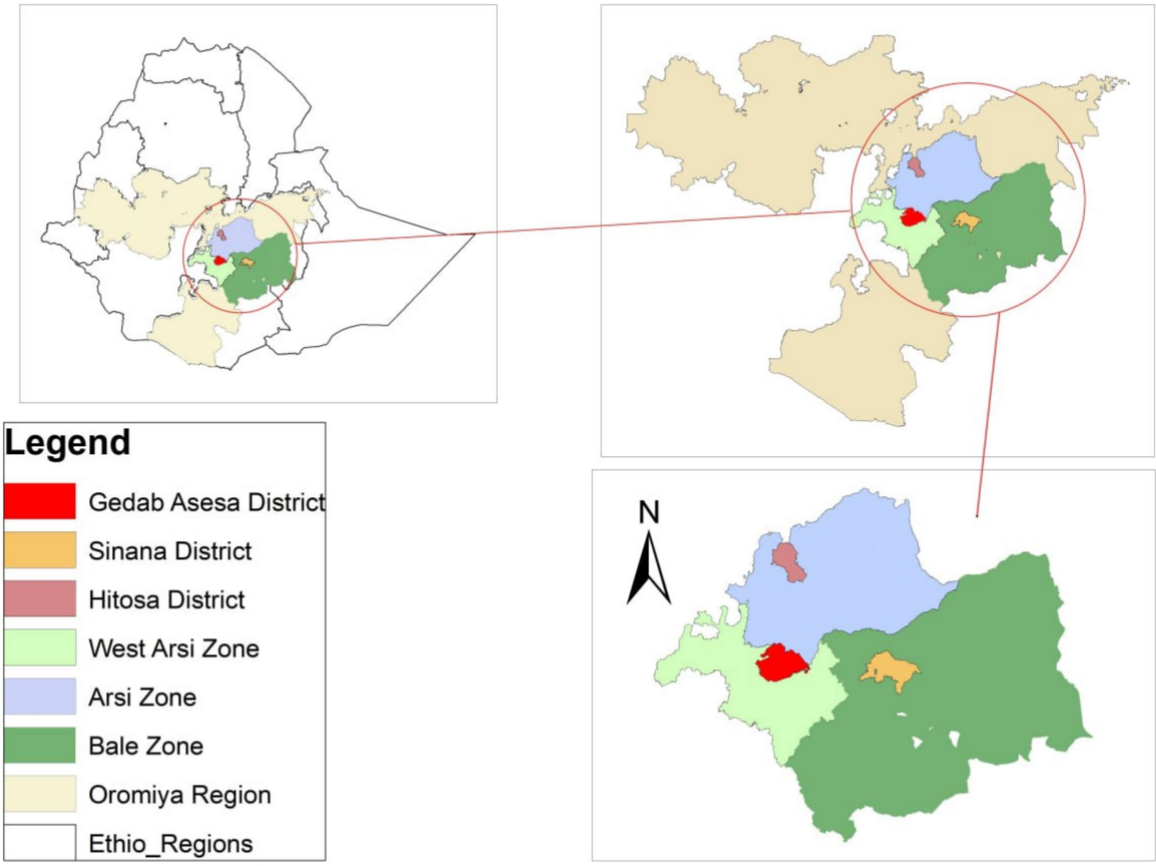

FIGURE 1
Study area map (Hetosa, Gedeb-Asasa, and Sinana districts).

Following (Meeusen and van Broeck, 1977), the SFPF for wheat production with two error terms ($v_{i,} and\ \upsilon_i$) can be modeled as follows.

$$\ln Y_i = \beta_0 + \sum_{j=1}^{7}\beta_j \ln X_{ij} + \frac{1}{2}\sum_{j=1}^{7}\sum_{k=1}^{7}\beta_{jk} \ln X_{ij} \ln X_{ik} + \left(V_i - U_i\right) \quad (1)$$

Where the subscript, i indicates the i^{th} farmer in the sample (i = 1, 2, …, 345), Y, is the amount of wheat produced (kg); $X_1$to X_7 denotes wheat farm size (ha); amounts of labor (person-days), wheat seed (kg), agrochemicals (L), fertilizers (kg), oxen (oxen-days), and machine quantity [proxied by tractor and combine harvester expenditure (ETB)]. ln is the natural logarithm; $lnX_{ik}lnX_{ik}$ includes the squares and interaction terms of the input variables; β_j's are unknown parameters to be estimated; v_i's are symmetric component of the error term and assumed to be iid with distribution of $N(0, \sigma^2_v)$; the u_i's are the inefficiency component of the error term, that are assumed to be independently distributed such that u_i is defined by truncation (at zero) of the normal distribution with mean μ_i and variance $\sigma 2$ (Bogale, 2010), where μ_i is defined by Equation 2:

$$U_i = \delta_0 + \sum_{j=1}^{n}\delta_j Z_{ji} + W_i \quad (2)$$

Where δ_j is parameter to be estimated Z_j are socioeconomic, institutional, and demographic variables that are assumed to determine inefficiency components of the model. TE is estimated from observed output and the maximum possible output and expressed in its natural and logarithmic forms (Equations 3, 4), respectively.

$$\mathrm{TE} = \frac{\text{observed output}}{\text{maximum possible output}} = \frac{\beta_0 + \beta_i X_i + v_i - u_i}{\beta_0 + \beta_i X_i + v_i} = \frac{Y_i}{\beta_0 + \beta_i X_i + v_i} \quad (3)$$

$$\mathrm{TE} = e^{-u} or \exp\left(-U_i\right) \quad (4)$$

Here, the exp. ($-U_i$) lies between zero and one and is inversely related to the level of the technical inefficiency effect. The parameters of SFPF are estimated by using the maximum likelihood function using Stata version 17.

The variance parameters were also estimated in terms of $\delta^2 = \delta^2_u + \delta^2_v$ and lambda = δ_u/δ_v. The γ parameters have a value between 0 and 1. The discrepancy parameter γ is an indicator of the relative variability of the two error terms $\left(\delta_{u^2}\ and\ \delta_{v^2}\right)$ and given expressed as Equation 5:

$$\gamma = \frac{\lambda^2}{\lambda^2 + 1} \quad (5)$$

The closer γ is to zero, the more the random effect dominates the fluctuation between the frontier and realized output levels. As

γ approaches one, it indicates that production changes are due to technical inefficiencies (Bekele and Assefa, 2009).

2.3.3 Estimation of yield gap due to technical inefficiency

The analysis employed Stata Version 17 to estimate the parameters of the Stochastic Frontier Production Function (SFPF) and the associated inefficiency model using the maximum likelihood estimation method. The log-likelihood ratio (LR) test was applied to assess the validity of the model, using the Equation 6:

$$\text{LR} = -2\ \ln\left[L\left(H_0\right)/L\left(H_1\right)\right], \tag{6}$$

where $L(H_0)$ and $L(H_1)$ represent the log-likelihood values under the null and alternative hypotheses, respectively (Kumbhakar et al., 2015).

2.3.4 Yield gap due to technical inefficiency

The yield gap due to technical inefficiency is defined as the difference between the technically efficient observation's yield that can be produced at a frontier and the observed actual yield of the sample households. Therefore, the yield gap is the amount that represents lower yields due to technical inefficiency. From the Stochastic model defined in Equation 1, TE of the ith farmer was also estimated in Equations 3, 4 above.

Then, solving for Y_i^* in Equation 3, the potential yield of each wheat producer can be represented as Equation 7:

$$Y_i^* = \frac{Y_i}{\text{TE}} = \frac{f\left(X_i;\beta\right).\exp\left(V_i - U_i\right)}{f\left(X_i;\beta\right).\exp\left(-U_i\right)} = f\left(X_i;\beta\right).\exp\left(V_i\right) \tag{7}$$

Where TE_i = technical efficiency of the ith wheat producer.

Y_i^* = the frontier/potential output of the ith wheat producer, and

Y_i = the actual/observed output of the ith household in wheat production.

Then, the yield gap between the potential and actual yield of the farmers is calculated using Equation 8 as follows:

$$\text{Yieldgap} = Y_i^* - Y_i \tag{8}$$

3 Results and discussion

3.1 Descriptive analysis

There are three types of farm households: only animal power users, only tractor users, and mixed types of power source users, in terms of draught power usage. On average, farmers plow their wheat farmlands twice when they are using only a tractor and five times and three times when they are using draught animal power (DAP) and mixed (both tractor and DAP), respectively (Table 1). According to the key informant interview and in-depth interview results, primary tillage starts early in March and April for tractor users, while most of the DAP users start in the months of April and May. Planting starts early in June in West Arsi and continues in July in Arsi and Bale zones.

Table 2 shows that around 94% of the sample families were led by men, with the remaining households being headed by women. The sample household's mean educational background was around 6 years of schooling, and its average age fell into the active working group, which is approximately 45 years old. The average household size consisted of seven people. In the research region, the average agricultural experience ranged from 24 to 65 years. While all of the families utilize combine harvesters to harvest their wheat farm, about 78% of them use tractors for main tillage. Cooperative members made up 68% of the homes in the sample. Each farmer had an average of 2.35 farm plots, which is a sign of land fragmentation, and their monthly interaction with development agents was about 1.5, while some farmers have a poor relationship with development agents.

Each household is cultivating a wheat crop on average on around 2 hectares of land and employing on average about 35 person-days of labor, 19.5 oxen-days, 464 kg of different chemical fertilizers, which includes DAP, UREA, and NPS, 1.35 L of weedicide, 1.52 L of other pesticides, and the expense of 8,405 ETB of machinery, which are tractor and combine harvesters. The mean wheat output of the sample households in the study area was 6.80 t, with a minimum and maximum production of four and four hundred quintals, respectively. The mean yield of the sample households was around 3.40 t ha^{-1}, which is well above both the national and Oromia regional yield averages, which were reported to be 2.97 and 3.19 t ha^{-1}, respectively (Table 3).

3.2 Econometric results

3.2.1 Hypothesis testing and checking for model robustness

Two null hypotheses were tested: (1) that the Translog SFPF could be simplified to a Cobb–Douglas functional form, and (2) that none of the variables included in the inefficiency model had a significant effect on technical inefficiency. The LR test results rejected both null hypotheses. This indicates that the Translog specification provides a better fit than the Cobb–Douglas, and that technical inefficiency is present and influenced by multiple explanatory variables (Table 4).

Furthermore, the test results for Corrected Mean Absolute Deviation (CMAD) and Corrected Ordinary Least Squares (COLS) show that the methods are not robust in estimating technical inefficiency (Table 5). Hence, a further stochastic frontier analysis (SFA) test was required. As a result, the Translog frontier production model was used to run the SFA model. The test showed that there is evidence for inefficiency in wheat production.

TABLE 1 Frequency of tillage using different power sources.

Variable	Mean	Std. Dev.	Minimum	Maximum
Only tractor users	1.70	1.22	2	4
Only draught animal power	4.59	1.13	3	8
Mixed power users	2.46	1.28	2	7

TABLE 2 Summary of inefficiency determinant variables.

Variable	Mean	Std. Dev.	Minimum	Maximum
Age of household head	44.77	12.68	21	84
Sex of household head (dummy, 1 = male)	0.94	0.41	0	1
Education (school years)	5.67	3.45	0	12
Total family size (count)	7.35	2.99	1	21
Total land cultivated (hectare)	2.4	1.58	0.20	12
Wheat farming experience (years)	24.09	13.40	1	65
Land fragmentation (number of plots)	2.35	1.44	1	9
Development agents contact (frequency per month)	1.50	1.30	0	5
Market distance (km)	4.10	3.35	0.2	18
Livestock owned (TLU)[a]	5.74	4.09	0	34.60
Use tractor (1 = yes)	0.78	0.87	0	1
Coop_ membership (1 = yes)	0.98	0.65	0	1

[a]TLU is a tropical livestock unit that measures total livestock owned converted based on conversion factors as given in Table A2.

TABLE 3 Input and output variables summary of wheat production.

Variables	Mean	Std. Dev.	Minimum	Maximum
Wheat output (kg)	6,828.41	5,959.74	400	40,000
Yield (kg)	3,395.50	1,542.47	250	12,400
Wheat land (ha)	2.07	1.53	0.2	12
Seed (kg)	463.31	368.20	40	2,400
Weedicide (L)	1.35	0.75	0.25	5
Pesticide (L)	1.52	0.81	0.25	4
Fertilizer (kg)	464.72	537.18	25	6,000
Labor (person-days)[a]	35.30	23.40	6	205
Oxen-day	19.47	11.80	0	80
Machine cost (ETB)[b]	8,405.16	9,601.74	200	72,000

[a]It includes both hired and family labor converted to adult equivalent as indicated in Table A3.
[b]ETB is Ethiopian Birr, while the value (machine cost) includes both tractor and combine harvester costs.

TABLE 4 Tests of hypotheses for parameters of SPF and technical inefficiency factors.

Null hypothesis	LL value of H_0	LL value of H_1	LR statistic	Df	Critical value[a]	Decision
Production function is CD (*non-translog form*) $H_0 : \beta_{ij} = 0$	−40.54	56.99	195.06	21	40.765	Reject H_0
Join efficiency effects are insignificant H_0: $\delta_0 = \delta_1 = \delta_2 \ldots = \delta_{15} = 0$	−1846.28	−1770.46	151.64	15	25.00	Reject H_0

[a]95% confidence.

3.2.2 Parameter estimates for translog stochastic frontier production function (SFPF)

Table 6 presents the coefficients from the maximum likelihood estimates of the parameters in the translog SFPF for the sample of wheat producers. The results indicate that various production inputs, along with their interactions, significantly contribute to wheat yield in the study area. Specifically, the number of oxen-days, the amount of agrochemicals used, and expenses on farm machinery (including tractors and combine harvesters), all expressed in their natural logarithmic forms, were found to have positive and statistically significant effects on wheat yield at the 5, 5, and 10% significance levels, respectively. These findings suggest that increased use of agrochemicals can enhance wheat production efficiency. Similarly, a higher number of oxen-days also positively influences efficiency.

TABLE 5 Mean efficiency of COLS and corrected mean absolute deviation (CMAD).

Variables description	Mean value	Minimum	Maximum
eff_COLS	0.51 (0.13)	0.16	1
eff_CMAD	0.54 (0.14)	0.15	1

Values in parentheses are standard errors.

TABLE 6 Maximum likelihood estimates of the stochastic frontier translog production function.

Variables	Coefficients	*Z*	*t*-value
Lnlabor	0.33 (0.57)	0.58	0.57
LnLand	−0.45 (1.54)	−0.29	0.77
LnSeed	0.08 (0.93)	0.08	0.094
LnChemicals	0.93 (0.42)	2.21**	0.007
LnFertlizer	0.32 (0.58)	0.55	0.58
LnOx	0.78 (0.32)	2.44**	0.006
LnMachinary	0.81 (0.38)	2.15*	0.031
Lnlabor-squared	−0.02 (0.09)	−0.23	0.82
Lnland-squared	−0.116 (0.35)	−0.33	0.74
Lnseed-squared	0.16 (0.15)	1.08	0.28
Lnchemicals-squared	−0.08 (0.08)	−1.06	0.29
Lnfertlizer-squared	−0.08 (0.10)	−0.80	0.42
Lnox-squared	−0.11 (0.06)	1.99**	0.046
Lnmachine-squared	−0.03 (0.04)	−0.81	0.42
Ox × machinery	0.08 (0.03)	2.22**	0.02
Land × seed	0.01 (0.21)	0.03	0.98
Land × fertilizer	0.16 (0.12)	1.24	0.21
Land × machinery	−0.09 (0.08)	−1.19	0.233
Labor × chemicals	−0.10 (0.05)	−1.90**	0.058
Labor × fertilizer	0.07 (0.06)	1.22	0.22
Labor × ox	−0.07 (0.06)	−1.09	0.28
Labor × machinery	−0.08 (0.04)	−2.06*	0.04
Seed × chemicals	−0.01 (0.11)	−0.84	0.4
Seed × fertilizer	−0.102 (0.10)	−0.99	0.32
Seed × ox	−0.11 (0.07)	−1.69	0.05
Seed × machinery	−0.02 (0.05)	−0.34	0.73
Chemicals × fertilizer	−0.066 (0.07)	−0.96	0.33
Chemicals × ox	0.01 (0.04)	0.14	0.89
Chemicals × machinery	0.04 (0.04)	0.92	0.36
Fertilizer × ox	−0.04 (0.05)	−0.75	0.05
Fertilizer × machinery	0.08 (0.05)	1.57	0.12
Labor × seed	0.04 (0.09)	0.43	0.67
Land × labor	0.01 (0.11)	0.06	0.95
Land × chemicals	0.17 (0.14)	1.22	0.22
Land × ox	0.04 (0.10)	0.39	0.7
Constant	−1.54 (3.75)	−0.41	0.68

* is for t significance at 10%. ** is for p significance at 5%.

Accordingly, the increased use of machinery has a positive impact on wheat production efficiency in the study area. In other words, the more mechanized the farm, the greater the efficiency in wheat production. Furthermore, the results indicate that while a higher number of oxen-days per hectare positively affects efficiency, its second-order term has a negative effect. This suggests that exceeding the optimal use of oxen-days can lead to inefficiencies by increasing production costs and potentially reducing productivity, possibly due to issues such as soil erosion.

Additionally, the interaction between certain inputs, such as oxen-days and machinery, as well as labor and machinery, positively contributes to wheat production efficiency. The positive interaction between oxen-days and machinery use indicates complementarity between animal traction and mechanized services, whereby combined use enhances land preparation quality and timeliness, leading to higher wheat productivity. In contrast, interactions between other inputs, specifically, seed quantity and oxen-days, and labor-days and agrochemical use, negatively impact efficiency. This highlights the importance of carefully selecting the optimal combinations of inputs (e.g., seed relative to oxen-days, and labor relative to agrochemical use) to enhance production efficiency (Table 6).

The estimated gamma (γ) value was 0.89 and statistically significant at the 1% level, as shown in Table 7. This high value indicates that approximately 89% of the total variation in wheat output among producers can be attributed to differences in technical efficiency, while the remaining 11% is due to random factors such as measurement errors and uncontrollable environmental disturbances. This result underscores the critical role of technical efficiency in explaining yield variation among wheat farmers in the study area. The implication is clear: substantial gains in wheat production could be achieved not necessarily by increasing input use or expanding cultivated area, but by improving the efficiency with which existing resources are utilized. Enhancing farmers' managerial capacity, promoting access to training, and encouraging the adoption of best practices could therefore significantly boost wheat productivity through improved technical efficiency.

3.2.3 Determinants of technical efficiency (sources of inefficiency)

In line with previous research on technical efficiency (TE) analysis, this study included eleven socioeconomic and institutional variables in the inefficiency model to identify their impact on the TE of wheat producers. Of these, four variables were found to significantly influence technical efficiency, as presented in Table 8.

One notable result is the impact of total family size, which was used as a proxy for available family labor. The analysis indicates that family size has a positive and statistically significant effect on technical inefficiency at the 5% significance level. This suggests that households with smaller family sizes tend to be more technically efficient in wheat production. A possible explanation for this counterintuitive finding could be that in larger households, labor may not be effectively organized or productively engaged, potentially leading to inefficiencies. Additionally, the presence of more non-productive members (e.g., children or the elderly) may reduce the per capita labor efficiency available for wheat farming.

This finding contrasts with the conclusions of several earlier studies, which affirmed that there is negative relationship between family size and technical inefficiency, i.e., larger family sizes were associated with greater efficiency due to increased labor availability (Gelaw and Emana, 2008; Hailu, 2020; Lagiso and Geta, 2019; Zewdie et al., 2021). The divergence in findings may be attributed to differences in crop types, regional labor dynamics, or the quality and productivity of household labor across study areas. In general, the fact that household size does not always correspond to effective labor availability may be the reason for the negative correlation between family size and technical efficiency. Larger households frequently have a higher percentage of dependents, which puts more pressure on consumption and limits the amount of resources that can be allocated to inputs that boost productivity. Furthermore, excessive family labor in relation to the size of the land can lead to labor misallocation and declining marginal production, while increased coordination and supervision requirements may lower the timeliness and quality of agricultural operations. Larger households may experience reduced observed technical efficiency as a result of these factors taken together. These results highlight the importance of considering not only the quantity but also the quality and effective utilization of household labor when assessing technical efficiency in smallholder agriculture.

Another important finding of this study is the significant and positive relationship between total cultivated land and technical inefficiency in wheat production. The variable is statistically significant at the 1% level, suggesting that larger farm sizes are associated with higher levels of inefficiency. This indicates that smallholder farmers tend to be technically more efficient than those managing larger landholdings. A plausible explanation for this result is that as farm size increases, households may diversify their agricultural activities across various enterprises. This diversification could lead to a dispersion of resources, making it more challenging to allocate inputs efficiently for wheat production specifically. Additionally, managing larger areas may introduce complexities related to labor allocation, supervision, and the timeliness of input application, which can negatively affect efficiency. Therefore, in situations of partial mechanization and seasonal input limitations, a higher operational scale may worsen labor and managerial constraints. This result is not indicative of declining returns to scale in wheat production, but rather of scale-related managerial issues.

This finding is consistent with earlier studies, which also reported a negative association between farm size and technical efficiency (Abate et al., 2019; Wana and Dhugasa, 2019). These studies emphasized that small-scale farmers often utilize their limited resources more intensively and effectively, potentially due to closer oversight and better adaptation to local conditions. Therefore, while larger farms may benefit from economies of scale in some contexts, the current result highlights the importance of efficient input use and management practices, particularly in smallholder-dominated systems like Ethiopia's wheat sector.

Membership in cooperatives also has a positive and significant impact on wheat production efficiency at the 5% level, which is attributed to several institutional, economic, and social benefits that cooperatives provide to their members. Membership facilitates access to agricultural inputs like improved seed, fertilizer, and others (Blekking et al., 2021; Khan et al., 2022; Sisay et al., 2017). Second, cooperative members are more likely to receive agricultural extension services and technical training, either directly through cooperative activities or via partnerships with government extension agents that enhance farmers agronomic practices and decision-making and help to improve efficiency (Gashaw and Kibret, 2018). Furthermore, cooperative membership can offer better market access through collective marketing arrangements, to rural finance, and promote social capital and peer learning (Hao et al., 2018; Shiferaw et al., 2016). Finally, government policy also supports cooperative development. As evidence, the provision of subsidized inputs, farm machinery services, and other capacity-building initiatives is provided to cooperative members (Davis et al., 2023; Dhakal et al., 2021; Etefa, 2022). Hence, consistent with this study, different findings attested that the TE of different crops, like wheat and maize, is significantly affected by cooperative membership (Debebe et al., 2015; Olagunju et al., 2021; Oyakhilomen et al., 2015; Tiruneh and Geta, 2016).

The results of this study reveal that mechanization, particularly the use of tractors, plays a significant role in enhancing the technical

TABLE 7 Variance parameters estimation.

Variance parameters	
$\sigma_U^2 = 0.07$ ($p = 0.000$)	$\lambda = \sigma_U / \sigma_V = 2.87$
$\sigma^2 = \sigma_V^2 + \sigma_U^2 = 0.16$	$\gamma = \left\lvert \lambda^2 / \left(\lambda^2 + 1\right) \right\rvert = 0.89$
Number of observations = 345	Wald chi^2 (27) = 6689.45
Prob > chi^2 = 0.000	Log likelihood = 56.99

***$p < 0.001$.

TABLE 8 Determinants of technical inefficiency.

Variables	Coefficient (std. error)	Z-values	t-values
Ln (age)	−0.06 (0.06)	−1.09	0.27
Educational background (school years)	−0.01 (0.01)	−0.86	0.38
Total family size (count)	0.01 (0.01)	1.71*	0.05
Total cultivated (ha)	0.06 (0.02)	2.53***	0.01
Ln of experience in wheat farming (years)	−0.01 (0.02)	−0.41	0.68
Farmland fragmentation (count of farm plots)	0.02 (0.01)	1.48	0.13
DA_contact (frequency per month)	−0.01 (0.01)	−0.68	0.49
Coop_membership (yes = 1)	−0.08 (0.04)	−2.05**	0.04
Market_distance (km)	−0.01 (0.01)	−1.31	0.18
Use of a tractor (yes = 1)	−1.65 (0.41)	−4.04***	0.000
Tropical livestock unit (TLU)	0.003 (0.004)	0.75	0.45
Constant	−0.90 (0.47)	−1.90*	0.05

Values in parentheses are standard errors. *, **, *** values are significant at 10%, 5% and 1% level of significance.

efficiency (TE) of wheat producers in Ethiopia. As indicated in Table 6, farmers who utilized tractors were found to be significantly more efficient than those who did not, with the variable showing statistical significance at the 1% level. This underscores the crucial role of mechanized farming in improving resource use and minimizing inefficiencies in smallholder wheat production systems. This finding aligns with international evidence, reinforcing the broader relevance of mechanization in enhancing farm-level efficiency. For instance, Hormozi et al. (2012) reported similar outcomes among rice farmers in Iran, where mechanization was found to have a positive and significant effect on technical efficiency. Similar findings attested to the positive impacts of farm mechanization on farmer TE (Liu and Li, 2023; Sun et al., 2024; Zhu et al., 2025). The study concluded that mechanized operations reduced labor intensity, improved the timeliness of farming activities, and enhanced the overall productivity of agricultural inputs, thereby improving TE.

3.2.4 Ranges of technical efficiency

The result in Table 9 below presents a summary of wheat production TE scores in the central and southern west highlands of Ethiopia. According to the results, wheat producers operate at a mean efficiency of around 62% with minimum and maximum efficiency levels of 20 and 98%, respectively. This implies that the most efficient farmer is producing at a 98% level of efficiency, while the least efficient is operating at a 20.36% level of efficiency. The result implies that there is around 38% of efficiency level that can be improved. This output is somehow less than the result reported by Alemu et al. (2014) which was 75%. However, some findings are consistent with our findings (Dessale, 2019; Hailu, 2020; Wana and Dhugasa, 2019). The other authors' results, such as Yami et al. (2013) and Tiruneh and Geta (2016) are below the result of this finding, which are 53 and 57%, respectively.

The distribution of technical efficiency scores reveals substantial heterogeneity in wheat production performance across smallholder farms. The left-skewed distribution indicates that the majority of farmers operate below the sample mean efficiency level of 0.62, with nearly 43% clustered around an efficiency score of approximately 0.53 (Figure 2). In contrast, only one-quarter of households achieve efficiency levels of 0.75 or higher, suggesting that relatively few farmers operate close to the production frontier. This wide dispersion in efficiency highlights significant unrealized productivity potential that could be harnessed without expanding input use. From a policy perspective, these findings underscore the importance of targeted interventions—such as improved access to scale-appropriate mechanization, strengthened farmer organizations, and tailored extension services—that facilitate better input coordination and management practices. Focusing on the large share of farmers operating below the mean could yield substantial productivity gains and contribute to more sustainable wheat intensification in the region.

The analysis of technical efficiency across the three zones: Arsi, West Arsi, and Bale, revealed substantial spatial variation (Table 9). The maximum efficiency scores were recorded in both Arsi and West Arsi zones, each achieving approximately 98%, whereas the Bale zone exhibited the lowest recorded efficiency score of just 20%. This considerable disparity underscores spatial differences in wheat production efficiency.

The results of the *F*-test confirm that these variations in efficiency scores are statistically significant. These differences can largely be attributed to factors such as land productivity potential, the extent of technological exposure, particularly mechanization, and the level and depth of agricultural extension services available in each zone. Zones with better access to machinery, improved inputs, and advisory services tend to exhibit higher efficiency scores. Additionally, the effect of mechanization on efficiency was further analyzed using ANOVA, specifically comparing efficiency scores across different levels of tractor use. As shown in Table 9, the use of tractors, especially in combination with the draught animal power, was found to have a statistically significant impact on improving technical efficiency in wheat production (p-value = 0.054). This finding highlights the synergistic benefits of integrating mechanization with appropriate draught power animals use to enhance production efficiency.

The first 25% of the producers are producing at a mean technical efficiency of 37.97% and the next 25% of the farmers are producing at a mean efficiency of 51.268% while the last 25% are producing at a technical efficiency of 93.75% and the upper 50% of producers are producing at 79.85% of technical efficiency. Most of the wheat producers, which are the upper 75% of the sample households, were producing at a technical efficiency of 70.36%. Overall, it can be inferred that the majority of producers (75%) exhibit above-average technical efficiency (Table 10).

Based on Equation 6 and using the values of the actual wheat output obtained and the predicted TE indices, the estimated potential wheat output for each household in wheat production on a hectare

TABLE 9 Mean efficiency score distribution by districts and type of plowing methods.

Base of categories	Categories	Mean	Minimum	Maximum	*F*-value	Significance
Zone	Arsi	76.56	30.10	98.10	85.50	0.000***
	West Arsi	56.70	30.10	98.10		
	Bale	46.29	20.40	97.00		
	Total	62.29	20.40	98.10		
Farm power source	Animal	57.02	28.00	98.10	2.95	0.05*
	Mixed (animal with machinery)	63.77	20.00	98.21		
	Only tractor	57.84	44.00	80.00		
	Total	62.29	20.00	98.00		

*, ***significant at 10 and 1% significance level.

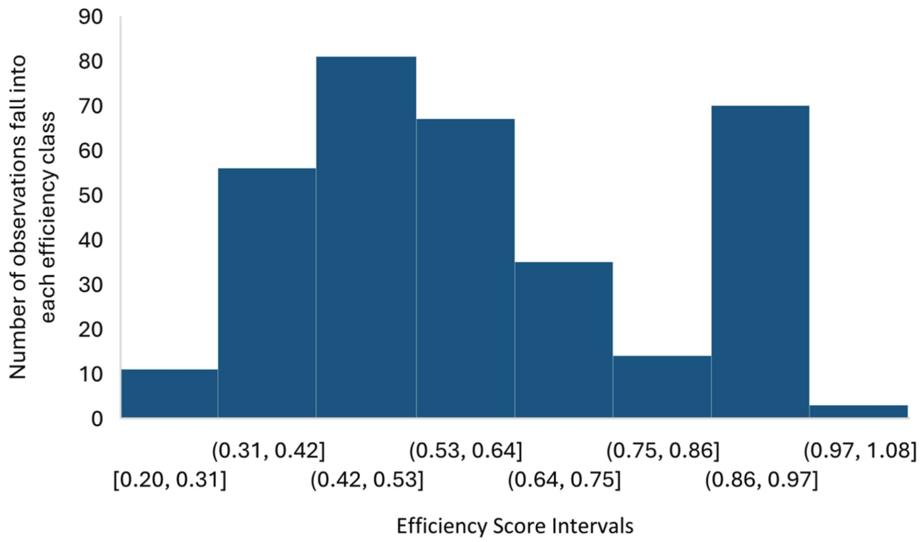

FIGURE 2
Distribution of wheat farmers' technical efficiency in central and southern Oromia.

TABLE 10 Efficiency index distribution of wheat producers.

Group categories	TE score (%)	Group categories	TE score (%)
First 25% of the sample	37.97	Fourth, 25% of the sample	93.75
The second 25% of the sample	51.27	Upper 50% of the sample	79.85
Third 25% of the sample	65.79	Upper 75% of the sample	70.36

TABLE 11 The wheat yield gap due to the technical inefficiency of the sample households.

No.	Variables	Mean	Standard deviation	Minimum	Maximum
1	Actual yield (kg/ha)	3395.50	1542.47	250	12,400
2	Mean technical efficiency	0.623	0.214	0.203	0.981
3	Potential yield (kg/ha) (1/2)	5450.24	7207.8	1231.53	12640.16
4	Yield gap (kg/ha) (3–1)	2054.74	5565.33	981.53	240.16

Source: Author's computation.

basis was presented in Table 11 as follows. The average overall technical inefficiency was 37.70%, resulting in an average wheat yield gap of approximately 2,055 kg/ha. The mean actual output and potential output were 3,395.50 kg/ha and 5,450.24 kg/ha, respectively. This indicates that, on average, wheat producers in the study area are achieving yields that are 2,055 kg/ha lower than their potential.

3.3 Possible limitations of the study

This study has several limitations that should be considered when interpreting the findings. The analysis is based on wheat-producing households in central and southeastern Oromia, which may limit the generalizability of the results to areas with different agro-ecological and institutional contexts. The use of cross-sectional data from a single production season does not capture temporal variation in technical efficiency or dynamic aspects of farm decision-making. Reliance on self-reported input, output, and cost data may introduce recall bias and measurement error, while the absence of plot-level environmental and biophysical controls may influence productivity estimates. Although the Translog production function offers greater flexibility than the Cobb–Douglas specification, it still imposes a parametric structure, and mechanization is proxied using tractor use and machinery expenditure even though in settings with limited price variation, expenditure closely tracks quantity of machinery services used. Hence, these limitations could be addressed in the future research by using panel data, plot-level biophysical variables, and quantity of machinery services used.

4 Conclusion and recommendations

This study provides empirical evidence on wheat production efficiency in central and southeastern Oromia, Ethiopia. The results show that wheat output is strongly influenced by key production inputs and their interactions, highlighting the importance of balanced input use and appropriate mechanization in smallholder systems. The estimated mean technical efficiency indicates substantial scope for increasing wheat production through improved efficiency rather than additional input use. Technical inefficiency explains a large share of the observed yield gap, suggesting that productivity gains can be achieved by better management and institutional support. Cooperative membership and access to tractor services were found to enhance efficiency, while larger household size and farm size were associated with higher inefficiency, underscoring the role of labor management and scale-related constraints. Overall, the findings emphasize the need for policies and interventions that strengthen institutional linkages, promote efficient mechanization, and support improved farm management practices to enhance the sustainability and productivity of wheat-based farming systems.

According to the study's conclusions, specific interventions that improve input usage, institutional support, and mechanization are needed to increase the technical efficiency of wheat producers in the study area. More effective wheat production can be achieved by improving farmers' access to and appropriate use of agrochemicals through training and dependable supply systems. By improving access to markets, knowledge, credit, and inputs, strengthening farmer cooperatives and encouraging institutional involvement can further increase efficiency. Additionally, labor and timeliness constraints can be addressed by increasing access to mechanized services, such as tractors and combine harvesters, through cooperative-based rental programs and private service providers. Together, these interventions have the potential to improve wheat productivity, reduce production costs, and support sustainable rural livelihoods, provided that other key production constraints are adequately addressed.

5 Contribution to the UN sustainable development goals (SDGs)

By identifying solutions to increase smallholder wheat farmers' productivity and revenue through increased technical efficiency, this study directly contributes to SDG 2 (Zero Hunger). Through productivity-driven income growth in rural regions, the research supports SDGs 8 (Decent Work and Economic Growth) and 1 (No Poverty) by emphasizing the complementary roles of oxen and machinery use and the significance of cooperative participation. Furthermore, the results support sustainable resource management by encouraging effective use of agricultural inputs and scale-appropriate automation, which is in line with SDG 12 (Responsible Consumption and Production). By reducing environmental pressures from food production, increasing input efficiency, and decreasing resource waste, thus indirectly supports SDG 13 (Climate Action).

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the [patients/ participants OR patients/participants legal guardian/ next of kin] was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

TC: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. EF: Conceptualization, Methodology, Software, Validation, Writing – review & editing. FA: Conceptualization, Methodology, Supervision, Validation, Writing – review & editing. TM: Data curation, Formal analysis, Methodology, Software, Validation, Writing – review & editing. RO: Investigation, Methodology, Software, Supervision, Writing – review & editing. GF: Investigation, Methodology, Software, Supervision, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix

TABLE A1 Wheat production in study area compared to region and national production.

Producing party	Holders	Area (ha)	Production (MMT)	Yield (t ha^{-1})
National	4,879,932	1,789,372.23	5.3	2.97
Oromia	1,831,185	970,517.66	3.1	3.19
Arsi	401,404	205,872.72	0.70	3.31
W/Arsi	163,379	129,623.46	0.44	3.43
Bale	174,89	176,804.44	0.60	3.40
Total of three zones	739,678	512,300.62	1.73	33.72
National share (%)	15.16%	28.63%	32.50%	
Regional share (%)	40.39%	52.79%	55.84%	

Source: author's computation from CSA, 2021.

TABLE A2 Conversion factors used to estimate TLU.

Types of animals	TLU factor	Types of animals	TLU factor
Cow	1	Sheep/Goat	0.10
Ox	1	Donkey	0.50
Bull	1	Horse/mule	0.80
Heifers	0.75	Camel	1
Calve	0.40		

Source: Storck et al. (1991).

TABLE A3 Conversion factors used to estimate adult equivalent.

Age group	Male	Female	TLU factor
Less than 10	0	0	
10–13	0.2	0.2	
14–16	0.5	0.4	
17–60	1	0.8	
>60	0.7	0.5	

Source: Storck et al. (1991).