# Fertilizer Use and Production Efficency in Swedish Agriculture:

## A Meta-Frontier Stochastic Analysis of Farm-Level Data

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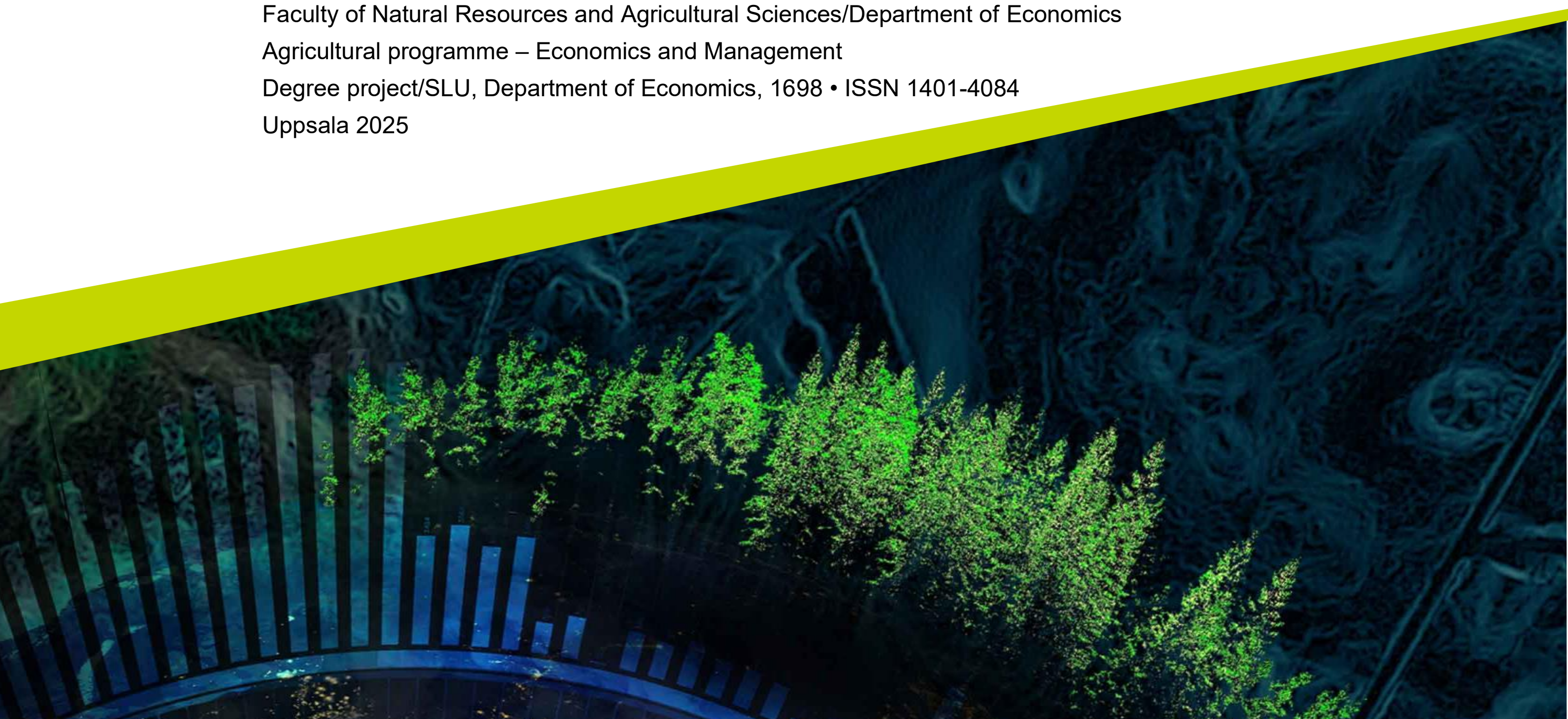

# Fertilizer Use and Production Efficiency in Swedish Agriculture: A Meta-Frontier Stochastic Analysis of Farm-Level Data

*Gödselanvändning och produktionseffektivitet inom svenskt jordbruk: En meta-frontier stokastisk analys av data på gårdsnivå.*

*Asja Tinjic*

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# Abstract

This thesis examines the efficiency and sustainability of Swedish agriculture, with a particular focus on fertilizer use, through a two-stage stochastic frontier analysis (SFA) framework. Using farm-level panel data from the EU Farm Accountancy Data Network (FADN), technical efficiency (TE) is estimated for field crop, dairy, and grazing livestock farms via Translog production functions. To account for structural and technological heterogeneity, a meta-frontier approach is applied, yielding Technology Gap Ratios (TGR) and Meta-Technical Efficiency (MTE) scores.

Fertilizer Use Efficiency (FUE) is derived from a Cobb-Douglas specification to evaluate input-specific performance and is complemented by the estimation of Meta-FUE (MTFUE) and Fertilizer Overuse Efficiency (FOUE). These indicators enable a multidimensional assessment of both economic and environmental efficiency.

The results indicate that dairy farms exhibit high TE and MTFUE, while field crop farms show the lowest fertilizer efficiency and the highest overuse. Grazing livestock farms display moderate input efficiency but face the widest technology gaps. The study also explores how structural and policy-related variables—such as subsidies, farm size, and regional location—affect inefficiency.

Overall, the findings reveal substantial heterogeneity across farm types in both productivity and sustainable input use, offering evidence-based insights for more targeted and differentiated agricultural and environmental policy design in Sweden.

*Keywords: Stochastic Frontier Analysis, Fertilizer Use Efficiency, Meta-Frontier, Technical Efficiency, Technology Gap Ratio,Sustainable Farming, Panel Data, FADN*

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# Abbreviations

| Abbreviation | Description |
| --- | --- |
| SFA | Stochastic Frontier Analysis |
| TE | Technical Efficiency |
| TGR | Technology Gap Ratio |
| MTE | Meta-Technical Efficiency |
| FUE | Fertilizer Use Efficiency |
| FOUE | Fertilizer Overuse Efficiency |
| MTFUE | Meta Fertilizer Use Efficiency |
| CD | Cobb-Douglas (Production Function) |
| TL | Translog (Production Function) |
| FADN | Farm Accountancy Data Network |
| AWU | Annual Work Unit |

# 1. Introduction

Sustainable intensification is increasingly seen as the cornerstone of agricultural policy across Europe. For countries like Sweden—where agriculture is both highly productive and environmentally scrutinized—the challenge lies not in producing more, but in producing efficiently and responsibly. Fertilizer management, in particular, sits at the intersection of productivity and environmental stewardship. Overuse of fertilizers has been linked to nitrogen leakage, groundwater contamination, and greenhouse gas emissions, placing pressure on Sweden's ability to meet national environmental targets and its obligations under the EU Common Agricultural Policy (CAP) (Swedish Board of Agriculture, 2012).

Swedish agriculture is marked by substantial heterogeneity in climate, farm structure, and policy exposure (Liu et al., 2021). From intensive arable farms in the south to extensive grazing systems in the north, structural variation shapes resource use and production efficiency (Alem, Lien, & Hardaker, 2018). Adding to this complexity, Sweden's reliance on imported fertilizers (Jordbruksverket, 2021) and its vulnerability to global price fluctuations make it vital to evaluate how efficiently farms use fertilizer inputs across different systems.

To investigate these challenges, this study applies Stochastic Frontier Analysis (SFA) using a flexible translog production function to estimate technical efficiency (TE) across three main farm types defined in the EU Farm Accountancy Data Network (FADN): field crops (TF8 = 1), dairy (TF8 = 5), and other grazing livestock (TF8 = 6) (European Commission, 2024). A meta-frontier framework is then used to account for technological heterogeneity, allowing the comparison of group-specific frontiers with a common technology frontier. This step yields the Technology Gap Ratio (TGR) and Meta-Frontier Technical Efficiency (Meta-TE) scores, quantifying how far different farm groups are from the technological potential.

To complement this, the study also estimates Fertilizer Use Efficiency (FUE) using a Cobb-Douglas specification that isolates the responsiveness of output to fertilizer input. From this, a Fertilizer Overuse Efficiency (FOUE) index is derived to capture potential excess application. Together, these measures—TE, TGR, Meta-TE, FUE, and FOUE—offer a multidimensional view of both performance and sustainability in fertilizer use.

This two-stage approach, inspired by Huang & Jiang (2019) and Liu et al. (2021), first estimates farm-level efficiency and technology gaps, and then explains observed inefficiencies using a rich set of structural and policy variables, including subsidy types, regional location, and economic size.

Sweden presents a compelling case for such analysis not only due to its agro-ecological diversity and environmental policy ambitions, but also due to the regionally differentiated subsidy structures under the CAP (European Commission, 2023; Jordbruksverket, 2021). Yet, despite its advanced farming systems, micro-level analysis of fertilizer use efficiency remains limited. Existing studies often assume technological homogeneity and rarely integrate environmental inputs like fertilizers into frontier efficiency frameworks. This thesis addresses these gaps by explicitly modeling fertilizer inputs, incorporating a meta-frontier structure, and analyzing the role of subsidies and structural conditions in shaping inefficiency. Accordingly, the thesis is guided by the following research questions:

(1) What are the technical efficiency and fertilizer use efficiency levels across Swedish farm types and regions?
(2) How do farms perform relative to their group-specific frontiers and a common meta-frontier, and what does this reveal about technology heterogeneity?
(3) What role do selected structural and policy factors play in explaining farm-level inefficiencies?

This study contributes to the literature in three ways. First, it offers new empirical insights from Sweden, a context underrepresented in the efficiency literature. Second, it advances methodological applications by integrating fertilizer-specific measures with meta-frontier SFA, allowing for the decomposition of technology gaps. Third, it evaluates the differentiated impact of subsidy types and structural characteristics on efficiency, offering nuanced, policy-relevant insights for promoting sustainable agriculture.

The remainder of the thesis is structured as follows: Chapter 2 reviews the relevant literature on efficiency, sustainability, and meta-frontier models. Chapter 3 presents the data and variable definitions. Chapter 4 outlines the empirical methodology. Chapter 5 discusses the main findings. Chapter 6 concludes with policy implications and directions for future research.

# 2. Literature Review

## 2.1 Efficiency and Sustainability in Agriculture: The Case for Fertilizer Use Efficiency

Improving the sustainability of agricultural production has become a central priority for both researchers and policymakers due to the environmental risks of intensive input use. Among these inputs, mineral fertilizers—especially nitrogen-based—play a dual role: enhancing productivity while contributing to environmental degradation (Zhang et al., 2015). Fertilizer Use Efficiency (FUE) thus emerges as a critical metric that links input optimization with both output performance and sustainability outcomes. While technical efficiency (TE) assesses the general capacity to transform inputs into output, it may not capture overuse of specific inputs like fertilizers. Huang and Jiang (2019), using SFA on Chinese crop farms, show that farms with high TE can still have low FUE, suggesting that fertilizer input use may exceed agronomic needs. This supports the argument for evaluating FUE as a distinct efficiency dimension.

Environmental costs of fertilizer overuse have also been quantified. Dakpo et al. (2023), for example, estimate a marginal abatement cost of €21 per kilogram of excess nitrogen on French wheat farms. They simulate an EU-wide expansion of the Nitrates Directive to include synthetic fertilizers, estimating a 9.5% reduction in nitrogen use with only a 3.1% decrease in revenue—indicating the feasibility of targeted sustainability policies. Zhu et al. (2023), applying a dynamic DEA model to Dutch dairy farms, emphasize that environmental inefficiency often exceeds economic or social inefficiency. Their findings highlight the need to separately measure FUE, especially in high-input sectors like dairy and field crops, where trade-offs across sustainability dimensions are common.

At the macro level, Expósito and Velasco (2020) use DEA-Malmquist methods to evaluate trends in fertilizer-related environmental efficiency across EU countries. Their results show only modest improvements, with persistent inefficiencies in countries such as Sweden. They argue that input reduction alone is insufficient, and more efficient fertilizer management is necessary to reduce eutrophication risks. Finally, ecological policy reforms can have mixed short-term effects on TE. Huang et al. (2025) find that environmental policies may initially reduce efficiency due to compliance costs and adaptation time, highlighting the importance of analyzing both TE and FUE to assess policy trade-offs.

Taken together, these studies justify a dual-efficiency framework. TE reflects the overall production capacity, while FUE reveals whether input use aligns with environmental and economic efficiency. In a Swedish context—characterized by high productivity and strict environmental standards—this combined analysis is essential. This thesis contributes by estimating TE and FUE through translog SFA and extending the analysis with meta-frontier and technology gap approaches to examine structural differences in sustainability.

## 2.2 Measuring Technical Efficiency in Agriculture: Methodological Developments and Debates

Measurement of technical efficiency (TE) in agriculture has commonly relied on two frontier approaches: Data Envelopment Analysis (DEA) (Nowak et al., 2015; Zhu et al., 2023; Expósito & Velasco, 2020) and Stochastic Frontier Analysis (SFA). While DEA offers a non-parametric and flexible benchmarking framework, it assumes that all deviations from the frontier are due to inefficiency, making it sensitive to noise and outliers. In contrast, SFA explicitly separates inefficiency from statistical noise, which is particularly important in agricultural settings where random shocks—such as weather variability—can affect output independently of managerial performance (Coelli et al., 2005; Kumbhakar & Lovell, 2000). Given the availability of farm-level panel data and the need to control for such noise, SFA is the more appropriate framework for this study, especially when paired with the estimation of inefficiency determinants using a one-step approach (Battese & Coelli, 1995). Recent developments such as Greene's (2005) "true" fixed/random effects models and Belotti et al.'s (2013) sfpanel command in Stata have expanded the flexibility of SFA to include heteroskedasticity, time-varying inefficiency, and multiple distributional assumptions. These features are particularly valuable for modeling heterogeneous farm systems under varying regional and policy conditions.

Functional form selection also shapes efficiency estimates. While the Cobb-Douglas function is commonly used for its simplicity, it imposes restrictive assumptions about input substitutability and constant returns to scale. In contrast, the translog production function allows for flexible elasticities and interaction effects among inputs, making it more appropriate for diverse farm types (Belotti et al., 2013). Given the structural variation in Swedish agriculture, a translog specification is adopted in this study, with Cobb-Douglas used as a robustness check.

The modeling of inefficiency effects is another key consideration. The one-step approach introduced by Battese and Coelli (1995) simultaneously estimates the production frontier and links inefficiency to farm-level characteristics, reducing potential bias found in two-step models. This approach is widely adopted in the literature (e.g., Huang & Jiang, 2019; Liu et al., 2021) to evaluate policy-relevant determinants such as subsidies, farm size, and regional context. Finally, the choice of inefficiency distribution (e.g., half-normal, truncated-normal) can affect the interpretation of TE scores. Testing alternative distributions, as recommended by Greene (2005) and implemented via sfpanel, improves model robustness and accounts for heterogeneity in inefficiency patterns.

This thesis applies a translog panel SFA model using a one-step inefficiency specification to jointly estimate the production frontier and farm-level determinants of inefficiency. Both Cobb-Douglas and translog functional forms are compared, and a half-normal distribution is adopted for the inefficiency term—reflecting the classical assumption that inefficiency is non-negative and most farms operate close to the frontier. These modeling choices balance flexibility with tractability and enable a more context-sensitive assessment of technical inefficiency in Swedish agriculture.

## 2.3 Fertilizer Use Efficiency and Environmental Impacts in Agriculture

Fertilizer Use Efficiency (FUE) has become an important metric for assessing both the economic and environmental performance of farms, especially in input-intensive systems like arable and dairy production. Unlike traditional technical efficiency (TE) measures, which may overlook excessive input use, FUE provides insight into whether fertilizers are applied proportionally to output gains—thereby capturing potential environmental inefficiencies embedded in high-yield systems.

Huang and Jiang (2019) provide one of the most direct empirical contributions to this literature. Using a stochastic frontier framework with Chinese farm-level data, they estimate both TE and FUE (fertilizer overuse index) as the ratio of predicted optimal fertilizer use to actual fertilizer use. Their results indicate substantial overapplication, showing that fertilizer input could be reduced by an average of 23.1% without sacrificing output. Crucially, they find that farms with high TE are not necessarily efficient in fertilizer use, revealing a disconnect between production efficiency and input-specific sustainability. This underscores the importance of evaluating fertilizer use as a distinct dimension of farm performance.

This thesis applies a comparable approach by estimating FUE through stochastic frontier models, using a Cobb-Douglas specification to obtain predicted fertilizer demand. These FUE scores are then further adjusted using the Technology Gap Ratio (TGR) to derive Meta-Fertilizer Use Efficiency (MTFUE), reflecting both input-specific efficiency and cross-group technological heterogeneity. The term MTFUE in its construction aligns with the meta-frontier frameworks applied by Liu et al. (2021) and O'Donnell et al. (2008), where meta-efficiency scores are estimated to benchmark performance across heterogeneous production technologies.

Approaches to quantifying FUE vary widely—from output-to-input ratios to simulations of optimal fertilizer levels—highlighting the conceptual and methodological complexity. The frontier-based approach adopted in this study offers a robust alternative that accommodates production heterogeneity, enables farm-level benchmarking, and integrates sustainability concerns into technical efficiency measurement.

In sum, the literature underscores that TE alone is insufficient to assess environmental performance. By integrating FUE and MTFUE within a stochastic frontier and meta-frontier framework, this study aims to provide a comprehensive and policy-relevant assessment of sustainability in fertilizer use.

## 2.4 Meta-Frontier and Technology Gap Analysis in Agricultural Efficiency Research

Traditional efficiency models often assume a common production frontier, which may obscure structural disparities across diverse agricultural systems. The meta-frontier approach addresses this limitation by estimating group-specific frontiers (e.g., by farm type or region) alongside a global meta-frontier. This enables the computation of Technology Gap Ratios (TGRs), quantifying how far each group operates from the best-practice technology. This distinction is crucial in agricultural contexts where heterogeneity in resources, climate, or access to technology is prevalent.

Despite the conceptual appeal of meta-frontier models, empirical applications remain relatively rare in Nordic and European agriculture. One notable exception is a study of Norwegian grain farms using a stochastic meta-frontier SFA (published in Economies, 2021), which classified farms by region and found significant regional Technology Gap Ratios (TGRs)—demonstrating technology gaps even within a single country (Flaten et al., 2021). The study used Greene's (2005) true random effects model and reported average group-specific TE scores between 0.70 and 0.75, with TGRs as low as 0.52 in some regions.

This evidence aligns with findings from Liu et al. (2021) on Chinese farm heterogeneity, providing cross-regional empirical support for the use of meta-frontier methods. The Norwegian case is particularly relevant to the Swedish context, illustrating how farm technology adoption and regional characteristics can create measurable inefficiencies. A meta-frontier analysis thus serves not only as a theoretical solution but also as a practical tool to quantify technological disparities in agriculture.

Harimaya et al., (2022) show that structural conditions like infrastructure and market access shape cost frontiers in Japanese cooperatives, supporting regional decomposition in meta-frontier models. Zhu et al. (2023), while not using a meta-frontier, acknowledge technological heterogeneity by grouping farms in DEA-based sustainability assessments. Their findings highlight that peer-group efficiency (high TE) may still fall short of broader benchmarks (low FUE), reinforcing the case for meta-efficiency analysis. DEA-based meta-frontiers (Makieła et al., 2025) risk distortion from noise, whereas SFA-based models (Liu et al., 2021) offer greater robustness and accommodate inefficiency determinants.

A key insight from the meta-frontier literature is that low TGR values may reflect structural constraints rather than managerial inefficiency (Garzón Delvaux et al., 2020; O'Donnell et al., 2007; Huang and Jiang, 2019). For instance, extensive grazing farms receiving targeted subsidies may operate below the meta-frontier by design. This underpins the inclusion of policy and regional controls in the inefficiency model to disentangle structural disadvantage from suboptimal input use.

In summary, meta-frontier analysis enhances efficiency evaluation by distinguishing between within-group performance (TE) and cross-group technological potential (TGR). The use of this methodology—particularly in linking Meta-FUE scores to regional and structural factors—fills a notable gap in the current literature, where fertilizer-specific efficiency comparisons across farm types remain rare, especially in the Nordic context.

## 2.5 Structural and Policy Determinants of Farm Inefficiency

Understanding farm-level inefficiency requires looking beyond input-output relations and considering structural, regional, and policy-related constraints. The inefficiency effects model in SFA allows technical inefficiency to be expressed as a function of such contextual variables (Battese & Coelli, 1995), offering insight into how external conditions affect a farm's ability to convert inputs into output efficiently. Subsidies, farm size, and regional characteristics are frequently cited as important inefficiency determinants.

Liu et al. (2021), in a meta-frontier study of Chinese farms, show that access to extension services significantly improves efficiency, while the relationship with farm size is nonlinear—mid-sized farms perform better than small or very large ones. Similarly, Huang and Jiang (2019) report that subsidies may reduce efficiency by weakening incentives for input optimization. This supports decomposing total subsidies into environmental, LFA, and rural development components in order to examine their differential impacts. Makieła et al. (2025) and Kusz & Kusz (2024) further confirm that regional variation—linked to infrastructure, input prices, and ecological conditions—remains a strong determinant of technical efficiency even after controlling for farm characteristics.

Farm structural features are also pivotal. Economic size, production orientation (e.g., field crops, dairy, grazing), and geographic region determine input intensity, specialization, and technology access. Kusz & Kusz (2024) find larger farms tend to be more efficient due to capital-labour substitution and economies of scale. However, Nowak et al. (2015) caution that these results are conditional on soil quality, age, and farm type.

Specialization may improve efficiency through better resource allocation (Makieła et al., 2025), though environmental trade-offs exist in highly specialized systems (Zhu et al., 2023). The type of production (e.g., field crops, milk, grazing livestock) plays a particularly important role in Sweden. In Makieła et al. (2025), the authors use regional FADN data to compare crop farm efficiency across countries and note that specialized farms tend to outperform mixed systems. Conversely, Zhu et al. (2023) show that intensive specialization in Dutch dairy farms can lead to higher economic efficiency but worse environmental performance due to increased input density.

Moreover, regional differences influence both technology adoption and policy exposure. Expósito & Velasco (2020) highlight that fertilizer efficiency varies more with institutional and environmental conditions than with farm-level inputs alone. Liu et al. (2021) find significant cross-province TGR differences in China, reinforcing the value of regional dummy variables. These findings justify modelling group-specific frontiers and including region and farm type as both grouping and inefficiency variables in this thesis.

In addition to core structural indicators, this study includes the share of family farm income—defined as the ratio of SE420 (Family Farm Income) to SE410 (Net Value Added)—to capture the degree to which a farm's generated value is retained by the family unit. This metric reflects internal profitability, managerial autonomy, and the economic sustainability of family-based production. A higher ratio may indicate strong internal cost control and low reliance on external labor or capital, while a lower ratio could suggest more commercialized or externally dependent operations. Davidova and Thomson (2014) emphasize that family farms' sustainability often hinges on how income and labor are internally managed, particularly in smaller-scale or diversified systems. Including this ratio allows the inefficiency model to capture a nuanced structural dimension of performance that is often overlooked in purely input-based assessments.

Production frontiers must account for specialization and regional constraints; otherwise, efficiency comparisons lose validity (Harimaya, et al., 2022). Thus, together, these studies provide strong support for the inclusion of structural and policy variables in the inefficiency model. Region dummies, TF8 farm type, and decomposed subsidies are essential not only for explaining heterogeneity in technical efficiency and FUE, but also for distinguishing between managerial inefficiency and structural disadvantage—crucial for formulating effective, targeted agricultural policy.

## 2.6 Integrating Sustainability into Efficiency Analysis: Economic, Environmental, and Social Dimensions

The growing urgency around environmental degradation and agricultural restructuring has led to an expanded view of farm performance that goes beyond traditional technical or economic efficiency. Recent literature emphasizes the need to incorporate environmental—and to a lesser extent, social—dimensions into efficiency assessments to capture sustainability more holistically.

Zhu et al. (2023) offer one of the most comprehensive examples by applying a dynamic DEA by-production model that distinguishes between economic, environmental, and social inefficiency in Dutch dairy farms. Their findings show that environmental inefficiency is consistently higher than economic inefficiency, indicating that profit-maximizing farms may still misuse inputs in ways that harm the environment. This supports this thesis's dual focus on technical efficiency (TE) and fertilizer use efficiency (FUE), positioning FUE as a core sustainability indicator.

Moreover, Expósito and Velasco (2020) also highlight environmental inefficiency, using dynamic DEA to assess fertilizer use efficiency across EU countries. They show persistent underperformance in nitrogen-intensive systems, even in economically productive regions.

This aligns with the use of Meta-FUE in this thesis to capture sustainability gaps across farm types and regions.

Other studies provide additional insights into sustainability integration. Huang et al. (2025) assess ecologization policies and find that participation in environmental schemes can increase inefficiency due to compliance burdens. This justifies analyzing the effects of environmental subsidies (SE621) separately in the inefficiency model. Dakpo et al. (2023) contribute by estimating shadow prices of excess nitrogen, highlighting the economic cost of environmental inefficiency—a concept parallel to this thesis's use of FUE as a measurable link between environmental performance and input management.

The social dimension is less developed in the literature. While some studies include proxies such as labour intensity or entrepreneur age, social inefficiency remains difficult to operationalize. Although this thesis does not model it explicitly, it engages indirectly with social sustainability by examining subsidy types and structural characteristics that reflect farm resilience and policy dependency.

In conclusion, while sustainability integration into efficiency analysis is conceptually accepted, empirical implementation varies. This thesis contributes by embedding Fertilizer Use Efficiency (FUE) directly within a stochastic frontier framework, positioning it as a core sustainability metric rather than a supplementary indicator, and by analyzing its determinants through structural and policy-related inefficiency effects

# 3. Method

## 3.1 Theoretical Framework and Model

Agricultural production involves the transformation of multiple inputs—land, labour, capital, and intermediate goods—into outputs under conditions of uncertainty and environmental constraint. Evaluating the efficiency of this transformation is central to both microeconomic analysis and sustainability assessment, particularly where excessive input use, such as fertilizers, can generate economic waste and environmental harm. This study applies a Stochastic Frontier Analysis (SFA) framework to assess the technical efficiency (TE) of Swedish farms, with special attention to fertilizer use efficiency (FUE) and fertilizer overuse efficiency (FOUE).

Building on the approach of Huang and Jiang (2019), who applied a panel SFA model with time-varying inefficiency in Chinese agriculture, this study adapts the Battese and Coelli (1995) framework to a cross-sectional design suited for meta-frontier analysis. The methodology integrates parametric frontier estimation, a one-step inefficiency effects model based on Battese and Coelli (1995), and a meta-frontier analysis that enables a comprehensive decomposition of performance gaps across heterogeneous farm types and regions. Importantly, the SFA models are estimated using cross-sectional snapshots rather than panel data. This approach is methodologically aligned with the study's goal: to estimate group-specific frontiers for different farm types (TF8 = 1, 5, 6) and to calculate technology gap ratios (TGR) and meta-technical efficiency (MTE).

Unlike standard panel SFA models, which assume a shared production technology across all units, the cross-sectional design accommodates structural heterogeneity in production technologies—an essential requirement for the meta-frontier framework. Temporal dynamics are addressed by including a normalized time trend and its square in the production function, which helps capture broad time-related effects without requiring a panel specification. Although a panel SFA was explored as a robustness check, it was not pursued further, as it neither supported meta-frontier estimation nor yielded additional insights relevant to the study's central questions on structural and input-specific efficiency.

Through the combination of TE, TGR, MTE, and input-specific measures such as FUE and FOUE, the study provides a diagnostic framework to distinguish between managerial inefficiency, technological disparity, and potential input overuse—thereby supporting more targeted strategies for sustainable and efficient agricultural production.

### 3.1.1 Technical Efficiency and the Stochastic Production Frontier

Technical efficiency refers to a farm's ability to obtain the maximum possible output from a given set of inputs. Following Farrell's (1957) foundational work, a technically efficient producer lies on the production frontier, while inefficient producers fall below it. Unlike deterministic frontier models, which attribute all deviations from the frontier to inefficiency, SFA introduces a composed error structure, distinguishing between random shocks (e.g. weather, measurement error) and systematic inefficiency. This feature makes SFA particularly suitable for agricultural applications, where stochastic elements are inherent in production processes (Coelli et al., 2005; Kumbhakar & Lovell, 2000).

The stochastic production frontier for output $y_{it}$ of farm i in year t is specified as:

$$\ln y_{it}=f(x_{it};\beta)+v_{it}-u_{it}$$

where $x_{it}$ is a vector of logged inputs, F (·) is the production function (e.g., Cobb-Douglas or Translog); $v_{it}$ ~ N (0, $\sigma_u^2$) represents statistical noise; and $u_{it} \geq 0$ captures technical inefficiency. In this study, the inefficiency term is assumed to follow a half-normal distribution $u_{it}$ ~\$\mathcal{N}(0, \sigma_u^2)$\, consistent with standard practice and the default assumption in Stata's frontier command (Belotti et al., 2013). This implies that inefficiency is non-negative and right skewed, with most farms operating near the frontier.

## 3.1.2 Functional Form: The Translog Production Function

The choice of functional form is critical in frontier estimation. While the Cobb-Douglas function easily interpretable, it imposes constant elasticities of substitution and unitary returns to scale—assumptions often unrealistic in heterogeneous farm systems. This study therefore adopts a Translog production function, which provides a second-order approximation to any twice-differentiable production technology and allows for input interactions (cross terms), variable returns to scale, and nonlinear relationships between inputs and output.

The Translog specification takes the form:

$$\ln y_{it} = \beta_0 + \sum_k \beta_k \ln x_{kit} + \frac{1}{2}\sum_k \sum_j \beta_{kj} \ln x_{kit} \ln x_{jit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + v_{it} - u_{it}$$

Where $X_k \in$ {land, labour, fixed assets, energy, other inputs, fertilizer}; t is a normalized time trend; $\beta_{kj}$ represent second-order interaction terms.

The inclusion of both squared and interaction terms enhances model flexibility. Empirically, the Translog specification was statistically preferred over the Cobb-Douglas alternative based on log-likelihood values and likelihood-ratio (LR) tests, confirming the presence of significant nonlinearities in the data (LR statistic = 1989.14, $p<0.001$).

## 3.1.3 Inefficiency Effects Model

To explain differences in inefficiency across farms, the study employs the Battese and Coelli (1995) one-step model, which specifies the inefficiency term $u_{it}$ as a function of farm-specific characteristics:

$$u_{it}=z_{it}\delta+w_{it}$$

where $z_{it}$ includes normalized determinants of inefficiency (subsidies and region); $\delta$ is a vector of parameters; $w_{it} \sim \mathcal{N}(0, \sigma_w^2)$ is the error term in the inefficiency equation. This formulation allows for simultaneous estimation of the production frontier and the influence of explanatory variables on inefficiency, ensuring statistical consistency and avoiding bias inherent in two-stage procedures (Kumbhakar & Lovell, 2000).

### 3.1.4 Meta-Frontier Approach and Technology Gap Ratios (TGR)

While the standard SFA model estimates a single production frontier, it assumes a homogeneous technology across all observations. However, in heterogeneous agricultural systems—such as Sweden's field crop, dairy, and grazing livestock farms—this assumption may obscure structural differences. To address this, the study applies a meta-frontier framework, allowing for group-specific frontiers and an overarching meta-frontier (Battese et al., 2004). In the first stage, separate stochastic frontiers are estimated for each farm type {TF8} =1,5,6. In the second stage, a pooled frontier is estimated for the full sample, representing the meta-frontier against which each group is benchmarked.

The Technology Gap Ratio (TGR) is computed for each farm as:

$$\mathrm{TGR}_{it} = \exp\left(\widehat{y_{it}^{\mathrm{group}}} - \widehat{y_{it}^{\mathrm{meta}}}\right)$$

A TGR of 1 indicates that the farm's group-specific technology is equivalent to the meta-frontier, while values below 1 indicate technology constraints or lagging technological access. This decomposition allows us to differentiate between managerial inefficiency (TE) and technology-related inefficiency (TGR), culminating in a meta-technical efficiency score:

$$\text{Meta-TE}_{it}=\mathrm{TE}_{it}\times\mathrm{TGR}_{it}$$

This approach is particularly important for identifying structural constraints and policy-relevant inefficiency, especially where technological adoption differs across production systems (Liu et al., 2021).

### 3.1.4 FUE, FOUE, and MTFUE Using Cobb-Douglas

To evaluate input-specific efficiency, this study estimates fertilizer use efficiency (FUE) using the Cobb-Douglas functional form. Unlike the translog specification, which allows for flexible substitution among all inputs but complicates marginal analysis, the Cobb-Douglas model enables direct derivation of input elasticities and marginal productivities. Following the approach of Huang and Jiang (2019), FUE is computed as the ratio of optimal to observed fertilizer use, where the optimal level is derived from the farm's technical efficiency and the estimated output elasticity of fertilizer. Fertilizer Overuse Efficiency (FOUE) is derived further by comparing predicted optimal fertilizer use to actual observed use. This measure specifically

identifies the extent of fertilizer overapplication, offering a more targeted perspective on input sustainability.
This method captures how effectively fertilizer is converted into output, while holding other inputs constant.

$$FUE_i = TE_i / \beta_{fertilizer}$$

To extend the analysis, fertilizer overuse efficiency (FOUE) is calculated using the expression:

$$FOUE_i = (1 / FUE_i) - 1$$

providing a direct measure of the extent to which fertilizer input exceeds the technically efficient level. FOUE is particularly relevant in cropping systems, where overapplication contributes to both economic inefficiency and environmental pressure (Huang & Jiang, 2019; Dakpo et al., 2023). It highlights cases where farms may appear efficient in aggregate but misallocate key inputs.
Furthermore, a meta-level fertilizer use efficiency measure (MTFUE) is introduced to account for technological heterogeneity across farm types. MTFUE is calculated as the product of Cobb-Douglas FUE and the group-specific Cobb-Douglas technology gap ratio (TGR), analogous to the construction of meta-technical efficiency (Battese et al., 2004).

$$MTFUE_i = TGR_i \times FUE_i$$

This measure reflects both within-group efficiency and a farm's access to frontier technologies in fertilizer application. It is especially useful for identifying farms that are efficient within their group yet remain disadvantaged in relation to the meta-frontier. This dual-layer metric supports a more equitable and informed interpretation of fertilizer efficiency by recognizing both input misallocation and structural constraints (Garzón Delvaux et al., 2020; Latruffe, 2010).

Taken together, the integration of FUE, FOUE, and MTFUE enables a multi-dimensional assessment of fertilizer performance—capturing technical inefficiency, overuse behaviour, and technological disadvantage in a unified framework.

## 3.2 Data and Descriptive Statistics

This study utilizes farm-level panel data from the Swedish subset of the Farm Accountancy Data Network (FADN), covering the period 2007 to 2021. The dataset includes observations for three farm types based on the TF8 classification: field crop farms (TF8 = 1), dairy farms (TF8 = 5), and other grazing livestock farms (TF8 = 6). After excluding observations with missing, zero, or implausible values for key variables—such as output, fertilizer expenditure, or land area—the cleaned dataset forms a consistent and balanced sample suitable for reliable efficiency estimation.

All continuous variables used in the production and inefficiency effects models were normalized by dividing each by its sample mean, and log-transformed where appropriate. This preprocessing step reduces skewness, facilitates elasticity interpretation within the Cobb-Douglas and translog functional forms, and mitigates scale-related heteroskedasticity. Such standardization enhances comparability across variables with differing units and magnitudes and follows established best practices in SFA estimation (Kumbhakar & Lovell, 2000; Belotti et al., 2013).

So the final sample structure supports both cross-sectional SFA by farm type and meta-frontier estimation across heterogeneous technologies, allowing for decomposition into technical efficiency, technology gaps, and input-specific performance measures.

### 3.2.1 Data and Descriptive Statistics

The dependent variable in the production function is total output, denoted as y, measured in euros and sourced from variable SE131 in the FADN dataset. This variable captures the farm's total economic output, including all market revenues from both crop and livestock production, adjusted for on-farm consumption and inventory changes. As a value-based measure, it reflects the farm's overall financial performance rather than physical yields, which are not directly comparable across heterogeneous farm types.

To prepare the variable for estimation, total output was normalized by its sample mean and then log-transformed (resulting in lny). This transformation addresses skewness and facilitates elasticity interpretation in the Cobb-Douglas and translog functional forms. Using a monetary output measure ensures consistency across farm types and aligns with standard practice in stochastic frontier modeling (e.g., Coelli et al., 2005; Kumbhakar & Lovell, 2000).

### 3.2.2 Input Variables

The production frontier includes six key input variables, selected based on their theoretical relevance, data availability in the FADN system, and empirical precedence in the farm efficiency literature (Coelli et al., 2005; Kumbhakar & Lovell, 2000; Latruffe, 2010; Huang & Jiang, 2019).

These inputs are (1) Land (SE025) defined as total utilised agricultural area (hectares); (2) Labour (SE010) defined as total labour input measured in annual work units (AWU); (3) Capital (SE441) defined as fixed assets in euros, serving as a proxy for capital stock; (4) Energy (SE345) defined as total expenditure on fuel and electricity; (5) Other intermediate inputs calculated as SE281 (specific costs) minus SE295 (fertilizer), isolating non-fertilizer intermediate expenses; (6) Fertilizer (SE295): crop-specific input costs for fertilizers.

This specification reflects an input-oriented view of the production process and enables precise estimation of input-specific efficiency measures such as fertilizer use efficiency (FUE). Moreover, Fertilizer expenditure (SE295) is excluded from intermediate inputs to model it as a distinct environmental input. This separation not only aligns with the study's sustainability focus but also reduces potential multicollinearity with other cost variables in the production function. Log-transformed and normalized versions of these variables are used in the frontier estimation to ensure comparability and to allow for elasticity interpretation. The selection is consistent with established frontier modeling practices, while the decomposition of intermediate costs allows the model to isolate fertilizer-specific effects more cleanly (Huang & Jiang, 2019; Latruffe, 2010).

*Table 1* presents the summary statistics for the raw inputs, output, and time across the full sample. The variables exhibit considerable variation, particularly SE441 and SE131, which show high standard deviations, indicating substantial differences in scale among observations. The time variable spans from 2007 to 2021, with a mean year of approximately 2014.

*Table 1- Summary Statistics for Raw Output, Inputs, and Year*

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| SE131 | 296645.84 | 487312.26 | 669.97 | 13079698.00 |
| SE025 | 143.64 | 153.96 | 1.00 | 2671.90 |
| SE010 | 1.99 | 2.19 | 0.04 | 76.51 |
| SE441 | 967077.97 | 1225772.66 | 1084.33 | 18656006.00 |
| SE345 | 23168.97 | 30007.45 | 66.69 | 515815.53 |
| SE281 | 145280.51 | 232281.45 | 322.84 | 4368531.00 |
| SE295 | 12539.52 | 23884.66 | 0.00 | 601104.00 |
| Year | 2014.16 | 4.27 | 2007.00 | 2021.00 |

*Table 2* shows the summary statistics for the log-transformed variables used in the estimation. The log transformation reduces the scale of the data and helps to normalize distributions, as seen in the narrower range of values. All variables have been mean-centered, and their distributions show reasonable variability, making them suitable for regression analysis.

*Table 2 - Summary Statistics for Log-Transformed Inputs, Output, and Time*

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| lnx1 | -0.351 | 0.816 | -4.967 | 2.923 |
| lnx2 | -0.267 | 0.712 | -3.906 | 3.650 |
| lnx3 | -0.495 | 1.019 | -6.793 | 2.960 |
| lnx4 | -0.473 | 0.960 | -5.850 | 3.103 |
| lnx5 | -0.721 | 1.268 | -8.295 | 3.469 |
| lnx6 | -0.524 | 1.275 | -8.867 | 3.870 |
| lny | -0.620 | 1.110 | -6.093 | 3.787 |
| lnt | -0.151 | 0.736 | -1.968 | 0.671 |
| Observations | 12328 | | | |

### 3.2.3 Inefficiency Variables

To explain variation in technical inefficiency, the model incorporates several farm-specific determinants, selected based on findings from previous efficiency studies and their relevance to Swedish agricultural policy and structural diversity. These variables enter the inefficiency effects model (the *z*-vector in the Battese and Coelli, 1995 specification), and all are centered (demeaned) prior to estimation, following standard practice in one-step stochastic frontier analysis.

The inefficiencies variables include (1) Total subsidies (SE605); (2) Environmental subsidies (SE621); (3) Less Favoured Area (LFA) subsidies (SE622); (4) Other rural development subsidies (SE623); (5) Share of family farm income, calculated as the ratio SE420 / SE410; (6) Region (Southern, Middle, Northern).

The choice of inefficiency determinants is grounded in established SFA literature. Subsidy variables (SE605, SE621, SE622, SE623) are included due to their well-documented impact on technical and allocative efficiency (Latruffe, 2010; Dakpo et al., 2023). The share of family farm income (SE420/SE410) reflects farm structure and labor reliance, which has been shown to influence management performance and input responsiveness (Liu et al., 2021; Bravo-Ureta & Evenson, 1994). Regional dummies (Southern, Middle, Northern) control for agro-climatic and structural variation across Sweden, consistent with prior studies that incorporate spatial heterogeneity in inefficiency modeling (Huang & Jiang, 2019; Liu et al., 2021). In addition, geographical location is captured using regional dummies for Southern (region code 710), Middle (720), and Northern Sweden (730), which allow the model to account for agro-climatic and structural differences across the country's major farming zones. These dummies are binary indicators, coded as 1 if the farm is located in the respective region, and 0 otherwise.

Tables 3 and 4 summarize the variables used to model inefficiency in the production process. Table 3 presents the raw values for the inefficiency determinants, including different types of subsidies, the share of family labor, and the farm's economic size. These variables show substantial variability, reflecting the diversity in support schemes and structural characteristics across farms. Table 4 provides the normalized versions of these variables, which are used in the inefficiency effects model to ensure comparability and to stabilize the estimation by reducing scale-related distortions.

*Table 3 - Summary Statistics for Inefficiency Determinants*

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| Total subsidies | 64606.816 | 75371.120 | 0.000 | 1131744.875 |
| Environmental subs~s | 13173.532 | 24074.271 | 0.000 | 492288.469 |
| LFA subsidies | 9187.641 | 18465.259 | 0.000 | 308748.563 |
| Other rural develo~e | 259.700 | 3462.783 | 0.000 | 147009.328 |
| Share of family fa~e | 0.118 | 20.542 | -1027.536 | 921.029 |
| Economic size | 242.070 | 349.608 | 0.503 | 7431.619 |
| Observations | 12328 | | | |

*Table 4 - Summary Statistics for Normalized Inefficiency Determinants*

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| tn | 1.000 | 0.597 | 0.000 | 1.957 |
| z1n | 0.999 | 1.166 | 0.000 | 17.504 |
| z2n | 1.000 | 1.828 | 0.000 | 37.378 |
| z3n | 1.000 | 2.010 | 0.000 | 33.612 |
| z4n | 0.812 | 10.825 | 0.000 | 459.544 |
| z5n | 0.898 | 156.023 | -7804.516 | 6995.556 |
| z6n | 1.000 | 1.445 | 0.002 | 30.707 |
| Observations | 12328 | | | |

A key methodological contribution of this study is the decomposition of agricultural subsidies into distinct policy instruments. Rather than relying on a single aggregate subsidy variable, the inefficiency effects model separates environmental payments (SE621), Less Favoured Area (LFA) support (SE622), and other rural development subsidies (SE623). This decomposition allows for a more nuanced assessment of how different forms of public support affect farm efficiency. It is particularly relevant in the Swedish context, where subsidy allocation varies both regionally and by farm type under the Common Agricultural Policy (CAP) framework (Latruffe, 2010; Dakpo et al., 2023).

Regional dummies—for Southern, Middle (reference category), and Northern Sweden—are included to control for structural and agroecological variation, as well as differential access to infrastructure and policy targeting (Huang & Jiang, 2019; Liu et al., 2021). Time is modelled through a normalized time trend, with both linear and quadratic terms included in the production function to account for potential technical change over the study period. The inclusion of these variables supports a context-sensitive and policy-relevant understanding of inefficiency in Swedish agriculture.

## 3.3 Empirical Model Specification

The empirical strategy adopted in this study is based on a multi-stage stochastic frontier framework, designed to estimate technical efficiency (TE), fertilizer use efficiency (FUE), and meta-efficiency scores (MTE) across heterogeneous farm types in Swedish agriculture. The model addresses both managerial inefficiencies, through the estimation of farm-level technical efficiency scores within each farm type, and structural technology gaps, via meta-frontier decomposition that compares group-specific frontiers to a common technological benchmark.

This section outlines the key components of the empirical strategy, including: (1) the choice of functional form (Cobb-Douglas vs. translog), (2) the use of the one-step inefficiency effects model (Battese & Coelli, 1995), (3) the distributional assumptions on the inefficiency term, and (4) the logic of technology gap ratio (TGR) estimation and meta-efficiency (MTE) construction. Taken together, these specifications support a comprehensive and input-specific assessment of farm performance across structurally diverse production systems.

### 3.3.1 Stage 1: Farm-Type-Specific Stochastic Frontier Model

In the first stage, the technical efficiency of farms is estimated separately for each farm type—field crops (TF8 = 1), milk (TF8 = 5), and other grazing livestock (TF8 = 6)—using a Translog stochastic production frontier with inefficiency effects:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{6} \beta_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{6}\sum_{j=1}^{6} \beta_{kj} \ln x_{kit} \ln x_{jit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + v_{it} - u_{it}$$

$Y_{it}$ is total output (SE131); $x_{kit} \in$ {land, labor, fixed assets, energy, other inputs, fertilizer}; $v_{it} \sim \mathcal{N}(0, \sigma_v^2)$ is the noise term; and $u_{it} \sim \backslash \mathcal{N}(0, \sigma_u^2) \backslash$ is the non-negative inefficiency term (half-normal distribution).

The inefficiency component is modelled as a function of farm-specific variables:

$$u_{it} = \delta_0 + \sum_{m=1}^{M} \delta_m z_{mit} + w_{it}$$

Where $z_{mit} \in$ {subsidies & region}and $w_{it} \sim \mathcal{N}(0, \sigma_w^2)$ is the error term in the inefficiency equation.

The one-step estimation procedure is implemented using Stata's frontier command with the uhet() option to model heteroskedastic inefficiency effects, following the specification of Battese and Coelli (1995). A half-normal distribution for the inefficiency term is adopted based on its theoretical simplicity and empirical performance, consistent with the recommendations of Belotti et al. (2013). The translog functional form, used in the farm-type-specific models, includes squared and interaction terms to capture potential non-linearities and scale effects in input relationships.

Predicted technical efficiency scores $\widehat{TE_{it}} \in (0,1]$ are generated using the predict,te command and serve as the basis for subsequent meta-frontier decomposition and input-specific efficiency analysis.

### 3.3.2 Stage 2: Meta-Frontier Estimation and Technology Gap Ratios (TGR)

To compare efficiency across farm types that operate under potentially different technologies, this study applies a meta-frontier stochastic frontier approach, following the framework developed by Battese, Rao, and O'Donnell (2004**)**. Predicted output values from the first-stage farm-type-specific models (i.e.,$\widehat{y_{it}^{\text{group}}}$ ) are stacked and used as the dependent variable in a second stochastic frontier regression, which maintains the same translog input structure as in the group models:

$$\widehat{y_{it}^{\text{group}}} = \beta_0^M + \sum_{k=1}^{6} \beta_k^M \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{6}\sum_{j=1}^{6} \beta_{kj}^M \ln x_{kit} \ln x_{jit} + \beta_t^M t + \frac{1}{2}\beta_{tt}^M t^2 + v_{it}^M - u_{it}^M$$

From this model, the Technology Gap Ratio (TGR) is calculated for each observation as the ratio between predicted output from the group-specific frontier and predicted output from the meta-frontier. A TGR value less than one indicates that a farm is operating with a technology that is inferior to the best available technology across all farm types.

Meta-Technical Efficiency (MTE) is then calculated as the product of group-specific Technical Efficiency (TE) and the Technology Gap Ratio (TGR), thus capturing both within-group performance and the farm's proximity to the overall meta-frontier:

$$MTE_{it} = TE_{it} \times TGR_{it}$$

This decomposition separates managerial inefficiency (TE) from structural technological disadvantage (TGR), enabling a more comprehensive assessment of farm performance. This approach is particularly useful for identifying farms that are efficient within their group but constrained by outdated or limited technology, and it has been used in agricultural studies such as Liu et al. (2021) and Huang, Huang, & Liu (2014) to inform targeted policy interventions.

### 3.3.3 Fertilizer Use Efficiency (FUE) and Cobb-Douglas Transformation

As stated previously, in addition to TE and MTE derived from SFA, this study derives Fertilizer Use Efficiency (FUE) from the Cobb-Douglas production function, where input coefficients correspond to output elasticities. The Cobb-Douglas form is chosen for this purpose due to its interpretability and its ability to produce stable, farm-level fertilizer elasticity estimates necessary for computing FUE. While the translog form offers greater flexibility by allowing variable elasticities and input interactions, it may lead to overparameterization and multicollinearity, particularly when estimating input-specific measures like FUE. Consequently, using Cobb-Douglas for FUE estimation ensures consistency and tractability without undermining the broader frontier estimation performed via the translog model. Specifically, FUE is calculated as:

$$\mathrm{FUE}_{it} = \exp\left(\frac{\ln \widehat{TE_{it}}}{\beta_{\mathrm{fertilizer}}}\right)$$

Where $\beta_{\mathrm{fertilizer}}$ is the estimated elasticity of fertilizer input from the Cobb-Douglas model. This transformation yields an interpretable index of how efficiently fertilizer contributes to output, conditional on each farm's technical efficiency. Values of FUE below 1 indicate overuse of fertilizer relative to the optimal level implied by the frontier. Based on this, the Fertilizer Overuse Efficiency (FOUE) is also computed to directly quantify the degree of overapplication:

$$FOUEi = (1/FUE_i) - 1$$

Furthermore, to account for technology heterogeneity across farm types, the Meta-Fertilizer Use Efficiency (MTFUE) is calculated as the product of FUE and the Technology Gap Ratio (TGR):

$$MTFUE_i = TGR_i \times FUE_{i.}$$

These metric captures both input overuse and structural disadvantages in access to superior technology. The Cobb-Douglas specification is retained for estimating Fertilizer Use Efficiency (FUE) and related metrics due to its direct interpretability and alignment with policy-oriented analysis. This choice reflects established practices in the stochastic frontier literature, where the Cobb-Douglas form is frequently applied for its simplicity, ease of elasticity interpretation, and analytical tractability—particularly when deriving input-specific efficiency indices. Although more flexible forms like the translog are advantageous for capturing input interactions and scale effects, the Cobb-Douglas remains well-suited for contexts emphasizing marginal productivity and policy relevance (Kumbhakar and Lovell, 2000; Coelli et al., 2005; Battese and Coelli, 1995).

# 4. Results and Discussion

This chapter presents the empirical results of the cross-sectional stochastic frontier analysis conducted to evaluate the technical and fertilizer use efficiency of Swedish farms. The model is estimated using a one-step inefficiency effects approach following Battese and Coelli (1995), where inefficiency is allowed to vary systematically with farm-specific characteristics. These include regional location and subsidy composition, entered through the uhet() specification in Stata. Although the dataset is a panel, the estimation is performed cross-sectionally to allow for group-specific frontiers and a subsequent meta-frontier analysis. Temporal dynamics are captured by including a normalized time trend (lnt) and its square in the production function.

The results begin with an interpretation of the estimated production frontiers, including input elasticities and scale properties, as well as the inefficiency determinants modeled through uhet(). This is followed by an analysis of technical efficiency (TE) scores across farm types. Next, Technology Gap Ratios (TGRs) are introduced, derived from a meta-frontier model, to capture structural disparities in access to best-practice technologies. These are combined with TE to compute Meta-Technical Efficiency (MTE).

Finally, fertilizer-specific efficiency is assessed using a Cobb-Douglas specification to estimate Fertilizer Use Efficiency (FUE), Fertilizer Overuse Efficiency (FOUE), and Meta-FUE (MTFUE). These measures provide insight into the economic and environmental implications of input use. Taken together, the results offer a comprehensive evaluation of productivity, inefficiency drivers, and sustainability trade-offs in Swedish agriculture.

## 4.1 Stochastic Frontier Estimates: Translog Translog Frontier Estimation by Farm Type

The estimation of translog stochastic frontier production functions reveals important differences in input elasticities and efficiency patterns across farm types. This heterogeneity justifies the meta-frontier approach and is consistent with prior literature emphasizing structural variability in European farming systems (Latruffe et al., 2009; Huang & Jiang, 2019).

For field crop farms, fertilizer and other intermediate inputs display strong and significant output elasticities (0.183 and 0.342, respectively), affirming their central role in crop-oriented production systems. The significance of fertilizer underpins its use in Fertilizer Use Efficiency (FUE) metrics and aligns with findings in Huang & Jiang (2019), who emphasize fertilizer's productivity link in similar cross-sectional settings. Labour and energy also show statistically significant elasticities, while the negative coefficient on fixed assets suggests potential overcapitalization—consistent with inefficiencies observed in capital-intensive settings (Latruffe et al., 2012).

In dairy farms (TF8 = 5), the highest output elasticity is observed for other intermediate inputs (0.672), likely capturing feed, veterinary costs, and contract services. Fertilizer's lower elasticity (0.055) reflects its more limited direct impact on dairy output, in line with Dakpo et al. (2023), who caution against overemphasizing fertilizer efficiency in livestock-oriented systems. Energy and labour remain significant, while land contributes modestly.

Grazing livestock farms (TF8 = 6) show positive and significant coefficients for fertilizer (0.096) and energy (0.305), though land (−0.158) is negatively associated with output. This likely reflects the extensive nature of pasture-based systems and reduced marginal productivity from additional land, echoing patterns discussed in European extensive farming systems by Latruffe et al. (2009).

The statistical significance of squared and interaction terms supports the choice of the translog specification. The consistently negative and significant interaction between energy and intermediate inputs suggests diminishing marginal returns when these inputs are scaled together—indicative of input complementarity saturation (Bravo-Ureta & Pinheiro, 1997).

On the inefficiency side, total subsidies (z1) are associated with reduced inefficiency across all models, reinforcing their potential to stabilize input allocation and mitigate risk (Dakpo et al., 2023). However, as the variable reflects absolute subsidy levels, this effect may partly capture the efficiency advantages of larger farms, given that subsidy size is often correlated with farm scale. Moreover, environmental (z2) and LFA subsidies (z3) are positively related to inefficiency in field crop and grazing systems, suggesting that such payments may reduce incentives for tight input management, a finding in line with Huang & Jiang (2019) and Latruffe et al. (2009).

Geographically, farms in Southern Sweden show lower inefficiency, particularly in dairy systems, likely due to favorable agro-climatic conditions and infrastructure. Conversely, farms in Northern regions consistently exhibit higher inefficiency, which corresponds with structural constraints and less favorable conditions—a pattern also noted in studies on regional disparities in European agriculture (Latruffe et al., 2009). Together, these results validate the use of a flexible translog form and support a dual focus on both managerial performance and structural technological disparities—key objectives of this thesis.

## 4.2 Technical Efficiency

This section presents and interprets the technical efficiency (TE) scores estimated using Stochastic Frontier Analysis (SFA) based on the Translog production function by Farm Type. Table 5 reports summary statistics for technical efficiency scores across three different frontier specifications (te_tf1, te_tf5, and te_tf6) as well as the overall average (te_total).

*Table 5 - Technical Efficiency and Predicted Output Summary*

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| te_tf1 | 0.7353321 | 0.1617856 | 0.0180362 | 0.9999834 |
| te_tf5 | 0.8698613 | 0.0775792 | 0.2764187 | 0.9942517 |
| te_tf6 | 0.8725970 | 0.1311510 | 0.0860815 | 1.0000000 |
| te_total | 0.8220350 | 0.1314139 | 0.0172447 | 1.0000000 |
| Observations | 9480 | | | |

The technical efficiency (TE) scores derived from the translog stochastic frontier model reveal important variation across Swedish farm types. Field crop farms (TF8 = 1) exhibit the lowest average TE at 0.735, while dairy farms (TF8 = 5) and other grazing livestock farms (TF8 = 6) show significantly higher efficiency levels at 0.870 and 0.873, respectively. The overall mean TE for the full sample stands at 0.822, indicating that, on average, Swedish farms operate at approximately 82% of their production potential, given their current input mix and technology.

While field crop farms exhibit comparatively lower TE levels, such group-specific differences should be interpreted with caution, as efficiency estimates are inherently sample-dependent and may vary across contexts and datasets. For example, Huang, Manevska-Tasevska, and Hansson (2024) demonstrate that Swedish crop farms generally exhibit lower technical efficiency, particularly when constrained by environmental or diversification pressures. Liu et al. (2021) similarly highlight the sensitivity of crop systems to variability in input conditions and management quality, leading to greater dispersion in performance.

Indeed, field crop farms in this study also show the highest dispersion (SD = 0.162) and a minimum TE as low as 0.018, suggesting the presence of significant inefficiencies among a subset of farms. This may be related to differences in input quality, managerial capacity, or farm structure, in line with findings from studies on European crop sectors (Makieła et al., 2022). The relatively low and highly variable TE scores observed among Swedish field crop farms may reflect their exposure to climatic risks and market volatility, factors identified by Zhu et al. (2023) as key inefficiency drivers in crop production systems. In contrast, the high average TE for dairy farms likely reflects greater structural coherence and input coordination. Prior work by Huang and Jiang (2019) suggests that dairy systems benefit from more standardized technology adoption, regularity in input use, and economies of scale. Similar conclusions are drawn in studies from Norway and the Netherlands, where dairy farms tend to be more capital-intensive and better integrated into value chains (Alem et al., 2015; Zhu et al., 2023).

Grazing livestock farms, while showing efficiency levels comparable to dairy farms, may mask deeper structural inefficiencies when considered alongside their relatively low technology gap ratios (discussed in the next section). As shown by Huang et al. (2024), such farms often operate under constraints imposed by geography, land quality, or limited access to extension services, particularly in Northern Sweden.

Together, these findings emphasize the importance of differentiating between observed inefficiencies and underlying structural disadvantages. While TE captures how close farms are to their type-specific frontiers, it does not alone reflect broader constraints related to access to best-practice technologies or systemic barriers—a gap addressed in the meta-frontier analysis that follows.

## 4.3 Technology Gap Ratios (TGR) and Meta-Technical Efficiency (MTE)

Table 6 summarizes the Technology Gap Ratio (TGR) values derived from the metafrontier analysis. The TGR values, which measure the distance between group frontiers and the metafrontier, indicate the extent to which technological differences exist across groups. The mean TGR values are close to 1 for TGR1 and TGR5, suggesting relatively small gaps, whereas TGR6 exhibits a lower average, implying a wider technology gap. The variable te_tema reflects metafrontier technical efficiency and supports the interpretation of the productivity gap across technologies.

*Table 6 - Technology Gap Ratio (TGR)*

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| TGR1 | 0.9142908 | 0.1321863 | 0.1500000 | 1.6200000 |
| TGR5 | 0.9072748 | 0.0945791 | 0.4400000 | 1.1700000 |
| TGR6 | 0.7296962 | 0.0749840 | 0.2400000 | 1.1200000 |
| TGRtotal | 0.8677060 | 0.0669522 | 0.3909186 | 1.1169370 |
| te_tema | 0.8643102 | 0.0985822 | 0.1681620 | 1.0000000 |
| Observations | 9480 | | | |

While technical efficiency (TE) captures how well a farm uses its inputs relative to its own group frontier, Technology Gap Ratios (TGR) provide insight into how far a farm's group frontier is from the sector-wide meta-frontier, representing the best practice across all systems. Thus, TGR captures structural limitations in access to technology and institutional advantages, making it an essential complement to TE when assessing performance across heterogeneous farm types (Battese et al., 2004; Huang & Jiang, 2019).

The empirical results highlight stark contrasts across farm types. Dairy farms exhibit the highest average TGR (0.918), closely followed by field crop farms (0.916), while grazing livestock farms lag substantially with an average TGR of just 0.729. These findings indicate that livestock farms are structurally further from the sector's technological frontier—suggesting not only potential underinvestment but also a need for more targeted modernization policies. Such patterns are consistent with Liu et al. (2021), who document similar gaps in livestock sectors across Northern Europe and stress the importance of systemic constraints over managerial shortcomings.

The near-parity in TGR between dairy and crop farms, despite differing TE levels, reveals an important nuance: crop farms have access to modern technologies but are less effective at utilizing them—a theme echoed by Huang and Jiang (2019), who observe that technology availability does not guarantee its full exploitation due to structural, climatic, or behavioral limitations. Similarly, Zhu et al. (2023) point out that volatility in crop markets may discourage farms from making long-term investments in new practices, reinforcing this underutilization.

High TE and high TGR of dairy farms suggest a dual advantage: these farms are not only efficient within their group but are also operating close to the sector's technological frontier. This reflects the capital-intensive, professionally managed nature of Swedish dairy systems, which are supported by stable institutional frameworks, supply chain integration, and policy incentives—as also observed in other FADN-based research (Latruffe, 2010; Liu et al., 2021).

At the full sample level, the mean TGR is 0.906, with some values slightly above 1. As noted by Liu et al. (2021), such "overshooting" may occur due to smoothing assumptions in meta-frontier estimation or temporary shocks that elevate individual output beyond the predicted frontier. While these are statistical artefacts, they emphasize the importance of cautious interpretation when assessing best-practice boundaries.

In sum, the results underline a critical insight: farms may be efficient relative to their peers but remain disadvantaged in broader technological terms. A grazing livestock farm with high TE but low TGR still operates far below the potential of more advanced systems. This insight, emphasized by Garzón Delvaux et al. (2020), supports the dual focus of the meta-frontier framework on both behavioral (TE) and structural (TGR) drivers of performance.

Table 7 presents the summary statistics for Technical Efficiency (TE), Technology Gap Ratio (TGR), and Meta-Technical Efficiency (MTE). The average TE is approximately 0.83, indicating that on average, farms operate at 83% of their potential output under their respective technologies. The mean TGR is 0.87, reflecting a relatively small average gap between group frontiers and the metafrontier.

*Table 7 - Summary Statistics: Technical Efficiency (TE), Technology Gap Ratio (TGR), and Meta-Technical Efficiency (MTE)*

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| TE | 0.8305978 | 0.1360343 | 0.0180362 | 1.0000000 |
| TGR | 0.8668165 | 0.1288802 | 0.1500000 | 1.6200000 |
| MTE | 0.7190826 | 0.1547106 | 0.0162325 | 1.6151940 |
| Observations | 9480 | | | |

The Meta-Technical Efficiency (MTE), as a multiplicative product of TE and TGR, averages 0.72. This reflects the compounded effect of both managerial inefficiencies and technological disadvantages. The fact that MTE is substantially lower than either TE or TGR individually underscores that improving farm-level productivity requires addressing both behavioral (within-frontier) and structural (technology access) dimensions. This finding supports prior studies (e.g., Garzón Delvaux et al., 2020; Latruffe et al., 2009) which argue that sustainable efficiency gains in agriculture demand not only better use of current inputs but also equitable diffusion of innovation and technology.

The wide dispersion in MTE (standard deviation of 0.15, ranging from 0.016 to 1.62) reflects substantial inequality in farm performance relative to the meta-frontier. As emphasized by Battese et al. (2004) and reinforced by Huang & Huang (2009), such heterogeneity justifies the use of meta-frontier methods to differentiate between farms that are inefficient due to managerial reasons and those structurally disadvantaged.

## 4.4 Fertilizer Use Efficiency (FUE)

Table 8 reports the summary statistics for Fuel Use Efficiency (FUE) across three technological groups and in total.

*Table 8 - Cobb-Douglas Fertilizer Use Efficiency by Farm Type*

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| FUE1 | 0.440 | 0.239 | 0.000 | 1.000 |
| FUE5 | 0.798 | 0.091 | 0.244 | 0.954 |
| FUE6 | 0.772 | 0.179 | 0.015 | 1.000 |
| FUEtotal | 0.612 | 0.211 | 0.000 | 1.000 |
| N | 9480 | | | |

The Cobb-Douglas Fertilizer Use Efficiency (FUE) results reveal significant disparities in how effectively fertilizer inputs are converted into output across farm types in Sweden. The average CDFUE across all farms is approximately 0.685, indicating that farms, on average, could reduce fertilizer use by roughly 31.5% without compromising output if they were operating on the efficient frontier. However, this average mask important heterogeneity across production systems.

Field crop farms (TF8 = 1) exhibit the lowest mean FUE at 0.440, with a wide standard deviation (0.239) and a minimum value close to zero. This suggests that many crop farms are applying fertilizer well beyond the economically optimal level. These findings align with Zhu et al. (2023), who report that nutrient overuse, particularly nitrogen, is prevalent in cereal and field crop systems due to low marginal productivity and risk-averse behavior among farmers. Similar patterns are observed in Liu et al. (2021), where inefficiencies in crop production are partly attributed to climatic uncertainty and misaligned fertilizer application strategies. The environmental implications are significant: overapplication not only signals economic waste but also contributes to nitrate leaching and emissions, as discussed by Dakpo et al. (2023).

In contrast, dairy farms (TF8 = 5) show the highest at 0.798, with relatively low dispersion. This suggests that fertilizer—mostly applied indirectly via purchased feed crops and manure management—is used closer to its efficient level. This is consistent with findings by Huang and Jiang (2019), who note that dairy systems often operate in more vertically integrated input-output environments, allowing for more precise input control. The higher efficiency may also reflect the capital intensity and managerial sophistication typically found in these systems (Latruffe et al., 2009).

Grazing livestock farms (TF8 = 6) report a FUE of 0.772, slightly below dairy farms but significantly above field crop systems. This may appear surprising given their typically extensive nature, but it reflects a more restrained use of chemical fertilizers. These systems may rely more on natural forage and rotational grazing, which indirectly limits overuse. However, their relatively high fertilizer efficiency does not necessarily imply overall competitiveness, especially when considered in conjunction with their lower Technology Gap Ratios (TGRs) as shown earlier.

The total sample FUE value of 0.612 further underlines that fertilizer overuse is not limited to one specific group but is a systemic challenge. As emphasized by Garzón Delvaux et al. (2020), addressing input misallocation—particularly fertilizer—is crucial for aligning agricultural productivity with sustainability goals.

In sum, the results indicate that fertilizer use efficiency is highly farm-type specific, shaped by production systems, input strategies, and structural conditions. Policy responses should therefore be differentiated. These insights support the broader argument by Sauer and Latruffe (2015) that inefficiency in European agriculture is multi-dimensional and must be addressed through both behavioral and structural reforms.

### 4.4.1 Fertilizer Use Efficiency at Sector Level (MTFUE) and Overuse Efficiency (FOUE)

Table 9 presents the summary statistics for Meta-Technical Fuel Use Efficiency (MTFUE) and Fuel Overuse Efficiency (FOUE) across different technological groups and in total.

*Table 9 - Summary Statistics: Meta Fertilizer Use Efficiency and Fertilizer Overuse Efficiency*

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| MTFUE1 | 0.4064281 | 0.2202274 | 0.00000406 | 1.087641 |
| MTFUE5 | 0.6954089 | 0.1448218 | 0.140448 | 1.352518 |
| MTFUE6 | 0.4968679 | 0.1372107 | 0.0099548 | 0.9005559 |
| MTFUEtotal | 0.5055485 | 0.1828189 | 0.00011 | 0.9214448 |
| FOUE1 | 95.20497 | 4696.089 | 0.0000129 | 249029.8 |
| FOUE5 | 0.2740551 | 0.1946087 | 0.0486644 | 3.099192 |
| FOUE6 | 0.4444879 | 1.512107 | 0.0000000 | 65.90903 |
| FOUEtotal | 2.005614 | 75.44877 | 0.0000000 | 7306.927 |

The meta-fertilizer use efficiency (MTFUE) and fertilizer overuse efficiency (FOUE) measures offer deeper insights into sustainability and input optimization across heterogeneous Swedish farm types. MTFUE, derived from the product of Cobb-Douglas-based fertilizer use efficiency (FUE) and the corresponding technology gap ratio (TGR), encapsulates both within-group efficiency and structural disadvantages across technological frontiers (Huang & Jiang, 2019; Liu et al., 2021).

The results reveal substantial variation in MTFUE across farm types. Dairy farms (TF8 = 5) exhibit the highest mean MTFUE (0.695), indicating that they not only apply fertilizers more efficiently but also do so within technological settings that are closer to the sector-wide frontier. This pattern aligns with their high TE and TGR scores and reflects structural advantages such as more capital-intensive operations and better access to technologies and advisory services, as documented by Latruffe et al. (2012) and Čechura et al. (2015).

Field crop farms (TF8 = 1), by contrast, display a much lower average MTFUE (0.406), suggesting inefficiencies both in fertilizer application and in their relative position to the meta-frontier. This supports prior findings that crop farms tend to underutilize available technological advances, either due to managerial constraints or exposure to higher climatic and price variability (Zhu et al., 2023; Liu et al., 2021). Grazing livestock farms (TF8 = 6) show intermediate performance (mean MTCDFUE = 0.497), reflecting partial inefficiency mitigation but continued distance from the sector's best practices—an observation consistent with findings on extensive systems in marginal regions (Garzón Delvaux et al., 2020; Sauer & Latruffe, 2015).

FOUE results offer a complementary view. While dairy farms show the lowest average FOUE (0.274), indicating relatively minor overuse of fertilizers, grazing farms (mean FOUE = 0.444) and especially crop farms (mean FOUE = 95.2, with extreme upper bounds) demonstrate higher inefficiency in fertilizer application. The extremely skewed distribution of FOUE in field crop systems, including maximum values exceeding 249,000 and a standard deviation of over 4,600, likely reflects both measurement challenges and the structural diversity within this group. Similar volatility in nitrogen-related input inefficiencies was observed by Dakpo et al. (2023) in French cropping systems, underscoring the environmental implications of misallocation.

The gap between MTFUE and FOUE further highlights that overuse is not merely a matter of inefficient management but also of underlying technological or structural limitations. As emphasized by Liu et al. (2021) and Huang & Jiang (2019), meta-efficiency frameworks are critical in making this distinction and guiding policy efforts accordingly.

In sum, the integration of MTFUE and FOUE reveals that Swedish agriculture exhibits substantial heterogeneity not only in productivity but also in environmental efficiency. Addressing both managerial behavior and structural constraints remains central to aligning farm-level practices with national sustainability goals.

## 4.5 Meta-Efficiency (MTE)

The results in Table 10 reveal substantial variation in Meta-Technical Efficiency (MTE) across farm types. Dairy farms (TF8 = 5) demonstrate the highest average MTE (0.790), indicating that they are closest to the meta-frontier and thus operate with relatively fewer structural or technological disadvantages. This aligns with Liu et al. (2021), who highlight the positive role of technological access and advisory services—commonly more available in capital-intensive sectors like dairy.

In contrast, grazing livestock farms (TF8 = 6) show the lowest average MTE (0.636), suggesting a significant structural gap between their group frontier and the overall meta-frontier. This finding is consistent with the literature on regional and sectoral technological heterogeneity (Garzón Delvaux et al., 2020; O'Donnell et al., 2007), and supports policy concerns about the under-capitalization and geographic constraints faced by extensive livestock systems (Alem et al., 2019). Field crop farms (TF8 = 1) also lag behind dairy but outperform grazing livestock, with an MTE of 0.675.

*Table 10 - Meta-Technical Efficiency (MTE) by Farm Type*

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| 1 | 0.675 | 0.186 | 0.016 | 1.615 |
| 5 | 0.790 | 0.114 | 0.213 | 1.055 |
| 6 | 0.636 | 0.114 | 0.065 | 1.120 |
| Total | 0.719 | 0.155 | 0.016 | 1.615 |
| Observations | 9480 | | | |

Table 11 displays the distribution of the selected performance indicator across three geographic regions. Farms in the Middle region exhibit the highest MTE (0.753), followed by the Southern region (0.743), while the Northern region shows the lowest average (0.693). These differences likely reflect regional disparities in climate, infrastructure, access to advisory services, and market connectivity. A lower MTE indicates that farms in that region are operating further away from the sector's best-practice technology frontier—suggesting greater structural or technological disadvantages that limit their potential efficiency.

The meta-efficiency analysis reinforces the idea that improving farm performance requires addressing both internal and external inefficiency sources. Some farms—particularly in the grazing sector and in northern regions—operate relatively efficiently within their group but remain far from the technological frontier. This supports the argument that generalized farm management programs may be insufficient. Instead, differentiated strategies are needed. For instance, Dakpo et al. (2023) argue that input-efficiency policies should be sensitive to technology availability, while Battese et al. (2004) and Garzón Delvaux et al. (2020) suggest that structural modernization and diffusion of innovation are essential for bridging meta-efficiency gaps.

*Table 11 - MTE by Region*

| Region | Mean | SD | Min | Max |
|---|---|---|---|---|
| Middle | 0.753 | 0.159 | 0.070 | 1.220 |
| Northern | 0.693 | 0.157 | 0.033 | 1.046 |
| Southern | 0.743 | 0.171 | 0.047 | 1.520 |

# 5. Conclusion

## 5.1 Summary of Key Findings

This study employed a two-stage stochastic frontier analysis (SFA) within a meta-frontier framework to assess technical and fertilizer use efficiency (FUE) across different Swedish farm types—namely, field crops, dairy, and other grazing livestock.

The analysis revealed several important dynamics. (1) Overall, farms exhibited relatively high technical efficiency, though field crop farms tended to underperform and showed greater variability in comparison to dairy and grazing livestock farms. (2) Fertilizer application patterns highlighted significant inefficiencies, particularly among crop producers, where the Fertilizer Overuse Efficiency (FOUE) index suggested that substantial reductions in fertilizer use could be achieved without compromising yield. (3) The examination of Technology Gap Ratios (TGRs) underscored structural limitations faced by grazing livestock farms, which appear to have restricted access to technologies available to other farm types. These structural differences contributed to lower meta-frontier efficiency (MTE) scores among those farms. (4) When analyzing the determinants of inefficiency, total subsidies were generally associated with improved efficiency. In contrast, more targeted support—such as environmental and Less Favored Area (LFA) subsidies—was linked to higher inefficiency levels in specific farm types, potentially due to compliance burdens or limitations in policy targeting.

These results confirm the presence of both managerial inefficiencies and structural constraints within Swedish agriculture, reinforcing the importance of tailored interventions.

## 5.2 Policy Implications

The observed variation in technical efficiency (TE) and meta-frontier performance across Swedish farm types underscores the need for differentiated and context-sensitive policy responses. Field crop farms, which exhibited the lowest average TE and highest variability, may require targeted support aimed at improving input allocation, managerial capacity, and resilience to market and climatic volatility. Given their tendency for fertilizer overuse, efficiency programs should maybe emphasize agronomic training, precision input application, and tailored digital advisory tools. In contrast, dairy and grazing livestock farms showed higher and more stable TE, suggesting that these systems are closer to the production frontier. For these farms, maintaining efficiency levels will depend on sustained investment in technology renewal and infrastructure—particularly in structurally disadvantaged regions where Technology Gap Ratios (TGRs) remain low. As highlighted by Dakpo et al. (2023), inefficiency is not only an economic issue but also an environmental one. Farms operating significantly below the frontier are likely consuming more inputs per unit of output, exacerbating issues like nitrogen surplus and excess energy use. Addressing these inefficiencies can thus contribute to both productivity and environmental sustainability.

For field crop systems, where both TE and FUE are lower, a dual strategy is needed: facilitating access to best-practice technologies and correcting misallocated inputs. Policy instruments might include better-targeted subsidies, investment in regional infrastructure, and climate-adaptive extension services (Zhu et al., 2023; Garzón Delvaux et al., 2020). In grazing livestock systems, improving TGRs requires going beyond farm-level interventions. Investment in transport, digital connectivity, and regionally tailored technologies is crucial for enabling these farms to approach the meta-frontier. Conversely, in more technologically advanced systems like dairy, policy should shift toward consolidating gains through sustainable input management and environmental compliance tools. By distinguishing between within-group inefficiency and cross-group technological gaps, meta-frontier analysis provides a nuanced and equitable foundation for designing agricultural policy that supports both performance and sustainability.

## 5.3 Final Remarks and Future Research

This thesis contributes to filling several important gaps in the agricultural efficiency literature. While prior research has examined fertilizer use efficiency (FUE), technology heterogeneity, and environmental performance, few studies have combined these dimensions within a single, statistically robust framework. Particularly in the context of Northern and Nordic European agriculture, such integration is rare.

Existing literature is heavily weighted toward Asian case studies using stochastic frontier methods (e.g., Huang & Jiang, 2019; Liu et al., 2021), or European studies employing deterministic DEA (e.g., Zhu et al., 2023; Expósito & Velasco, 2020), which do not separate inefficiency from noise. Moreover, institutional, climatic, and policy differences limit the relevance of findings from non-European contexts for Sweden.

By applying a panel-based translog SFA with inefficiency effects and meta-frontier estimation, this study provides a novel empirical application. It focuses on three key farm types—field crops, dairy, and grazing livestock—and explores structural, regional, and policy-driven sources of inefficiency. The decomposition of subsidies (SE621, SE622, SE623) and input categories (fertilizer, capital, energy) enhances policy relevance.

Future research could build on these findings in several important directions. One potential avenue is the incorporation of dynamic efficiency analysis to examine how farm performance evolves over time. Additionally, expanding the model to include environmental outcome indicators—such as nitrogen surplus or carbon footprint—would provide a more holistic view of farm sustainability. Exploring spatial econometric techniques could also help capture regional spillover effects and the influence of neighboring farm practices. Finally, comparing the results with non-parametric approaches like Data Envelopment Analysis (DEA) would strengthen the robustness and credibility of the efficiency estimates.

In sum, the study not only advances methodological applications of meta-frontier SFA but also deepens the empirical understanding of input sustainability and policy targeting in Swedish agriculture.

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**Popular Science Summary**

Swedish agriculture plays a crucial role in food production, but farmers face growing pressure to balance productivity with environmental sustainability. In this thesis, I examined how efficiently different types of farms—such as those focused on crops, dairy, or grazing livestock—use resources, especially fertilizers. By using advanced statistical methods, I was able to measure both how close farms are to their optimal performance and how much they might be overusing inputs like fertilizer.

The results show that many farms could produce the same amount with less fertilizer, especially crop farms. This means there is potential to reduce environmental impact without sacrificing yield. Additionally, the study found that some farms, particularly those with grazing animals, face disadvantages when it comes to accessing the best technologies, which affects their efficiency. The findings highlight the need for smarter, more targeted policies that support both productivity and environmental goals in Swedish farming.

**Populärvetenskaplig Sammanfattning**

Det svenska jordbruket spelar en viktig roll i livsmedelsproduktionen, men lantbrukare står inför ökande krav på att kombinera hög produktivitet med miljömässig hållbarhet. I detta examensarbete har jag undersökt hur effektivt olika typer av gårdar – såsom växtodling, mjölkproduktion och betesbaserad djurhållning – använder sina resurser, särskilt med fokus på gödselanvändning.

Genom att använda avancerade statistiska metoder kunde jag mäta hur nära gårdarna ligger sin optimala prestanda, samt om de överanvänder insatsvaror som gödsel. Resultaten visar att många gårdar, särskilt växtodlingsgårdar, skulle kunna producera lika mycket med mindre gödsel. Det innebär att miljöpåverkan kan minskas utan att skörden påverkas negativt.

Studien visade också att vissa gårdar – särskilt de med betande djur – har sämre tillgång till modern teknik, vilket påverkar deras effektivitet. Sammantaget understryker resultaten behovet av mer träffsäkra och anpassade jordbrukspolitiska åtgärder som både främjar produktivitet och miljöhänsyn inom svenskt jordbruk.

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