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Abstract

The agriculture sector's contribution to global greenhouse gas (GHG) emissions and its increasing vulnerability to the effects of climate change warrants assessments considering not only on-farm productivity but also the industry's environmental sustainability. Utilizing the concept of eco-efficiency, this study analyzes the environmental performance of Swedish crop farms by incorporating farm-level GHG emissions as an undesirable output in the production function. Eco-efficiency is the term used to describe production with efficient use of resources while reducing environmental damage. Using panel data from the Swedish Farm Accountancy Data Network (FADN) spanning from 2009 to 2020, GHG emissions at the farm level are quantified. Contrasting usual non-parametric eco-efficiency methods, a parametric estimation of an output-oriented directional distance function (DDF) is employed via a stochastic frontier analysis (SFA) to ascertain farmers' potential to simultaneously enhance farm net-value added (FNVA) while decreasing GHG emissions. Further analysis is conducted to investigate any potential effects of the common agricultural policy (CAP) subsidies on eco-efficiency levels. Results reveal that Swedish crop farmers emit an average of 295 tonnes of CO_2 equivalent, predominantly from nitrous oxide (N_2O) due to fertilizer use. These farmers are highly eco-efficient at an average level of 0.90, suggesting that they can concurrently increase FNVA and decrease emissions by 10%. Investigating the factors affecting eco-inefficiency, it is found that crop and environmental subsidies significantly lead to reduced efficiency. Meanwhile, results suggest that the implementation of the 2013 CAP reform, and increased crop diversification foster more eco-efficient practices. From these findings, implications, and conclusions are drawn, which offer valuable insights for policymakers.

Keywords: Swedish agriculture, environmental efficiency, output distance function, CAP reform, relative shadow price, inefficiency

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Abbreviations

CAP	Common Agricultural Policy
CH_4	Methane
CO_2	Carbon dioxide
COP	Cereals, Oilseeds, and Protein
DDF	Directional Distance Function
DEA	Data Envelopment Analysis
EE	Eco-efficiency
FADN	Farm Accountancy Data Network
FNVA	Farm Net Value Added
GHGs	Greenhouse gases
IPCC	Intergovernmental Panel on Climate Change
N	Nitrogen
N_2O	Nitrous Oxide
SFA	Stochastic Frontier Analysis
tCO2e	Tonnes of CO_2 equivalent

1. Introduction

It has been a worldwide issue that agriculture is far from being environmentally sustainable. While the green revolution has boosted agricultural productivity and ensured food security in Europe, its effects have backfired, triggering severe climatic changes. Agriculture is a significant contributor to greenhouse gas (GHG) emissions, yet vulnerable to the effects of climate change, which poses risks to economic losses and ecological well-being. Given that the projected global food demand requires a 60% increase by 2050 (Alexandratos & Bruinsma, 2012), continuing the "business-as-usual" form of intensification will accelerate the negative environmental impacts (Food and Agricultural Organization (FAO), 2018). This further hinders achieving the 2030 sustainable development goals (SDG), particularly SDG 12 on responsible consumption and production, as well as SDG 13 on climate action. With this, there is a need to evaluate farm environmental performance, prompting farmers to reduce their farm emissions while increasing or maintaining their productivity.

In the European Union, the agricultural sector is responsible for 10% of total GHG emissions (European Commission (EC), 2017). This is associated mainly with two types of GHG, namely: methane (CH_4) and nitrous oxide (N_2O), which constitute more than 80% of total agricultural GHG emissions (European Environment Agency (EEA), 2022). Crop production mainly contributes to N_2O emissions from agricultural soils due to the application of mineral and/or nitrogen fertilizers. While livestock production, manure management, and rice cultivation mostly contribute to CH_4 emissions.

To address these negative environmental impacts of agriculture, the European Commission aims for sustainable intensification through the common agricultural policy (CAP). As part of the European Green Deal, the EU pledges to reduce emissions by at least 55% by 2030 and be a climate-neutral economy by 2050, to which all member states should contribute (EEA, 2022). This framework aims for a sustainable food system where farmers can satisfy food demand while protecting the climate (EC, 2017).

In Sweden, the agriculture sector contributes 15% of the country's total GHG emissions emitting 6.9 metric tonnes of CO_2 equivalent in 2020, as reported in the

National Inventory Report (Swedish Environmental Protection Agency, 2022). A significant proportion is from N_2O (52%) and CH_4 (46%), and a few CO_2 from crop production and animal husbandry. The report also stated that almost half of the total emissions in the sector (47.3%) come from agricultural soils. These are mainly derived from nitrogen application through the use of synthetic fertilizers, crop residues, and animal manure. These emission levels are lower compared to the 1990 levels by 10%; however, the levels started to increase in recent years. In 2020, emissions increased by 1.6% (around 100 kiloton of CO2 equivalent (ktCO2e)) due to increased sales of inorganic N-fertilizers leading to an increase in utilization (Swedish Environmental Protection Agency, 2022). Projections from the Swedish Board of Agriculture (2021) even indicated an 18% surge in sales of mineral fertilizer compared to previous years. Comparing utilization levels between 2019 and 2016, the usage of both nitrogen and phosphorus increased by 10% (Statistical Database of Sweden (SCB), 2020).

Sweden has taken several initiatives to curb GHG emissions and reduce fossil fuel use in the agriculture sector. With the reformed CAP in 2013 and through its second pillar for rural development, farmers can receive support for climate change mitigation and adaptation measures based on specific requirements (Government Offices of Sweden: Ministry of the Environment and Energy, 2017). The measures in Sweden's new rural development program for 2014-2020 include several facets, including grants for young farmers, capacity building, ecological farming, environment, climate actions, among others. These are all aimed at improved energy efficiency, more efficient nitrogen use, prevention of nitrogen leakage, improved manure management, and higher environmental performance.

Given these initiatives, Sweden is an interesting focus since the country also targets to have net-zero GHG emissions by 2045 (Government Offices of Sweden: Ministry of the Environment, 2020). With this, investigating the adverse environmental impacts (i.e., GHG emissions) of agricultural production resulting from the use of inorganic fertilizers and fossil fuel use, is crucial in assessing the current state of environmental performance in Swedish agriculture. To measure environmental performance, the concept of eco-efficiency is used. The term eco-efficiency first emerged in 1993, describing the creation of goods and services with efficient use of resources while reducing environmental pressures (Schmidheiny, 1992). OECD (1998) defines it as "the efficiency with which ecological resources are used to meet human needs." With this, the concept considers the economic and environmental impacts of agricultural production. It is commonly defined as the ratio between the desirable (i.e., economic revenues) and the undesirable (i.e., environmental damages from GHG emissions, soil degradation, and others) outputs. Although eco-efficiency does not guarantee sustainability because high eco-efficiency scores can be affiliated with potentially high environmental pressure, nevertheless, it is considered the most cost-effective approach to reducing environmental damage, allowing ease in implementing efficiency-enhancing policy instruments (Kuosmanen & Kortelainen, 2005).

While eco-efficiency studies involving Sweden exist, there is little to no focus on the crop sector. Studies mainly target the Swedish dairy sector (Honkasalo et al., 2005; Martinsson & Hansson, 2021), beef sector (Hessle et al., 2017), services sector (Pardo Martínez, 2013), pulp and paper industry (Helminen, 2000), and a country-to-country comparison of eco-efficiencies for the whole agricultural sector (Camarero et al., 2013; Pishgar-Komleh et al., 2021; van Grinsven et al., 2019). Most studies involving the crop sector analyze the sector's technical efficiency or total factor productivity (Heshmati & Kumbhakar, 1997; Koiry & Huang, 2023; Zhu & Lansink, 2010); however, these studies did not take into account the undesirable outputs of the production, e.g., GHG emissions. The role of subsidies in efficiency analysis is widely studied, but the results are ambiguous (Zhu & Lansink, 2010); where some authors found a positive effect on efficiency (Gadanakis et al., 2015), while others found a negative/insignificant effect (Latruffe et al., 2017; Cillero et al., 2021), hence the relationship between agricultural subsidies and eco-efficiency should be further analyzed.

Moreover, eco-efficiency studies mostly incorporate a non-parametric approach in determining the eco-efficiency scores through a data envelopment analysis (DEA) such as Bonfiglio et al. (2017) and Picazo-Tadeo et al. (2011), among others. Meanwhile, this study uses a parametric approach, the stochastic frontier analysis (SFA), and a directional distance function (DDF) approach to determine eco-efficiency. The DDF, unlike other eco-efficiency analyses, allows to determine the expansion and contraction of desirable and undesirable outputs and the extent to which a farm can increase its value-adding while contracting GHG emissions (Färe & Grosskopf, 2000; Picazo-Tadeo et al., 2012). Other eco-efficiency analyses mostly reported (1) the level at which value added can be increased while maintaining environmental pressures exerted or (2) the level at which environmental pressures can be reduced while maintaining value added.

This study fills these research gaps by determining the eco-efficiency of the Swedish crop sector, taking into account GHG emissions at the farm level. Specifically, it addresses the following research questions: How much GHG emissions are emitted at the farm level in Sweden? To what extent can Swedish crop farmers simultaneously increase their agricultural value added and decrease GHG emissions? Do CAP environmental subsidies play a significant role in their eco-efficiency level? What other factors affect farmers' eco-efficiency?

This study is a new significant contribution to the eco-efficiency literature by focusing on the Swedish crop sector. In addition, this is a contribution to the emerging literature on computing GHG emissions at the micro-level, specifically per crop farm, utilizing the new methods proposed by Coderoni & Espoti (2018) that are also employed by Baldoni et al. (2018) and Coderoni & Vanino (2022). Through this, the study provides valuable insights into the environmental performance of individual crop farms in Sweden. Furthermore, this research contributes to the ongoing debate on the role of subsidies, primarily environmental payments, on eco-efficiency from the perspective of crop farmers in Sweden. Examining the relationship between eco-efficiency and subsidies sheds light on the effectiveness of these policy instruments in promoting sustainable agricultural practices. The findings of this research can be used as recommendations or a basis for policymakers in designing cost-effective programs to increase the eco-efficiency of farms. Ultimately, this contributes to the broader challenge of making agricultural crop production environmentally sustainable.

2. Review of Related Literature

In light of climate change, policymakers worldwide are encouraged to shift towards sustainable intensification where agricultural production is economically productive and environmentally sustainable (Food and Agriculture Organization (FAO), 2011). This gives rise to the growing literature on evaluating the environmental sustainability of farms. Several indicators emerged to evaluate a farm's sustainability. For instance, Barnes & Thomson (2014) proposed 13 indicators encompassing ecosystem, economic and social aspects; however, a consensus has yet to be met (Picazo-Tadeo et al., 2011).

One of the emerging sustainability indicators is the concept of economic-ecological efficiency, commonly known as eco-efficiency. Popularized by the World Business Council for Sustainable Development (WBCSD) (2000), it refers to economic activity with fewer resources utilized and the least possible environmental impact. There has been an increasing interest in eco-efficiency as an effective index to measure sustainability in agricultural production at a macroeconomic- (national), regional-, and microeconomic-level (Zhang et al., 2008). The most commonly used methods to measure eco-efficiency are the ratio approach, the material flow analysis, and the frontier approach (Yang & Zhang, 2018). The ratio approach captures the relationship between economic value added and environmental pressures as numerator and denominator, respectively. The material flow analysis is mainly measured in life-cycle analysis (LCA), such as used in the eco-efficiency studies of Sanyé-Mengual et al. (2018) and Zhen et al. (2020); however, only a few are doing this because of the huge amount of data required to undertake the analysis. With the frontier approach, either a non-parametric approach through data envelopment analysis (DEA) operationalized by Kuosmanen & Kortelainen (2005); or a parametric approach through the stochastic frontier analysis (SFA) is used (Lansink & Wall, 2014).

Reviewing the literature, most eco-efficiency studies relating to the agriculture sector in the European Union applied a non-parametric approach, DEA (Beltrán-Esteve et al., 2012; Bonfiglio et al., 2017; Coluccia et al., 2020; Gadanakis et al., 2015; Stępień et al., 2021) or incorporating it with LCA (Beltrán-Esteve et al., 2017; Grassauer et al., 2021). DEA is popularly used because no assumptions are imposed on the functional form linking outputs and inputs, which is its major advantage (Charnes et al., 1978; Zhou et al., 2008). Further, a small sample size is enough to run the analysis, for instance, Grassauer et al. (2021) assessing only 47 farms. A two-stage DEA, wherein a bootstrapped left-truncated regression follows the first stage, is usually done with these mentioned studies to determine how inefficiencies in production are affected by other variables. Sometimes, DEA is merged with impact assessment methods like propensity score matching (PSM) and difference-in-difference (DID) methods to determine the impact of factors affecting inefficiencies (Ait Sidhoum et al., 2022). However, only a few studies in the EU, such as Stetter & Sauer (2022), are opting for the parametric approach, SFA, in eco-efficiency analysis. Although a huge sample size is required with parametrization, it has the advantage of accounting for stochastic noise (i.e., unexplained variability in the data), the effects of random shocks, outliers, and measurement errors, thereby overcoming the limitations of the DEA (Stetter & Sauer, 2022). Another advantage is that the factors explaining inefficiencies can also be assessed using a one-stage approach.

In addition, there is sparse literature analyzing the eco-efficiency of Swedish agriculture at the micro-level. For instance, Martinsson & Hansson (2021) did an eco-efficiency analysis focusing on the Swedish dairy sector. However, few to zero eco-efficiency studies are done in the crop sector, despite vast literature assessing its technical efficiency (Koiry & Huang, 2023; Zhu & Lansink, 2010). Technical efficiency only measures the ratio of desirable outputs to production inputs, while eco-efficiency relates the ratio of desirable outputs to the environmental pressures caused by production.

Given the definition of eco-efficiency analysis, these previously mentioned studies incorporated different measures of environmental pressures (considered bad outputs) of agricultural production into their frontier models. Since these studies involved European Agriculture, their data source is the Farm Accountancy Data Network (FADN), the most comprehensive farm micro-data available in each European member state. Given the limits of the dataset due to aggregation, measuring environmental pressure is a challenge. Some of these studies collected simultaneous primary data or used other secondary sources or proxies with available variables in the dataset. Martinsson & Hansson (2021), involving the Swedish dairy sector in their analysis, used expenditures on fuels, heating, and fertilizer expressed in national currency to proxy farm-level GHG emissions. Similarly, Stępień et al. (2021) used the same monetary variables in assessing Polish small-scale farms, as well as Ait Sidhoum et al. (2022) in their cross-country comparison of eco-efficiencies involving German, French, Italian, and Dutch farms. Using the same data source, FADN, this thesis addressed these limitations by calculating GHG emissions at the farm level, adopting the novel approach proposed by Coderoni & Espoti (2018). Their approach is an adaptation of the methodology of the UN's Intergovernmental Panel on Climate Change (IPCC) (2008).

Moreover, these mentioned studies follow Kuosmanen & Kortelainen (2005), wherein they only assess how much environmental pressures (undesirable outputs) can be reduced while maintaining value-added (desirable outputs) in agricultural production or how the level of environmental pressures are maintained while increasing value-added. This study applies a directional distance function (DDF) approach wherein the extent to which value-added can be increased while simultaneously contracting environmental pressures is assessed. Similar studies involving DDF are Beltrán-Esteve et al. (2014) and Picazo-Tadeo et al. (2012) when they assessed olive farms in Spain, and Falavigna et al. (2013) analyzing agricultural systems in Italian regions. However, these studies employed the most commonly used non-parametric approach, DEA. Only a few studies used DDF to assess eco-efficiency through a parametric method, SFA. For instance, Huang et al. (2023) analyzed agriculture in the Middle East or North African region, and Huang & Bruemmer (2017) evaluated livestock production in Qinghai-Tibetan Plateau, China.

Given the literature above, this paper is a new contribution to the emerging literature on assessing eco-efficiency using DDF through a parametric approach and the sparse literature on assessing eco-efficiency in Swedish agriculture, particularly the crop sector. Determining the underlying factors affecting eco-inefficiency, and highlighting the roles of agricultural policies, are useful as a basis for policy-making in Sweden which could benefit the crop sector and the country as a whole in assessing the crop sector's performance in reaching the net-zero emissions target by 2045.

3. Methodology

3.1 Theoretical framework and model

In measuring the farm's eco-efficiency, a multi-input multi-output directional distance function (DDF) was specified. In addition to the desirable output (also called good output) in farm production, farm-level GHG emissions were incorporated as the undesirable output (also called bad output). Two axioms, namely null-jointness and weak disposability, are required in modeling a production where undesirable outputs are produced (Färe et al., 2005). On the one hand, null jointness means that no good outputs can be produced without producing undesirable outputs at the same time. Similarly, in farm production, crop yields are the desired outputs by the farmer where revenues and profits are obtained; however, undesirable outputs in the form of GHG emissions are also released during production because of chemical fertilizers and pesticides. Weak disposability, on the other hand, entails a simultaneous reduction in good and undesirable output. This means that a cost is incurred when reducing undesirable outputs. Likewise, in the reduction of farm GHG emissions, inputs such as chemical fertilizers should be reduced, which could lead to lower crop yields, thereby lowering revenues. Satisfying these two axioms, modeling farm GHG emissions as undesirable output in crop production is relevant.

The directional distance function (DDF) is an approach that has the ability to provide a complete representation of a pressure-generating technology that allows for simultaneously expanding desirable outputs while contracting undesirable outputs (Färe & Grosskopf, 2000). It has been popularly used in incorporating undesirable outputs of production. Studies encompass different sectors such as manufacturing and industrial activities (Long et al., 2017; Ramli et al., 2013; Stergiou & Kounetas, 2021), environmental assessment of watersheds (Bostian & Herlihy, 2014; Macpherson et al., 2010) or agricultural production (Beltrán-Esteve et al., 2017; Falavigna et al., 2013). In modeling agricultural production, different measurements of undesirable outputs are utilized. For instance, Huang & Bruemmer (2017) account the grazing pressure in livestock production, Huang et al. (2023) integrate GHG emissions in agricultural production in the Middle East and North African region, and Picazo-Tadeo et al. (2012) incorporate several facets like erosion, pollution and biodiversity loss in crop production.

In this study, an output-oriented DDF is specified using the model developed by Chambers (2002), Chambers et al. (1998), Färe & Grosskopf (2000), and Färe et al. (2005). This type of DDF allows for jointly estimating the increase in good outputs while simultaneously decreasing undesirable outputs, leaving all other inputs unaffected.

In this model, the desirable output is denoted as y, the undesirable output as b, and the vector of inputs as x. With the production relationship of inputs and outputs, the pressure-generating technology set, P, represents the feasible combination of desirable and undesirable outputs (y, b) that can be produced with the given input vector x. Assuming a farm improving its production along the directional vector $g = (g_y, -g_b)$, where ϑg_y is added to desirable output y, and ϑg_b is subtracted to undesirable output b, mathematically, the DDF is shown as:

$$\overrightarrow{D_o}(x, y, b;\ g_y, -g_b) = \sup\{\vartheta :\ (y + \vartheta g_y, b - \vartheta g_b) \in P\} \qquad \text{[Eq. 1]}$$

Given translation property, this can be derived as:

$$\overrightarrow{D_o}(x, y, b;\ g_y, -g_b) - \vartheta = \overrightarrow{D_o}(x, y + \vartheta g_y, b - \vartheta g_y; g_y, -g_b) \qquad \text{[Eq. 2]}$$

A parametric estimation using a stochastic frontier analysis was done in this study using the methodology of Kumbahakar & Lovell (2000). Assuming $\overrightarrow{D_o}(x, y, b;\ g_y, -g_b)$ is zero (0), and adding $\varepsilon_i = v_i - u_i$ to Eq. 2, then the model specification is written as:

$$-\vartheta_i = \overrightarrow{D_o}(x, y + \vartheta g_y, b - \vartheta g_y; g_y, -g_b) + v_i - u_i \qquad \text{[Eq. 3]}$$

The study assumed directional vector $g = (g_y, -g_b) = (1, -1)$ with four (4) inputs x and two (2) outputs, namely y for good output (measured in farm net value added (FNVA) and b for undesirable output (measured in farm GHG emission). With this, the quadratic directional output distance function is denoted as:

$$\begin{aligned}-b_i = \overrightarrow{D_o}(x, y + b, 0) + v_i - u_i \\ = \sum_{k=1}^{4} a_k x_k + \beta_1 y^* + \frac{1}{2}\sum_{k=1}^{4} a_{kk}(x_k)^2 + \frac{1}{2}\beta_{11}(y^*)^2 \\ + \frac{1}{2}\sum_{k=1}^{4}\sum_{k=1}^{4} a_{kl} x_k x_l + \sum_{k=1}^{4} \gamma_{k1} x_k y^* + v_i - u_i \qquad \text{[Eq. 4]}\end{aligned}$$

where $y_i{}^* = y_i + b_i$ and X is a vector of inputs where x_1 is hectares of land utilized, x_2 is labor in annual working units (AWU), x_3 is input costs, and x_4 is the fixed cost of production. The components of the error term are v_i which is the random error capturing all variables that cannot be controlled by the farmer, and u_i capturing inefficiencies in the production.

The eco-inefficiency model (also called the environmentally adjusted technical inefficiency model) can be denoted as:

$$u_i = \tau_0 + \sum_{m=1}^{8} \tau_m * Z_{mi} \qquad \text{[Eq. 5]}$$

where Z corresponds to the explanatory variables that are related to eco-inefficiency effects on the farm. In this study, a one-step approach is done using directional stochastic frontier analysis to determine the variables significantly causing eco-inefficiencies.

Furthermore, relative shadow prices are determined since agricultural emissions are non-market goods i.e., they are not directly tradable in the market. This also helps to further asses the relationship between the farm net value added (FNVA) and corresponding farm GHG emissions, and their trade-offs. Shadow prices also reflect the cost of abating farm GHG emissions in production. Following the methods of Färe & Primont (1996) and Shepard (1970) the relative shadow price are derived using Eq. 6:

$$R_{yb} = \frac{r_y^*}{r_b^*} = \frac{\delta \overrightarrow{D_o}(x, y, b; 1, -1)/\delta y}{\delta D_o(x, y, b; 1, -1)/\delta b} \qquad \text{[Eq. 6]}$$

where r_y^* and r_b^* are the shadow price for desirable and undesirable outputs, respectively.

3.2 Data and Descriptive Statistics

This study used data from the Swedish Farm Accountancy Data Network (FADN). The FADN is a source of harmonized micro-economic data in the European Union. The sample in FADN is considered representative of the “commercial” agricultural holdings in the EU. FADN is important to the EU because it is vital for assessing agricultural policies in the Common Agricultural Policy (CAP). The Swedish Board of Agriculture collects the FADN data in Sweden.

This study only focused on the TF8 classification "Field crops". This is the group that specializes in growing cereals, oilseeds, protein crops, mixed cropping, or general field cropping. Data cleaning was undertaken and an unbalanced panel with a total of 2197 observations from 2009-2020 was utilized in the analysis. Data across all variables used in this study that are measured in euros are deflated using a harmonized consumer price index (HCPI) with 2015 as the reference year obtained from the Statistical Database of Sweden (SCB, 2022). An HCPI is used because this makes the deflation comparable with other countries in the EU which is useful for further extensions or comparisons of this study. In the parametric estimation of eco-efficiency through the stochastic frontier analysis (SFA), all variables (i.e., input and output except dummy variables) are normalized by dividing them by their sample means to address measurement unit differences and mitigate magnitude bias. The data analysis done in this study is undertaken using Stata software. The summary statistics of the variables used in this study is presented in Table 1.

3.2.1 Output Variables

There are two output variables incorporated in the model, the good output y, and the undesirable output b. The good output is the farm net value added (FNVA) measured in euros from the FADN. This is measured by the gross farm income minus depreciation. In the calculation of gross farm income, the total farm output (i.e. including taxes and subsidies) is also deducted from the cost of intermediate inputs. This captures the net profit from the farm's output. The average FNVA of crop farmers is 76.44 thousand euros (Table 1). However, some farms are experiencing losses as indicated by negative FNVA values. These are those farms that have higher expenditures for intermediate inputs than farm revenues earned. The maximum FNVA obtained is more than 3 million euros.

Meanwhile, the undesirable output in this study is farm-level GHG emissions measured in tonnes of CO_2 equivalent (tCO2e). A series of calculations detailed in the Section 3.4 were performed to obtain these values. To highlight, calculations reveal that Swedish crop farms emit an average of 295 tonnes of CO_2 equivalent (tCO2e), with emissions ranging from a minimum of 5 tCO2e to a maximum of around 4000 tCO2e (Table 1). Comparing the trends of both output variables, GHG emissions peaked in 2015 and tend to decrease over time; meanwhile, the FNVA shows an erratic trend but generally increasing over time (Figure 1).

Table 1. Descriptive statistics of variables (n = 2197)

Variable	Symbol	Unit	Mean / %	Std. Dev.	Min.	Max.
Input variables						
Land	x_1	ha	156.66	202.34	9.20	2671.90
Labor	x_2	AWU	1.52	3.18	0.06	76.51
Variable Inputs	x_3	thou euros	251.57	523.66	10.17	8917.19
Total Assets excl. land	x_4	thou euros	549.76	721.71	11.94	6575.17
Output variables						
Farm Net Value Added	y_1	thou euros	76.44	193.92	-296.71	3555.83
Total GHG emissions	y_2	tCO2e	295.47	423.82	5.97	4243.02
Inefficiency variables						
Crop subsidies	z_1	thou euros	0.33	2.20	0.00	56.43
Environmental payments	z_2	thou euros	3.87	18.54	0.00	498.97
Crop diversification index (lagged)	z_3		0.47	0.17	0.00	0.96
2013 CAP reform implementation (dummy)	z_4					
2009-2014		%	51.84			
2015-2020		%	48.16			

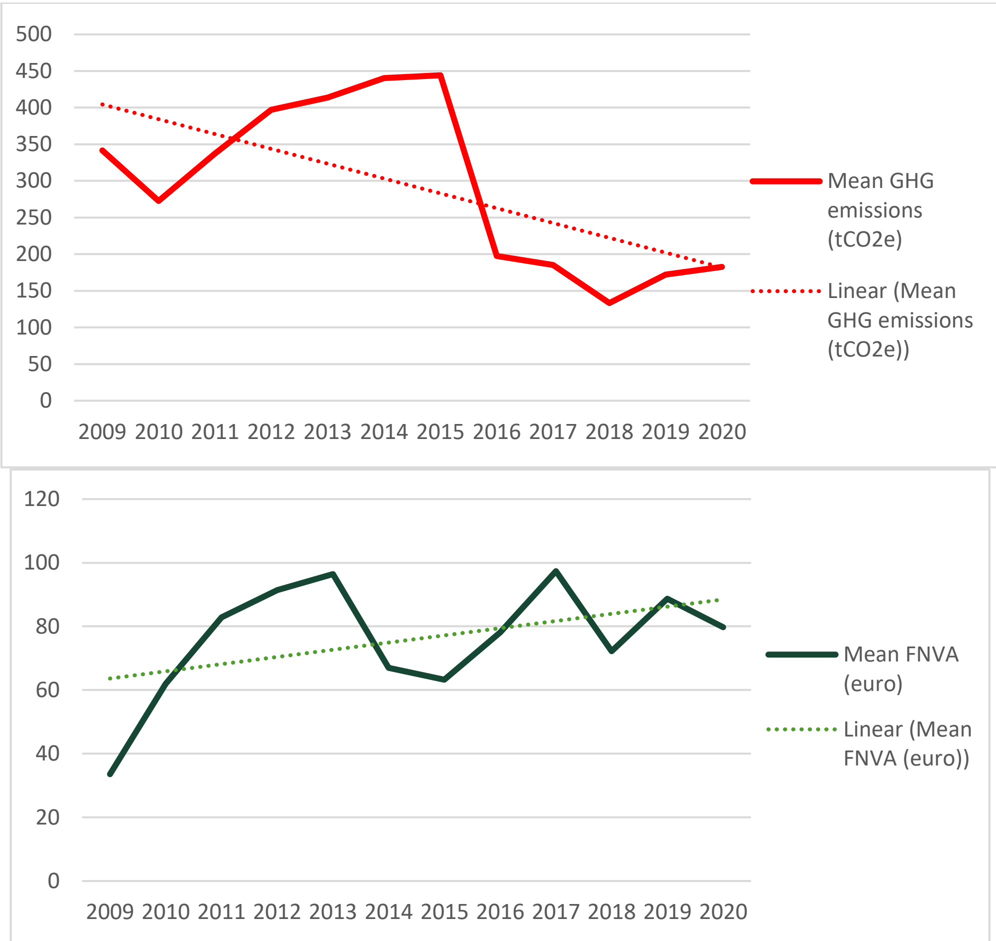

Figure 1. Trend of FNVA and farm GHG emissions

3.2.2 Input Variables

Furthermore, four inputs were included in the production function. These are (1) land (x_1) (measured in hectares), which refers to the utilized agricultural area (UAA) for the crop production either owned, rented, or in share-cropping, (2) labor (x_2) (measured in annual working units (AWU or full-time person equivalent)) which comprises family labor (unpaid) and hired labor, (3) variable inputs (x_3) (measured in thousand euros) which include all intermediate inputs like overheads and crop-specific input costs such as seeds, seedlings, fertilizers, other crop protection products, etc., and (4) total assets (x_4) (measured in thousand euros) which include the value of farm buildings, machinery, equipment, etc. but excluding land to avoid double-counting x_1.

Table 1 indicates that, on average, crop farmers in Sweden utilize 156.66 hectares of agricultural land and employ labor equivalent to 1.52 annual work units (AWU), wherein an AWU corresponds to the number of full-time employees based on time involvement. They spend an average of 251 thousand euros for intermediate inputs encompassing costs for seeds, fertilizers, pesticides, overheads, and other variable inputs. Additionally, they own farm assets (i.e., farm machinery, farmhouses, storage, among others) worth 549 thousand euros on average. Among the farms included in the study, the smallest area utilized for agriculture is 9.20 hectares, has employed less than 1 AWU for labor, spends 10 thousand euros for intermediate inputs, and possesses assets worth 11.94 thousand euros. Meanwhile, the largest farm utilizes more than 2000 hectares of agricultural land, employs 76.51 AWU, spends more than 8 million euros for intermediate inputs, and owns assets worth 6 million euros.

3.2.3 Inefficiency Variables

Four variables were included in the model to determine the factors explaining the production's eco-inefficiencies. Two types of specific subsidies (measured in thousand euros) were included to disentangle the different effects of various subsidies, as Latruffe et al. (2017) recommended when they opted to aggregate all subsidies into one variable. As previously mentioned, this thesis adds to the existing literature regarding the ambiguous influence of subsidies on farm efficiency (Gadanakis et al., 2015). First is (1) total crop subsidies (z_1), a coupled support that includes compensatory/area payments to producers of cereals, oilseeds, and protein (COP) crops and payments for energy crops; set-aside premiums mostly received by COP producers to set aside part of their land for other non-food crops; other farm subsidies for the field, permanent and horticultural crops; and other coupled support. Second is (2) environmental payments (z_2), which are payments that are supposed to encourage farmers to incorporate agri-environment-climate measures in their production, payments for organic farmers, or payments for having lands that are part of Natura 2000 or the Water Framework Directive. This variable is of particular interest given that these subsidies in the CAP are purposely geared towards making agriculture more environmentally friendly in the EU. Table 1 shows that not all crop farms receive crop subsidies and agri-environmental payments. On average, they receive less than a thousand euros per year on crop subsidies, with a maximum of 56 thousand euros. Moreover, crop farmers receive relatively higher environmental payments averaging 3.87 thousand euros; the largest premium received is 498 thousand euros.

Further, a dummy variable for 2015 to 2020 was included to capture the changes from the 2013 CAP reform. Despite the reform transition in 2014, the dummy started in 2015 to mark its full implementation (z_4). This CAP reform, also called "CAP greening", particularly aims to promote farm practices that will benefit the climate and environment wherein more stringent requirements are put in place than in the prior cross-compliance requirements. The reform focuses on receiving Pillar

1 direct payments where applying "greening" measures are prerequisite for the premiums received.

Fourth is the inclusion of a lagged crop diversification index (CDI) (z_3) in the model. A diversified crop production is said to contribute to food security and supports a wide range of ecosystem functions contributing to climate change adaptation and mitigation (Nilsson et al., 2022). This is interesting to assess since the crop diversity of Swedish crop farms has a declining trend implying more specialization in the sector (Nilsson et al., 2022; Schaak et al., 2023). In this study, the CDI is measured through the Herfindahl index (HI) as developed by Hirschman (1964), which is mostly used in the literature (Dessie et al., 2019; Fiszbein, 2022; Rahman, 2009). This index measures the extent of crop diversification of farms where a value of 0 means monoculture or perfect specialization while a value of 1 means that the crop farm tends to become more diversified. Mathematically, this is measured through the following series of computations:

$$\mathrm{P_c} = \frac{\mathrm{A_c}}{\sum_{\mathrm{c}=1}^{\mathrm{n}} \mathrm{A_c}} \qquad \text{[Eq. 7]}$$

where P_c is the proportion of the c^{th} crop cultivated under area A_c measured in hectares, and the denominator $\sum_{c=1}^{n} A_c$ is the total utilized agricultural area (in ha).

$$\text{Herfindhal index (HI)} = \sum_{\mathrm{c}=1}^{\mathrm{n}} \mathrm{P_c^2} \qquad \text{[Eq. 8]}$$

$$\text{Crop diversification index (CDI)} = 1 - \mathrm{HI} \qquad \text{[Eq. 9]}$$

The average crop diversification index is 0.47, implying that many farms specialize (Table 1). An index of 0 is found, suggesting that some crop farms have monoculture production, while the largest index of 0.96 implies that some farms have highly diversified production.

3.3 Empirical Model Specification

Given the theoretical framework and variables discussed in the previous sections, this study follows the quadratic form of an output-oriented directional distance function (Equation 4) to specify the stochastic production frontier. Empirically, the model is:

$$
\begin{aligned}
-\vartheta = {} & \beta_0 + \beta_1 \text{land} + \beta_2 \text{labor} + \beta_3 \text{var. inputs} + \beta_4 \text{assets} \\
& + \beta_5 0.5 \cdot (\text{land})^2 + \beta_6 0.5 \cdot (\text{labor})^2 + \beta_7 0.5 \cdot (\text{var. inputs})^2 \\
& + \beta_8 0.5 \cdot (\text{assets})^2 + \beta_9 \text{land} \cdot \text{labor} + \beta_{10} \text{land} \cdot \text{var. inputs} \\
& + \beta_{11} \text{land} \cdot \text{assets} + \beta_{12} \text{labor} \cdot \text{var. inputs} + \beta_{13} \text{labor} \cdot \text{assets} \\
& + \beta_{14} \text{var. inputs} \cdot \text{assets} + \beta_{15} \text{emission. y}^* \\
& + \beta_{16} 0.5(\text{emission. y}^*)^2 + \beta_{17} \text{land} \cdot \text{emission. y}^* \\
& + \beta_{18} \text{labor} \cdot \text{emission. y}^* + \beta_{19} \text{var. inputs} \cdot \text{emission. y}^* \\
& + \beta_{20} \text{assets} \cdot \text{emission. y}^* - \eta \exp(\tau_0 + \tau_1 \text{crop. subsidies} \\
& + \tau_2 \text{envi. payments} + \tau_3 \text{CAPdummy} + \tau_4 \text{CDI}) + \text{v}_\text{i} \qquad \text{[Eq. 10]}
\end{aligned}
$$

where the dependent variable, ϑ, is the undesirable output, GHG emissions measured in tCO2e; β_0 , β_i , τ_0 , and τ_m are the parameters estimated; emission.$y_i{}^* = FNVA_i + GHGemission_i$; and v_i is the random error term. It is important to note that there is no dominant output in a DDF; hence the undesirable output is used as the dependent variable in this study. Since the dependent variable is negative, the signs of the detailed estimates, except for the inefficiency model, are reversed for straightforward interpretation (in Table 4).

3.4. Computation of farm-level GHG Emissions

In the computation of farm-level GHG emissions, the methodology proposed by Coderoni & Esposti (2018) was followed which is also applied by recent studies (Baldoni et al., 2018; Coderoni & Vanino, 2022; and Stetter & Sauer, 2022). The methodology adopted a process-based approach in their computation which means that GHG emissions are based on each farm's production processes, rather than per product or on consumer behavior. This method is an adaptation of the method used by the UN's Intergovernmental Panel on Climate Change (IPCC) (2008) in computing GHG emissions per country, but computing it at the farm level instead. In Coderoni's & Esposti's (2018) conceptual framework, the computation of GHG emissions assumes a linear relationship between the emission factor (EF) and farm activity data. With this, this method can be easily applied to other EU member states using the emission factors from their country (Coderoni & Vanino (2022)).

Firstly, data on implied emission factors (EF) in Sweden were obtained from the GHG Inventory database of the United Nations Framework Convention on Climate Change (UNFCC) (2022), while the farm activity data were obtained from the FADN dataset. The activity data corresponds to the sources of emission of the production system. Given the data availability of the FADN, only two sources of GHG emissions were computed for the field crops sector. These are emissions from energy use and agricultural soils (i.e. from the nitrogen content in fertilizers and crop residues utilization) (Table 2). Appendices 1 and 2 show the emission factors for Sweden, obtained from the UNFCC database from 2009-2020.

Table 2. Emission source and corresponding activity data in the FADN

GHG	Emission source	FADN Activity Data
N_2O	**Agricultural Soils – Direct emission**	
	Use of synthetic fertilizers	N fertilizers (N quantities/fertilizer expenditure)
	Crop residues	UAA / yield of crops
	Agricultural Soils – indirect emission	
	Atmospheric deposition	N fertilizers (N quantities/fertilizer expenditure)
	Leaching and runoff	N fertilizers (N quantities/fertilizer expenditure)
CO_2	**Energy**	Energy expenditure

In its general form, the equation used in determining farm-level emissions (E_i) for the ith farm and lth emission source is:

$$\mathrm{E_i} = \sum_{\mathrm{l}=1}^{\mathrm{L}} \mathrm{EF_l} \times \mathrm{AD_{i,l}} \quad \text{[Eq. 11]}$$

where EF is the emission factor, and AD is the activity data in the FADN data set.

3.4.1. Emissions from Agricultural Soils

The emissions from agricultural soils identified in this study are anthropogenic nitrous oxide (N_2O) emissions. When there is an increase in the available nitrogen (N) in the soil, the level of nitrous oxide naturally produced in soils also increases because of the faster rates of nitrification and denitrification process, which further causes a higher production of N_2O (Hergoualc'h et al., 2019). Two pathways are assessed separately in this study, direct and indirect emissions. For this section, the refined 2019 IPCC guidelines by Hergoualc'h et al. (2019) were followed. First, N_2O-N emissions are computed and then converted to N_2O emissions. Mathematically,

$$\mathrm{N_2O} = \mathrm{N_2O - N} \cdot \frac{44}{28} \quad \text{[Eq. 12]}$$

Direct N_2O emissions

Direct emissions pertain to the added or released nitrogen (N) into the soils. As mentioned, when there is an increase in the naturally available N in soils, from various sources, a higher production of N_2O occurs. The sources of added N included in the exhaustive calculation of N_2O emissions by Hergoualc'h et al. (2019) are from the direct application of synthetic fertilizer, organic fertilizer, urine and dung, crop residues, from N mineralization from land use change, or in management of organic soils. However, only two sources are computed in this study because of the lack of data available in the FADN. These are the use of synthetic N fertilizers and N in crop residues.

The total annual direct N_2O-N emission in inputs, $N_2O - N_{direct}$ (measured in kg N2O-N per year), comprises N in fertilizers and N in crop residues. This was computed using Eq. 13 with the necessary emission factor in Appendix 1.

$$\mathrm{N_2O - N_{direct}} = (\mathrm{F_{SN}} + \mathrm{F_{CR}}) \times \mathrm{EF_1} \qquad \text{[Eq. 13]}$$

where F_{SN} is the amount of N in fertilizer applied to soils (in kg N per year) and F_{CR} is the total amount of N in crop residues (in kg N per year). Data on the quantity of N in fertilizer applied is available in the FADN, but only from 2016 to 2020. This data was not compulsory to be reported in the prior years. In estimating the data gap of F_{SN} for 2009 to 2015, the ratio of the quantity of N to the fertilizer expenditure was computed for the years 2016 to 2020, which resulted in 1.47 kilograms, on average. This value is then multiplied by the corresponding fertilizer expenditures for the year 2009 to 2016. This method of estimation was also done by Coderoni & Vanino (2022) who were using the Italian FADN to fill data gaps.

Moreover, the F_{CR} (measured in kg N per year) constitutes the above-ground and below-ground crop residues. However, only the below-ground crop residues were estimated because of the lack of available data for the actual amount of above-ground crop residues applied. To proxy the amount of N for the above-ground crop residues and simplicity, the estimated N in below-ground crop residues was doubled. This was done after recommendations from experts. Eq. 14-16 adapted from Hergoualc'h et al. (2019) are used to compute for F_{CR}.

$$\mathrm{F_{CR}} = [\mathrm{BGR_{(T)}} \cdot \mathrm{N_{BG(T)}}] \cdot 2 \qquad \text{[Eq. 14]}$$
$$\mathrm{BGR_{(T)}} = \mathrm{Crop_{(T)}} \cdot \mathrm{RS_{(T)}} \cdot \mathrm{Area_{(T)}} \cdot \mathrm{Frac_{Renew(T)}} \qquad \text{[Eq. 15]}$$
$$\mathrm{Crop_{(T)}} = \mathrm{Yield\ Fresh_{(T)}} \cdot \mathrm{DRY} \qquad \text{[Eq. 16]}$$

where:

$\mathrm{BGR}_{(\mathrm{T})}$ = total below-ground crop residue for crop T (kg dry matter (d.m.) per year)
$\mathrm{N}_{\mathrm{BG}(\mathrm{T})}$ = N content of below-ground crop residues (kg N per d.m. per year) (default values in Appendix 3)
$\mathrm{Crop}_{(\mathrm{T})}$ = harvested yield of crop T (kg d.m. per year)
$\mathrm{RS}_{(\mathrm{T})}$ = ratio of below-ground root biomass to above-ground biomass (kg d.m. per ha per year) (Appendix 3)
$\mathrm{Area}_{(\mathrm{T})}$ = area of harvested crop T (ha per year)
$\mathrm{Frac}_{\mathrm{Renew}(\mathrm{T})}$ = fraction of area under crop T renewed annually where annual crops = 1, while crops renewed for more than X years is equal to 1/X.
$\mathrm{Yield\ Fresh}_{(\mathrm{T})}$ = harvested fresh yield for crop T (kg per ha per year)
DRY = dry matter fraction of harvested crop T (kg d.m.) (Appendix 3)

Indirect N_2O Emissions

For indirect N_2O emissions, two (2) pathways are involved. One path is when N volatilizes as ammonia (NH_3) and oxidizes as nitric oxide (NO_x), and the atmospheric deposition of these gases and their products goes to the surface of water bodies or lakes. Another path is when some excess N in or on the soil leaches and runs off from land and flows through pipe drains, ditches, rivers, water bodies, or groundwater under the land where N is applied (Hergoualc'h et al., 2019).

In the computation of N_2O emissions from atmospheric deposition from the volatilization of N ($N_2O - N_{deposition}$ measured in kg of N_2O-N per year), one source of indirect emissions was identified, i.e., the N in fertilizers applied. This was computed using Eq. 17.

$$\mathrm{N_2O - N_{deposition}} = \left(\mathrm{F_{SN}} \cdot \mathrm{Frac_{GASF}}\right) \cdot \mathrm{EF_2} \qquad \text{[Eq. 17]}$$

where $Frac_{GASF}$ is the fraction of N in fertilizer that volatilizes as NH_3 and NO_x (default values in Appendix 4), and EF_2 is the emission factor from atmospheric deposition (Appendix 1).

For the indirect N_2O emissions from leaching and runoff ($N_2O - N_{leaching}$ measured in kg N_2O-N per year), the emission sources identified were the N in fertilizer utilization and crop residues. Mathematically, Eq. 18 was utilized.

$$N_2O - N_{leaching} = ((F_{SN} + F_{CR}) \cdot Frac_{LEACH}) \cdot EF_3 \quad \text{[Eq. 18]}$$

where $Frac_{LEACH}$ is the fraction of N input to managed soils that is lost through leaching and runoff (Appendix 4), and EF_3 is the emission factor from N leaching and runoff (Appendix 1).

3.4.2. Emissions from Energy Use

Regarding energy use, Sweden had a decreasing trend in using fossil fuels but rising use of biofuel from 1970 to 2019 (Swedish Energy Agency, 2021). However, the agriculture sector is still utilizing petroleum products mainly for farm machinery and equipment. According to the report of the Swedish Board of Agriculture (2021), only around one-third of the share of energy use are biofuels; the rest are fossil fuels in 2019. With this, the study assumed that the energy expenditure of farms was from the use of fossil fuels. In addition, a few non-CO_2 GHGs are also emitted, such as CH_4 and N_2O (Amous, 2019), which are also considered in our computation.

In computing CO_2, CH_4, and N_2O emissions, Eq. 11 was used. In the UNFCC database, different emission factors are available depending on the classification of fuel, i.e., biomass, gaseous fuels, liquid fuels, and other fossil fuels, and the type of gas. This EF gives the amount of emission per gigajoules. However, the activity data available in the FADN does not have segregated classifications of utilized fuel to fulfill calculations. Instead, it aggregates all energy expenditures, measured in euros, encompassing motor fuels and lubricants, electricity, and heating fuels. With this, energy expenditures were converted to gigajoules through the use of average natural gas prices (measured in euro/gigajoule) in Sweden from 2009 to 2020. This was further converted to terajoules. Since there is no disaggregated fuel classification in energy expenditure, the average EF across all fuel classifications was computed (shown in Appendix 2) and multiplied by the converted energy expenditure data.

3.4.3. Total Farm GHG Emissions

To sum up, the various types of GHGs emitted from the identified sources, CH_4 and N_2O emissions, were converted to tonnes of CO_2 equivalent (tCO2e) based on their global warming potential (GWP). The GWP of CH_4 and N_2O at 25 and 298, respectively, were used in the computation (Forster et al., 2007).

Disentangling the different sources of emission, Table 3 shows that direct N_2O emission from nitrogen in fertilizers used is the most significant source (with a mean of 129 tCO2e). However, its indirect emissions are found to be minimal. This finding aligns with the report of the Swedish Environmental Protection Agency (2022) that the utilization of mineral fertilizer has increased in Sweden in recent years due to increased sales. Another significant contributor to farm-level GHGs is carbon dioxide (CO_2) emissions from energy use (mean of 84 tCO2e). This is due to the fact that farm machinery in Europe, especially in Sweden, predominantly relies on fossil fuel use because of technology design (Paris et al., 2022).

Table 3. Descriptive statistics of total farm GHG emissions (in tonne CO_2 equivalent) (n=2197)

Variable	Symbol	Mean	Std. Dev.	Min.	Max.
Total GHG Emissions	y_2	295.4741	423.8168	5.9722	4.24E+03
Energy					
CO_2 emission		84.0357	127.3318	0.6613	1.84E+03
CH_4 emission		0.2374	0.3550	0.0016	5.4308
N_2O emission		0.7376	1.1128	0.0058	16.2963
Fertilizer					
Direct N_2O emission		129.6081	243.1479	0.0047	3.10E+03
Indirect N_2O emission:					
Atmospheric Deposition		2.5922	4.8630	0.0001	61.9867
Leaching / Runoff		25.3558	40.8592	0.0625	439.5222
Crop Residues					
Direct N_2O emission		52.9074	94.6394	0.3231	1.29E+03

4. Results and Discussion

4.4. Parametric estimation of the DDF, elasticities, and relative shadow price

In the parametric estimation of the directional distance function (DDF), different models were compared through a likelihood ratio test (LR test) to determine the model with the best fit. Appendix 5 presents four models with distinct specifications and their respective log-likelihood values and degrees of freedom (df). Initially, a basic model (M1) with only output and input variables was evaluated to determine if there was a need to include inefficiency variables. M1 shows a σ_u of 0.7013, which is significant at 1% level (Appendix 6), implying that certain farm-specific characteristics significantly influence the dependent variable; hence, adding inefficiency terms to the model is justified and necessary.

From the LR test results in Appendix 5, Model M4 exhibited the highest log-likelihood value of -1005.05 and a df of 347, among other models, suggesting that including inefficiency variables substantially improved the model specification. With this, M4 is selected as the final model, and the results are presented in Table 4.

As described in the methodology, all variables are normalized with their means before doing the one-step estimation of the DDF and the eco-inefficiency model. Results indicate mostly significant coefficients among variables (Table 4). Of particular importance are variables $emission.y^*$ and $0.5 \cdot (emission.y^*)^2$, with corresponding parameter estimates of β_{15} and β_{16} in the model specification. It demonstrates positive coefficients of 0.345 and 0.021, which are significant at 1% level. These findings imply that GHG emissions are indeed an undesirable output and pose a significant problem that should not be ignored in the Swedish crop sector. While Sweden has commendable performance in reducing GHGs over time (Figure 1), the recent increase in GHG emissions from 2018 should serve as a caution to take action.

Table 4. Parametric estimation of the directional distance function

Variables	**Coef.**	**Std. Err.**
Stochastic frontier normal/half-normal model		
Dependent variable: ϑ		
land	0.248*	0.129
labor	0.107*	0.062
var. inputs	0.486***	0.104
assets (excl. land)	0.163***	0.062
0.5•land^2	-0.240***	0.062
0.5•labor^2	0.013	0.012
0.5•var.inputs^2	-0.281***	0.033
0.5•assets^2	-0.133***	0.022
land•labor	-0.205***	0.025
land•var.inputs	-0.054**	0.026
land•assets	0.032	0.025
labor•var.inputs	0.114***	0.017
labor•assets	-0.180***	0.023
var.inputs•assets	0.311***	0.026
emission.y*	0.345***	0.021
0.5•(emission.y*)^2	0.021***	0.006
land• emission.y*	0.065***	0.012
labor• emission.y*	-0.033***	0.009
var.inputs• emission.y*	-0.007	0.013
assets• emission.y*	-0.049***	0.007
Usigma		
Crop subsidies	0.013*	0.008
Environmental Payments	0.159***	0.016
CAP 2013 reform implementation	-7.224***	1.698
Crop diversification index	-1.209***	0.365
Constant	-1.754***	0.392
Vsigma		
constant	-1.996***	0.035
E(sigma_u)	2.3619	
sigma_v	0.3686***	0.007
Log likelihood =	-1005.0513	
Number of observations	2121	
Prob > chi2 =	0.0000	
Wald chi2(20)	3832.63	

*Significant at 10% level (P < 0.10), **Significant at 5% level (P < 0.05), ***Significant at 1% level (P < 0.01)

In line with classical economic theory, the model also exhibits consistent results with regard to inputs. Specifically, all four inputs, land, labor, variable inputs, and assets (denoting capital), show the expected positive signs, indicating that an increase in these factors will enhance the production potential significantly ($p<0.01$). To highlight, variable inputs are the most important variable that contributes largely to improving the production potential and closing the frontier distance. It has the highest significant coefficient of 0.486, suggesting that variable inputs offer the highest level of flexibility for farmers to adapt when production conditions change.

Moreover, the estimates of the DDF were used to calculate the elasticity of distance with respect to outputs. A t-test followed to determine whether these elasticities are statistically different from 0. This comprehensive analysis aimed to understand the importance of the two outputs defined in this study in the context of production. Results adhered to the monotonicity condition for outputs, such that the good output is negative, i.e., $\partial\,(\overrightarrow{D_o}(x,y,b;1,-1))/\,\partial y\ \leq 0$, and undesirable output is positive, i.e., $\partial\,(\overrightarrow{D_o}(x,y,b;1,-1))/\,\partial b\ \geq 0$, which are both significant at 1% level (Table 5). The elasticity of distance to the frontier with respect to the good output, denoted as ε_y, is -0.3423, and with respect to the undesirable output, denoted as ε_b, is 0.6577. These findings imply that if the good output (FNVA) is increased by 1%, the distance to the frontier will be reduced by 0.342%, leading to better overall performance. Conversely, a 1% increase in undesirable output (farm-level GHG emissions) expands the distance by 0.658%, indicating poorer performance. This suggests that if crop farmers prioritize increasing FNVA while simultaneously reducing the use of mineral fertilizers and fossil fuel, which in turn lowers the level of farm GHG emissions, higher productivity can be achieved with lesser environmental damage, promoting sustainability.

Table 5. Elasticities of distance with respect to outputs (n=2197)

Variable	Mean	SD	Min.	Max.
Output elasticities				
ε_y	-0.3423***	0.0819	-1.408	0.8379
ε_b	0.6577***	0.0819	-0.408	1.8379

In testing whether the means are significantly different from 0,
*Significant at 10% level (P < 0.10), **Significant at 5% level (P < 0.05), ***Significant at 1% level (P < 0.01)

Furthermore, elasticity estimates in Table 5 were utilized to derive the relative shadow price of GHG emissions to the FNVA to understand the relationship between the two output variables. Shadow prices are usually negative indicating that the output is indeed undesirable (Färe et al., 1993); hence, it is converted to absolute values. Our finding reveals a relative shadow price of 1.94 at the sample mean (Table 6). This result imply that the cost of emitting one unit of GHG at the farm exceeds the net value-added of producing one unit of crop. Consequently, reducing a tonne of CO_2 equivalent GHG emissions from crop production in Sweden incurs substantial marginal abatement costs.

Table 6. Relative shadow price (n=2197)

Variable	Mean	Std. Dev.	Min.	Max.
Relative shadow price ($-p\ (\frac{\varepsilon_b}{\varepsilon_y})$)	1.942446	5.979363	-251.4883	79.6969

4.5. Eco-efficiency estimation and inefficiency model

After estimating the directional distance function and the inefficiency model, the eco-inefficiency scores were predicted and shown in Table 7. The result reveals that the average eco-efficiency score of crop farms is notably high at 0.90, signifying a 10% inefficiency of farms that can potentially be improved. Keeping their current input levels unchanged, Swedish crop farms can simultaneously increase their farm net value added by 10% and decrease farm GHG emissions at the same rate. Looking at the distribution of farms within different eco-efficiency ranges (Table 7 and Figure 2), the majority of farms (approximately 90% of them) have eco-efficiency of more than 0.80. Half of the sample (50.34%) have an eco-efficiency of more than 90% with a mean of 0.99, implying that most of the crop farms are producing with minimal environmental damage and only require relatively lesser effort to reach the production frontier. Around 39% fall within the range of 0.80 to less than 0.90 with a mean eco-efficiency of 0.84.

However, focusing on farms (approximately 10% of the sample) falling into the lower eco-efficiency ranges (less than 0.80) is also essential. Among this subset, 8.83% of the farmers fall between 0.70 and 0.80, with a mean of 0.76. Meanwhile, farmers with the lowest mean eco-efficiency score of 0.50 (2% of the sample) have substantial potential to increase both FNVA and reduce GHG emissions by 50% while using the same current level of inputs. In line with this, addressing the environmental performance of these specific farms through targeted policy instruments is crucial.

When comparing the eco-efficiency scores across the three regions in Sweden (Table 8), (1) southern and central plains, (2) southern and central forest and valley, and (3) northern, it shows that the regions only exhibit minimal differences in their eco-efficiency levels (i.e., means of 0.90, 0.91 and 0.92, respectively).

Table 7. Summary of eco-efficiency (n=2197)

Variable	n	%	Mean
EE < 0.70	38	1.73	0.50
0.70 ≤ EE < 0.80	194	8.83	0.77
0.80 ≤ EE < 0.90	859	39.10	0.84
EE > 0.90	1106	50.34	0.99
Total	2,197	100.00	0.90

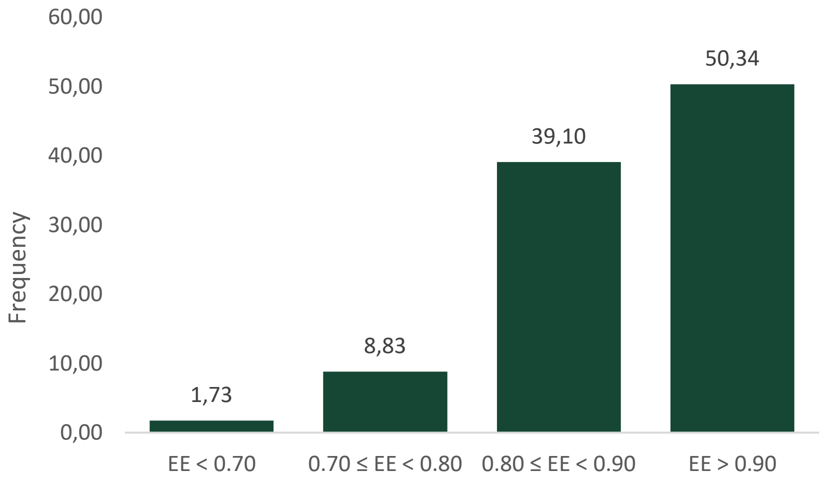

Figure 2. Frequency of crop farms in different eco-efficiency ranges

Table 8. Eco-efficiency scores by region

Region	n (%)	Mean
Southern and Central Plains	1841 (83.8)	0.90
Southern and Central Forest & Valley	223 (10.15)	0.91
Northern	133 (6.05)	0.92

Regarding the inefficiency component of the model, the determination of the final variables followed the general-to-specific modeling method of Hendry (1980). This method, which is also implemented in eco-efficiency studies of Huang et al. (2023) and Huang & Bruemmer (2017), selects only the variables that improved the likelihood ratio test. The results are presented in Table 4 under *Usigma*. In the interpretation, the dependent variable is inefficiency, so a negative coefficient contributes positively to eco-efficiency. Conversely, a positive coefficient indicates a contribution to inefficiency.

Surprisingly, results reveal that the variables of particular interest, crop subsidies and agri-environmental payments, resulted in positive coefficients of 0.013 and 0.159, which are statistically significant at 10% and 1% level, respectively. This result means that these variables have a positive relationship with inefficiency, meaning they contribute negatively to being eco-efficient. Moreover, the dummy variable capturing the CAP reform in 2013 and the level of crop diversification generate negative coefficients of -7.224 and -1.209 that are both significant at 1% level, suggesting a negative relationship with inefficiency; hence these variables lead to increased farm eco-efficiency.

4.3. Discussion on factors influencing inefficiency

The findings from the inefficiency model identify crop subsidies and agri-environmental payments as significant factors leading to reduced eco-efficiency. Increasing the crop subsidies received by farms does not result in an improvement in eco-efficiency; instead, it leads to increased inefficiency. This result is expected since the specific crop subsidy analyzed is a coupled subsidy, where farmers receive the premium as compensation for planting certain crops (e.g., COP or energy crops) and set aside land for non-food crops and other farm subsidies. This result supports previous findings linking subsidies to the decreased managerial effort of farmers (Latruffe et al., 2016; Cillero et al., 2021) and to changes in farmers' risk attitudes potentially due to an income safety (Serra et al., 2008) leading to reduced farm efficiency (Minviel & Latruffe, 2017).

Regarding agri-environmental payments in Sweden, premiums alone do not induce improvements in farm eco-efficiency performance. These payments support organic production, reduced nitrogen leaching, establishing buffer zones, implementing ley farming, and funding environmental investments to improve water and soil management. This result contradicts the conclusions of Picazo-Tadeo et al. (2011) when assessing Spanish farms and Bonfiglio et al. (2017) on Italian farms where they both found participation in agri-environmental schemes associated with higher eco-efficiency. However, our findings align with Cillero et al. (2021), who observed a negative relationship between environmental payments and farm efficiency, which could likely be due to the limited utilization of specific inputs when farmers receive this premium. By limiting certain inputs, it affects technical efficiency, thereby reducing eco-efficiency. However, the authors noted that the relationship is heterogenous and context-specific since they also found a positive relationship in other EU member states. Ait Sidhoum et al. (2022) even found insignificant association. Nevertheless, our finding coincides with studies criticizing the CAP's voluntary agri-environmental schemes (AES) due to its cost-ineffectiveness (i.e., it is expensive but has little to no impact) (European Court of Auditors (ECA), 2021; Pe'er et al., 2020) and poor policy design (Batáry et al., 2015).

Despite the inverse relationship between specific subsidies and eco-efficiency, the 2013 CAP reform significantly increases eco-efficiency. The dummy variable captures the policy changes of the reform from its implementation in 2015, where the reform focused on the changes in decoupled payments, i.e., the single payment scheme (SPS) and single area payment scheme (SAPS), and most importantly, the "CAP greening" measures introduced with it. Our finding could plausibly be due to the reform's more stringent conditions of CAP greening measures such that agri-environmental practices (e.g., crop diversification, maintenance of permanent grassland and ecological focus area (EFA)) should be done alongside production, and this provides the basis for farmers receiving decoupled payments at a reduced rate or forfeit it all (Ciaian et al., 2018). The results of our inefficiency model have shown that the design of the reform is significantly effective in improving eco-efficiency.

From these results, a heterogenous effect of the CAP policy is found when specific subsidies (measured in monetary values) like crop subsidies and agri-environmental payments lead to inefficiency, while the dummy variable capturing reform changes reversed the results. Even though the CAP greening measures in decoupled payments and environmental subsidies require the implementation of specific agri-environmental schemes in their farm, the former (as part of Pillar 1) is used as the basis for the amount received for basic payments, the SPS or SAPS; while the latter (as part of Pillar 2) is provided through voluntary contracting and received by farmers who chose to enroll. With this, introducing a substantial monetary consequence in receiving premiums creates a more demanding cross-compliance condition of the "greening" element, thus encouraging farmers to put more effort into increasing their farm eco-efficiency. Hence, as part of the CAP rural development program (Pillar 2), environmental payments should also impose stricter conditions or regulations accompanied by a monetary consequence. Other types of policy instruments could also be explored, such as results-based agri-environmental payments, where premiums are also based on implementation outcomes rather than just on prescribed practices (OECD, 2022). Although out of the scope of the thesis, this could be a promising avenue for future research.

Additionally, the study confirmed that past levels of crop farm diversity influence an improvement in current eco-efficiency performance. This result could plausibly be due to how high crop diversity mitigates environmental risks by improving nutrient cycling, thereby increasing soil fertility and diversity and water regulation (Tamburini et al., 2020), and also maximizes agriculture output by maximizing yields or minimizing production costs (Zeng et al., 2020). This finding also coincides with Nemecek et al. (2015), who found that diversification of intensive crop rotations in combination with nitrogen management improved the eco-efficiency of French cropping systems. Likewise, the same conclusions are drawn by Zeng et al. (2020), although they stated that regional differences could occur. Given Sweden's decline in crop diversification (Nilsson et al., 2022), implementing stronger regulations and incentives is essential to encourage farmers to adopt diverse crop rotations.

5. Conclusions and Limitations

This study delves into the concept of eco-efficiency (EE) by incorporating farm GHG emissions as undesirable output to analyze the environmental performance of Swedish crop farms. Specifically, this thesis aims to (1) determine farm-level GHG emissions, (2) assess the eco-efficiency of Swedish crop farms, and (3) investigate the factors influencing eco-efficiency levels, with a specific focus on the role of specific CAP subsidies.

Using an unbalanced panel from the Swedish FADN spanning 11 years from 2009 to 2020, this study contributes to the emerging literature in eco-efficiency estimation where a parametric estimation of the directional distance function (DDF) approach through a stochastic frontier analysis (SFA) was used. Through this, it allowed us to determine how much crop farms can increase their level of farm net value-added (desirable output) while decreasing their GHG emissions (undesirable output) simultaneously. This also contributes to the relatively novel literature on computing GHG emissions at the farm level using the innovative method proposed by Coderoni & Esposti (2018) while adhering to the IPCC guidelines, leveraging available data in the FADN.

Findings reveal that Swedish crop farms are emitting an average of 295 tonnes of CO_2 equivalent GHGs predominantly from nitrogen in fertilizer and energy use. Notably, Swedish crop farms are highly eco-efficient, with a mean of 0.90. The estimated eco-efficiency level suggests that crop farms can simultaneously increase farm net value added and reduce farm GHG emissions by 10%, while keeping current input levels. The distribution of eco-efficiency shows that high EE level is found for more than half of the farms, with only a few (10% of the farms) exhibiting lower EE levels. Moreover, our assessment highlighted that crop subsidies and environmental payments lead to reduced eco-efficiency. In contrast, the 2013 CAP reform implementation and higher levels of crop diversification contribute positively to eco-efficiency.

These findings hold significant implications for policymakers and crop farmers in Sweden. To support the environmental performance of crop farms, policy interventions targeting the reduction of mineral fertilizer use and promoting the adoption of new farm technology reliant on bio-fuels or fossil-energy-free energy are recommended. Incentivizing crop diversification could be done to encourage diversification as it increases eco-efficiency. Understanding the nuanced relationship between eco-efficiency and the CAP, including a substantial monetary consequence in receiving subsidies with stringent cross-compliance conditions, is essential to foster eco-efficient practices on crop farms.

It is important to note that only specific subsidy variables (measured in monetary values and dummy variables) are included in this study. Additional research could be done to explore other types of subsidies (measured in different ways) to disentangle their effects and provide more robust insights. Additionally, extending the analysis for a longer period would allow a deeper understanding of the impacts of different reforms. Moreover, an eco-efficiency comparison between production types (i.e., conventional vs. organic) is an avenue for further research. Since the sample of organic farms in Sweden is small (around 7%), a larger sample is needed to yield more comparable and comprehensive insights. Sensitivity analysis could also be done by varying the implied emission factors (EF) in the computation of farm-level GHGs.

Most importantly, this study faced limitations in calculating GHG emissions due to the data availability constraints in the FADN dataset. Data on nitrogen in fertilizer use was only available after 2015; energy expenditures were not disaggregated to fossil fuel or renewable energy, and no data available on the applied above-ground residues. With the importance of "greening" the common agricultural policy (CAP), it is recommended to add variables to capture the negative impacts of other practices, such as the use of pesticides, urine, and animal manure. An update on the measurement of certain variables in the FADN is also needed; for instance, green and fossil-fuel energy expenditures are disaggregated. A broader range of data and longer timeframes would allow for the assessment of farm environmental indicators more effectively. Improvements in the FADN are crucial for future research to produce more accurate results, which is essential in informing policy improvements and reforms.

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Appendix 1

Appendix Table 1. Default emission factors (EF) for emissions from agricultural soils in Sweden

Sources	2009-2020
	kg N_2O-N/kg N
Direct Emission	
N Fertilizers (EF_1)	0.01
Crop Residues (EF_1)	0.01
Indirect Emission	
Atmospheric Deposition (EF_2)	0.01
Nitrogen Leaching and Runoff (EF_3)	0.01

Source: UNFCC (2022)

Appendix 2

Appendix Table 2. Emission factor (EF) for emission from energy sources in Sweden

Year	Carbon Dioxide (CO_2)	Methane (CH_4)	Nitrous Oxide (N_2O)
	t/TJ	kg/TJ	kg/TJ
2009	74.43	12.54	2.34
2010	74.52	12.16	2.34
2011	74.45	10.87	2.32
2012	74.10	9.91	2.27
2013	73.67	7.65	2.20
2014	73.27	7.70	2.12
2015	72.89	7.13	2.02
2016	72.49	6.82	2.00
2017	72.50	6.89	2.04
2018	71.59	6.92	2.07
2019	72.55	6.85	2.10
2020	72.12	6.77	2.14

Source: UNFCC (2022) & averages from author’s calculation

Appendix 3

Appendix Table 3. Default values for NBG, RS, and DRY per crop type

Crops	**N content in below-ground residues (NBG)**	**Ratio of below-ground biomass to above-ground biomass (RS)**	**Dry matter fraction of harvested product (DRY)**
Generic value for crops not indicated	0.009	0.22	0.85
Generic grains	0.009	0.22	0.88
Winter Wheat	0.009	0.23	0.89
Spring Wheat	0.009	0.28	0.89
Oats	0.008	0.25	0.89
Maize	0.007	0.22	0.87
Rye	0.011	0.22	0.88
Potatoes and Tubers	0.014	0.20	0.22
Forages	0.022	0.40	0.90
Perennial Grasses	0.012	0.80	0.90

Source: 2019 refinement to 2006 IPCC Guidelines (Hergoualc'h et al., 2019)

Appendix 4

Appendix Table 4. Default values for the computation of indirect N_2O emissions for Sweden

Year	$FRAC_{GASF}$	$FRAC_{LEACH}$
2009	0.02	0.15
2010	0.02	0.14
2011	0.02	0.15
2012	0.02	0.15
2013	0.02	0.14
2014	0.02	0.13
2015	0.02	0.13
2016	0.02	0.13
2017	0.02	0.12
2018	0.02	0.13
2019	0.02	0.13
2020	0.02	0.12

Source: UNFCC (2022)

Appendix 5

Appendix Table 5. Hypothesis test for model selection

Model	Description	Log likelihood value	df
M1	Basic model without inefficiency (z) variables	-786.935	343
M2	Model with only subsidy variables in the inefficiency (z) term (z3=z4=0)	-617.063	345
M3	Model without subsidy variables in the inefficiency (z) term (z1=z2=0)	-757.730	344
M4	Final model presented in the paper with all inefficiency (z) variables	-1005.051	347

Appendix 6

Appendix Table 6. Parametric estimation of DDF with the basic model (without inefficiency component)

Variables	M1 (Basic Model)	
	Coef.	**Std. Err.**
Stochastic frontier normal/half-normal model		
Dependent variable: ϑ		
land	-0.418***	0.078
labor	0.072**	0.033
var. inputs	0.178**	0.075
assets (excl. Land)	0.260***	0.064
$0.5 \bullet land^2$	0.068***	0.024
$0.5 \bullet labor^2$	-0.029**	0.014
$0.5 \bullet inputs^2$	-0.294***	0.038
$0.5 \bullet assets^2$	-0.131***	0.027
land•labor	-0.030	0.021
land•inputs	0.046***	0.010
land•assets	-0.026	0.022
labor•inputs	0.155***	0.021
labor•assets	-0.231***	0.027
inputs•assets	0.275***	0.031
GHGemission	0.457***	0.019
$0.5 \bullet GHGemission^2$	0.039***	0.006
land•GHGemission	-0.050***	0.008
labor•GHGemission	-0.054***	0.008
inputs•GHGemission	-0.007	0.013
assets•GHGemission	-0.006	0.008
Usigma		
Constant	-0.710***	0.031
Vsigma		
constant	-21.172***	4.525
E(sigma_u)	.7012718***	.010773
sigma_v	.0000253	.0000572
Log likelihood =	-786.9353	
Number of observations	2121	
Prob > chi2 =	0.0000	
Wald chi2(20)	2.83e+07	

*Significant at 10% level (P < 0.10), **Significant at 5% level (P < 0.05),***Significant at 1% level (P<0.01)

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