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Does ecologization matter for technical efficiency in crop production? A case of Swedish agriculture

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ABSTRACT

The effect of ecologisation on crop production performance in Sweden, measured as technical efficiency, was investigated by incorporating ecologisation into the production function and technical inefficiency determinant model. An unbalanced panel of data from the Swedish Farm Accounting Data Network (FADN), comprising 1944 observations on 346 crop farms 2009–2019, was used in stochastic frontier analysis. Ecologisation indicators considered were crop diversity index, organic farming, and environmental subsidies. The results showed that ecologisation affected the technical efficiency of crop production. Crop diversity index for the current year and the two preceding years had a positive effect on performance, with crop diversity index for current year in particular being positively associated with production performance of crop production. Organic farming was estimated to be negatively significantly associated with production performance. Rural subsidies were positively associated with production performance, but no association was found between environmental subsidies and production performance. Mean technical efficiency was 0.715, with higher values in southern Sweden than northern Sweden. These findings on the impact of ecologisation on arable farming can be useful when designing policies to encourage farmers to adopt ecologisation approaches.

1. Introduction

The concept of ecologization reflects the growing significance of environmental concerns in agriculture and rural policies and practices, especially in light of the impact of European Union (EU) agriculture policies (Mormont, 2009). In response to criticism of conventional farming practices, ecologization has been widely adopted over the past decade as a way to address the negative effects of conventional farming practices on the environment, such as soil and water pollution, loss of biodiversity, and impacts on climate change and food safety. Unlike agroecology, which focuses on the ecological and societal dimensions of the entire food system, ecologization focuses specifically on the impacts of agriculture with respect to the environment and conservation efforts (Allen et al., 1991; Cárdenas Rodríguez et al., 2018; Lamine, 2011; van der Ploeg et al., 2019). Although ecologization is a holistic approach that seeks to understand and address the social, environmental, and economic impacts of agricultural policies and practices, it is unknown whether it affects production performance, and in what way. This paper investigated the effects of ecologization on crop production performance in Sweden.

Current research on ecologization in agriculture is focused on two main areas (Schnebelin et al., 2021). The first involves optimizing inputs and minimizing negative outputs from production to improve resource efficiency and productivity, such as transitioning to fossil-free agriculture and public subsidies. Agri-environmental subsidies through the EU Common Agricultural Policy (CAP) fall within this area, since the key motive for providing subsidies is to address market failures originating in positive or negative externalities. The second area involves promoting new practices that benefit the environment and mitigate climate change, such as organic farming. To identify the best way of implementing ecologization in agricultural practices, researchers have investigated practical changes from conventional to organic farming and integrated pest management (Lamine et al., 2011). Previous research has explored the coexistence and interrelation of the two main areas of ecologization research, while in this study we addressed the missing link by investigating how ecologization affects the production performance of farms.

The technical efficiency (TE) of agricultural production reflects the extent to which multiple inputs are optimally used by farmers in the production process to produce agricultural outputs (Farrell, 1957). It was used in the present study as a proxy for the production performance

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of farms. Existing research shows mixed results in terms of TE or productivity analysis on the impact of ecologization-related practices or policies on farm performance. For example, according to Guesmi and Serra (2015) efficient use of chemical inputs can improve both environmental and technical performance of farms. Crop diversity is reported to play a crucial role in agricultural production (Di Falco and Perrings, 2006; Chavas and Falco, 2012; Nilsson et al., 2022). The relationship between organic farming and production performance has also been widely discussed over the past few decades (De Ponti et al., 2012; Lakner and Breustedt, 2017; Subrata and Huang, 2023).

Parametric stochastic frontier analysis (SFA) (Battese and Coelli, 1995) was used in this study to calculate TE, defined by Farrell (1957) as the ratio of optimal output to observed output, given the level of technology. Battese and Coelli (1995) developed a stochastic frontier production function that includes firm-specific effects and time effects in the model of inefficiency, and this has become one of the standard models for measuring TE. During the past two decades, the Battese-Coelli model and its stochastic frontier production function have been applied for productivity and efficiency analyses in agricultural production (Greene, 2005; Karagiannis and Sarris, 2005; Coelli et al., 2013; Huang and Jiang, 2019; Subrata and Huang, 2023). However, no previous study has introduced the concept of ecologization systematically into TE measurement within the production function framework.

This paper makes three novel contributions to the literature. First, it sheds new light on the effects of ecologization on production performance in agricultural production. In particular, it addresses how ecologization influences the TE of crop farming in Sweden. The analytical framework used was based on the stochastic frontier production function proposed by Battese and Coelli (1992). That function and the technical inefficiency determinant model were updated to incorporate ecologization indicators, using an unbalanced panel of data from the Swedish Farm Accounting Data Network (FADN). Second, instead of providing an aggregating concept of ecologization, this study goes further than previous literature by applying multiple indicators to represent ecologization, in order to deepen understanding about the perspective that works best in relation to farm performance. In particular, it uses indicators such as crop diversity index, certified and in-transition organic farming, and environmental and non-environmental CAP subsidies to represent different aspects of ecologization for agricultural crop production. Third, this study provides new empirical evidence that can be used in designing policies to encourage farmers to adopt ecologization approaches, by accounting for the effectiveness of ecologization. It offers policymakers a clear understanding of TE scores, including differences in TE between southern and northern Swedish crop farms, with and without ecologization approaches, and factors that are negatively/positively associated with TE in agricultural production, thus helping them tailor policies to improve efficiency on farms and in the agricultural sector in future. In particular, the results obtained in this study show whether to encourage compensation or insurance supporting crop diversity in order to avoid crop diversity loss, or to continue rural subsidies for organic farming by considering its association with production performance. This information is crucial for farmers who are considering adopting ecologization approaches and for policymakers who are seeking to promote on-farm ecologization.

The rest of this paper is structured as follows. The theoretical framework used for assessing the impact of ecologization on performance, literature findings, and starting hypotheses in the present work are described in Section 2. Section 3 presents the data and descriptive statistics. The method and empirical model specification are described in Section 4, while Section 5 presents and discusses the empirical results. Some conclusions are drawn in Section 6.

2. Literature review and hypothesis

Ecologization describes the importance of environmental and ecological perspectives when implementing agricultural practices and policies (Lamine, 2011; Lucas, 2021; Schnebelin et al., 2021). It covers a range of social and economic activities aimed at reducing environmental impacts and protecting the environment, the effects of which can be measured as crop diversity, certified and in-transition organic farming, and payment of subsidies. Technical efficiency quantifies the managerial ability of a farmer to attain the highest level of output given a set of inputs (such as land, labor, and capital), and is the key measure of overall production performance. The theoretical framework for the relationship between production performance and the three selected indicators of ecologization (crop diversity, organic farming, subsidies) are presented below.

2.1. *Crop diversity and production performance*

Crop diversity plays a crucial role in agricultural production, as demonstrated in recent studies (Di Falco and Perrings, 2006; Chavas and Falco, 2012; Cardinale et al., 2012; Bareille and Letort, 2018; Nilsson et al., 2022). Higher crop diversity results in improved yields (Bareille and Letort, 2018) and enhances the value of production factors within the system (Chavas and Falco, 2012; Cardinale et al., 2012; Nilsson et al., 2022). For example, a study by Smale et al. (1998) investigating associations between crop diversity and wheat production in Pakistan found that greater variation in crop species is linked to higher yields. Another study examining the impact of genetic diversity on cereal production found that higher crop genetic diversity can lead to improved farm productivity and reduced risk (Di Falco and Perrings, 2006). Bareille and Letort (2018) applied a dynamic acreage farm-level model in which they considered the productive ability of crop biodiversity as a quasi-fixed input, and concluded that crop diversity should be considered productive capital in farmers' decision making.

Crop diversity is beneficial for sustainable crop production. First, the probability of growing the best-adapted species can be increased by growing more diverse crop species, e.g., crop species with different root systems can improve nutrient uptake efficiency (Clark and Tilman, 2017; Tilman et al., 2005). Second, crop management is facilitated by growing more diverse crop species, because different crops require different forms of management (Loreau and Hector, 2001), so use of production inputs such as labor and technical factors can be optimized. Third, farm resilience to biological risk is improved by crop diversity, while increasing crop diversity can also make pests and diseases easier to control. Fourth, the ability of farms to maintain production levels under climate change can be enhanced when growing more diverse crop species (Di Falco and Chavas, 2006, 2008). Based on these reported associations between crop diversity and crop production, crop diversity was selected as an indicator of ecologization for Swedish crop farms in this study, which tested the following hypothesis:

Hypothesis 1. (H1): Crop diversity improves crop production performance.

2.2. *Organic farming and production performance*

Organic agriculture is defined as "a holistic view of agriculture that aims to reflect the profound interrelationship that exists between farm biota, its production and the overall environment" (Pacini et al., 2003). Organic farming is widely recognized and regulated worldwide through legislation, regulations, and certification schemes (Feola et al., 2012), and was thus selected as another important indicator of ecologization in this study. There is a crop yield gap between organic and conventional farming, with average yields of individual organically cultivated crops being lower than those of their conventionally cultivated counterparts (De Ponti, Rijk, and Van Ittersum, 2012). The relationship between TE and organic/conventional farming has been investigated in depth in recent decades, with a comprehensive overview and synthesis on efficiency and organic farming provided by Lakner and Breustedt (2017).

The relationship between production performance of TE and organic farming has been examined in Western Europe (in particular dairy farming) and Southern Europe (in particular olive and grape production). In Northern Europe, studies by e.g., Kumbhakar et al. (2009) and Manevska-Tasevska et al. (2026) have estimated that TE is lower on organic dairy farms than on conventional dairy farms in Finland and Sweden, and that inefficiency decreases the probability of conversion to organic farming. However, organic farms in European countries tend to differ in structure and those based on organic grassland and dairy farming may differ in performance from those specializing in crop farming. The second hypothesis tested in this study was:

Hypothesis 2. (H2): Organic farming reduces crop production performance.

2.3. CAP subsidies and production performance

The concept of ecologization closely co-exists with, and is partially shaped by, the EU CAP system, as reflected in its recent reforms and developments. When first established in the 1960 s, the primary objective of CAP was to improve agricultural productivity. In the 1990 s, it was reformed to achieve additional goals such as protecting the environment, preserving biodiversity, preserving rural landscapes, and maintaining social viability in rural areas (CAP Pillar 1). The introduction of rural development programs (RDPs) in CAP shifted its focus to competitiveness, flexibility, and liberalization (CAP Pillar 2) (Potter and Tilzey, 2005; Erjavec and Erjavec, 2009). In 1992, mandatory implementation of agri-environment schemes (AES) aimed to encourage farmers to voluntarily manage their land in an environmentally friendly manner (EU Regulation 2078/92). The 2007–2013 CAP period set a new formal goal of improving the environment and countryside through RDPs. The 2014–2020 CAP reform placed more emphasis on conserving the environment and ecosystems, mitigating biodiversity loss, and improving ecosystem services in agricultural landscapes (Erjavec and Erjavec, 2009, 2015; Leduc et al., 2021). The latest revision of CAP, for the period 2021–27, increased its environmental and climate ambitions, but it still relies on voluntary participation by farmers in environmental measures (Kuhmonen, 2018). The 2023–27 CAP Strategic Plan combined direct payments and coupled support (Pillar 1) with rural development support (Pillar 2) for the first time, and earmarked around 25% of the Pillar I budget for an “Eco-scheme” to support and strengthen ecosystem protection and climate impact mitigation. This new instrument aims to incentivize farmers to prioritize environmental care and climate action. Together with the RDPs of Pillar 2, the Eco-scheme will work towards achieving sustainable environmental and climate objectives for EU agriculture (Kuhmonen, 2018).

A trend for ecologization has been evident in CAP since the introduction of AES in 1992 and continues to grow, as exemplified by the current environmental subsidies aimed at reducing negative agricultural impacts on the environment (Schnebelin et al., 2021). The increasing significance of ecologization is reflected in the recent reforms and developments of CAP. A study by Latruffe et al. (2017) on the relationship between CAP subsidies and dairy farm production performance in nine western EU countries from 1990 to 2007 found that CAP subsidies can have negative, null, or positive effects on production performance, depending on the country. A meta-analysis by Minviel and Latruffe (2017) on the impact of public subsidies on farm TE in France found that subsidies are commonly negatively associated with farm TE. Using FADN data for EU-15 countries, Rizov et al. (2013) investigated the impact of CAP subsidies on farm productivity and found that CAP subsidies had a negative impact on farm productivity before the CAP decoupling reform, but a positive impact after CAP decoupling. Overall, therefore, the effect of CAP subsidies has been found to differ for different farming types in different countries (Martinez Cillero et al., 2021). Our third hypothesis was thus:

Hypothesis 3. (H3): Subsidies reduce crop production performance.

3. Data and descriptive statistics

The empirical data comprised an unbalanced panel obtained from the Swedish FADN database[1] of 1944 observations on 346 individual Swedish crop farms during the period 2009–2019. The farms chosen were based on the FADN standard typology for farm specialization, with a specific focus on farms dedicated to field crop production such as specialist cereals, oilseeds, protein crops, general field crops, and mixed crops (identified by code TF8 in the FADN database). The FADN dataset supplied detailed information on variables needed for creating a stochastic frontier model and a TE model for crop farm production.

The empirical production function used consisted of a single output and four inputs, as outlined in Table 1. Farm *output*, denoted "y", measured in 1000 Euros, encompassing the *total value of output*, including all farms revenue obtained from kinds of agricultural production activities. The four inputs were aggregated as follows: (i) *Agricultural land area* (x_1), which encompassed total utilized agricultural area of the holding, measured in hectares (*ha*), and included land in owner occupation, rented land, and land in share-cropping where remuneration is linked to the output from the land made available. But excluded from this measure were used for mushrooms, land rented for less than one year on an occasional basis, woodland, and other non-farmed areas (such as roads and ponds). (ii) *Labor* (x_2), which represented the total labor input, including both family and hired labor, measured in total working hours. (iii) *Intermediate input* (x_3), which accounted for the total costs linked to agricultural activities and associated with the output of the accounting year, such as costs of seeds, fertilizers, pesticides, fuel, and other specific costs. (iv) *Fixed costs* (x_4), which represented total assets, including fixed and current assets. Statistics Sweden provided information on the national output price and

Table 1
Descriptive statistics on variables used in the analysis.

Continuous variables	Symbol	Units	Mean	Std. Dev.
Agricultural area	x_1	ha	152.15	196.81
Labor	x_2	annual work unit (AWU)	1.35	1.92
Intermediate inputs	x_3	1000 Euro	2.24E+ 02	4.01E+ 02
Fixed assets	x_4	1000 Euro	1.36E+ 03	1.62E+ 03
Total outputs	y	1000 Euro	2.01E+ 02	3.71E+ 02
Year	*t*			
Crop diversity index in current year	CDI	-	0.700	0.120
Crop diversity index in previous year	CDI-1	-	0.702	0.118
Crop diversity index two years earlier	CDI-2	-	0.703	0.119
Environmental subsidy	z_5	1000 Euro	4.021	19.279
Total subsidy for rural development	-	1000 Euro	38.669	54.582
Non-environmental subsidy	z_6	1000 Euro	34.647	42.847
Dummy variables	*Symbol*	*Mean*	*Obs. no. of 1*	*Obs. no. of 0*
Organic farming (1 = partly or fully organic production or in transition to organic production; 0 = no organic production at all)	z_4	0.09	168	1776
Year of policy shock (1 = year later than 2013, 0 = otherwise)	z_7	0.43	1112	832
Total observations: 1944.				
Total observed farms: 346.				

[1] Swedish FADN data from 2007 to 2017 were used to calculate crop diversity index over the past two years.

input price index.

Three indicators of degree of ecologization were used to investigate the impact effect of ecologization on the TE of Swedish crop production: (i) crop diversity index (CDI) in the current year and lagged for the past two years (z_1-z_3); (ii) organic farming (z_4); and (iii) CAP environmental subsidy (z_5).

Crop diversity index (z_1-z_3) was calculated as $CDI_t = 1 - HI_t$, where HI_t is the Herfindahl index and t is year defined as $HI_t = \sum_{i=1}^{n} P_{it}^2$, where P_{it} ($= \frac{A_{it}}{\sum_{i=1}^{n} A_{it}}$) is the proportion of area occupied by crop i and A_{it} is the area of crop i for crops such as ley, barley, wheat, oats, etc. A study by Smale et al. (2008) utilized the Herfindahl Index to measure the area distribution of crop diversity, where a value of 1 represents a single crop on a farm (i.e., monoculture) and a value of 0 represents a higher number of crop species. In the present study, HI was computed from the FADN dataset to calculate CDI and its one-year and two-year lagged values (CDI_{-1} and CDI_{-2}). CDI directly reflects the degree of diversification on a farm by considering the area of each crop, and its value ranges from 0 to 1, with higher values indicating a greater level of crop diversification.

To identify the *organic farming indicator* (z_4), a dummy variable with a value of either 1 or 0 was utilized, where a value of 1 indicated that a farm was either fully or partly engaged in organic production or was transforming into organic production, while a value of 0 indicated fully non-organic (conventional) production. Of the 1944 observations in the data panel, 168 (8.6%) had implemented organic production. CAP *environmental subsidy* (z_5) was represented by code SE621 in the FADN dataset and comprises two types: subsidies related to environmental protection (with measures taken to avoid double-counting of Direct Payments under Article 69 of 1782/2003) and subsidies related to environmental restrictions. Two relevant indicators were selected for crop production performance in this study. The first was the total subsidy for rural development (SE624), which includes the environmental subsidy, less favored area (LFA) subsidies, and other rural development payments. To avoid a correlation between the total subsidy for rural development (SE624) and the environmental subsidy (z_5), the model included a non-environmental subsidy (z_6), which was generated by deducting environmental subsidy (z_5) from the total subsidy for rural development (all in 1000 Euro). A subsidy supporting certified organic farming is included in the environmental subsidy, so a positive correlation between these could arise, but was not detected in the dataset. Another indicator used to evaluate crop performance (TE) was a dummy variable, *year of policy shock* (z_7), which was employed to assess how policy changes related to ecologization affected production performance. A mandatory greening component of direct payments was implemented by the EU in 2013, which is designed to encourage and promote sustainable land use practices. To generate this variable, we created a dummy variable with a value of 1 assigned to the period after the policy change in 2013 (i.e., for all years since 2014), and a value of 0 assigned to all other years. The dummy variable had a mean value of 0.43, based on 1112 farm observations since 2014. Notably, all the variables for inputs, outputs and determinant characteristics related to price were adjusted for inflation using the relevant national output price index, with the base year set is 2010.

4. Method and empirical model specification

Output-oriented SFA measures the distance between the observed and the optimal feasible input-output pairing of farms given the highest achievable output (revenue in this study) obtained while the input quantity constant (Battese and Coelli, 1992; Kumbhakar and Lovell, 2000). When dealing with the balanced panel data, panel data models are often favored as they can control for unobserved differences between observations and add a time dimension to the analysis by capturing the "firm effect." However, in this study, the analysis relied on a rotating unbalanced panel dataset with a numerous farms that appeared for a period shorter than three years, and thus a pooled data model was considered more suitable for this scenario. The Trans-log and Cobb-Douglas production functions were compared and tested (Table 2) and, based on the test results, the Trans-log production function was chosen. It takes the form:

$$\ln y_i = \alpha_0 + \sum_{k=1}^{4} \beta_k \ln x_{ik} + \frac{1}{2} \sum_{k=1}^{4} \sum_{l=1}^{4} \beta_{kl} \ln x_{ik} \ln x_{il} + \ln(t) + \ln(t)^2 v_i - u_i \quad (1)$$

In Trans-log SFA, farm output y_i obtained for farm i is express as a function of the four inputs denoted as x_i (here one single output and four inputs, see Table 1); t denotes year; ln is the natural logarithm; α_0 represents a constant term; $\beta_k and \beta_{kl}$ are parameters to be estimated; v_i represents random noise, assumed to be independently and identically distributed $N(0, \sigma_v^2)$; andu_i is an inefficiency term describing the disparity between maximum optional output and actual observed output. Then $u_i = lny_i^* - lny_i$ and the inefficiency term is: $\exp(-u_i) = \frac{y_i}{y_i^*}$. The predicted TE ranges between 0 and 1, because the actual observed output is always below the frontier output level, which represents the maximum optional output. As a result, farm efficiency is denoted by a percentage between 0% and 100%. Additionally, the lower bound of the observed output is set at 0, so the variable u_i (which represents the deviation of observed output from the frontier output) is greater than or equal to 0 ($u_i \geq 0$).

To elaborate further, the technical inefficiency determinant model was used to estimate the associated determinants of technical inefficiency and how they affect the level of inefficiency on each farm i. The vector of variables z_i in that model (Eq. 2) captures the factors that affect inefficiency, such as managerial skills, farm size, and environmental factors. The parameter δ is estimated to determine the strength of the association between z_i and technical inefficiency. The variable w_i is an unobservable random variable that captures the effects of other unmeasured factors affecting technical inefficiency. These factors may include weather conditions, pests and diseases, and other unpredictable factors that affect farm productivity. The variable w_i is assumed to follow a truncated normal distribution with a mean of zero and variance of σ_w^2. The truncation ensures that u_i is always non-negative, which is a necessary condition for efficiency scores ($u_i \geq 0$):

$$u_i = z_i^e \delta_i + w_i \quad (2)$$

In this study, the constant α_0 and parameters β (β_k and β_{kl}) in Eq. (1) and δ_i in Eq. (2) were estimated simultaneously. By estimating the technical inefficiency determinant model and the production frontier together in a single step, we were able to avoid any potential bias that might have arisen from using a two-step approach. Our model included seven inefficiency determinants (z_1-z_7), as described in detail in Section 3.

5. Results and discussion

5.1. Model specification testing and production function selection

The specifications of the final model were decided based on the results of five preliminary tests (Table 2). Test 1 was designed to test whether the Cobb-Douglas production function fitted better and Test 2 to test whether the Trans-log production function fitted better. The Trans-log production function was selected, as it fitted the data significantly better than the Cobb-Douglas production function in both tests. Additionally, the null hypothesis of no technical inefficiency was rejected (Test 3), affirming the necessity of incorporating a technical inefficiency determinant model. The Likelihood-Ratio (LR) results in Test 4 and Test 5 also rejected the null hypothesis that CDI and CDI-relevant variables and ecologization approaches does not have any effect on technical inefficiency, indicating that these variables should be included in the technical inefficiency determinant model.

Table 2
Null hypotheses used in Tests 1–5 for model specification and statistical assumptions.

Test	Null hypothesis	Log-likelihood value	Degrees of freedom	AIC[a]	BIC[2]
For selection of production function:					
1	Cobb-Douglas production function without technical inefficiency model	-659.94	9	1337.89	1388.04
	Trans-log production function without technical inefficiency model	-623.93	19	1285.86	1391.74
2	Cobb-Douglas production function with technical inefficiency model	-568.98	16	1169.96	1259.12
	Trans-log production function with technical inefficiency model	-540.66	26	1133.31	1278.20
For specification of technical inefficiency model:					
	Unlimited model	-540.66	26	1133.31	1278.20
3	$\omega_1=\omega_2=\omega_3=\omega_4=\omega_5=\omega_6=\omega_7=0$	-623.93	19	1285.86	1391.74
4	$\omega_1=\omega_2=\omega_3$	-568.48	23	1182.95	1311.12
5	$\omega_1=\omega_2=\omega_3=\omega_4=\omega_5=0$	-573.29	21	1188.58	1305.60

[a] Akaike information criterion. [2]Bayesian information criterion.

5.2. Estimates for the stochastic production function

The estimated parameters of the stochastic production function, derived through maximum likelihood estimation, are presented in Table 3. To make it easier to interpret the parameter estimates, both the output variable and four input variables (x_1-x_4) were normalized by dividing them by their respective sample means. This normalization allowed the estimated first-order parameters of the Trans-log production function to be interpreted as partial production elasticities with respect to a unit change in each input variable, while holding all other inputs at their sample mean values (Brümmer et al., 2002; Huang et al., 2016). Model 1 in Table 3 denotes the statistics for the estimation results of the production function with setting the technical inefficiency determinant model, which provided detailed estimates as the unlimited model for the hypotheses in Tests 2–5 (Table 2). Model 2 in Table 3 denotes the statistics for the estimation results of the production function without seeting the technical inefficiency determinant model, which was the hypothesis in Test 3. Model 3 was designed to examine how ecologization affected model specification, where all variables related to ecologization were excluded from the model. Model 4 was designed to examine how CDI in the current year and in lagged years affected model specification (all three variables, *CDI*, CDI_{-1}, and CDI_{-2}) (Table 3). In Model 1, the coefficient σ_u was estimated to be 0.557 and σ_v was estimated to be 0.169, indicating that the variance in the farm-specific error

Table 3
Maximum likelihood estimates of the stochastic frontier model.

Variables	Parameter	Model 1		Model 2		Model 3		Model 4	
		Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Dependent variable: lny									
Constant term	α_0	0.300 * **	0.014	0.342 * **	0.015	0.314 * **	0.014	0.311 * **	0.014
$\ln x_1$ area	β_1	-0.063	0.018	-0.013	0.019	-0.074 * *	0.018	-0.067 * **	0.018
$\ln x_2$ labor	β_2	0.133 * **	0.017	0.145 * **	0.020	0.134 * **	0.017	0.134 * **	0.017
$\ln x_3$ intermediate	β_3	0.894 * **	0.019	0.896 * **	0.022	0.899 * **	0.020	0.893 * **	0.020
$\ln x_4$ assets	β_4	0.002	0.010	0.008	0.012	0.006	0.010	0.006	0.010
$\ln {x_1}^2$	β_{11}	-0.128	0.036	-0.146 * **	0.036	-0.171 * **	0.034	-0.155 * **	0.034
$\ln {x_2}^2$	β_{22}	-0.022	0.037	-0.002	0.038	-0.024	0.038	-0.014	0.038
$\ln {x_3}^2$	β_{33}	-0.063	0.047	-0.102 * *	0.048	-0.089 *	0.046	-0.070	0.047
$\ln {x_4}^2$	β_{44}	0.035 * *	0.015	0.054 * **	0.016	0.040 * **	0.016	0.040 * *	0.015
$\ln x_1 \bullet \ln x_2$	β_{12}	-0.065 * *	0.031	-0.068 * *	0.031	-0.066 * *	0.029	-0.060 * *	0.030
$\ln x_1 \bullet \ln x_3$	β_{13}	0.126 * **	0.036	0.156 * **	0.035	0.167 * **	0.034	0.151 * **	0.035
$\ln x_1 \bullet \ln x_4$	β_{14}	0.059 * **	0.019	0.058 * **	0.021	0.048 * *	0.020	0.049 * *	0.020
$\ln x_2 \bullet \ln x_3$	β_{23}	0.059 *	0.035	0.052	0.035	0.055	0.035	0.043	0.035
$\ln x_2 \bullet \ln x_4$	β_{24}	-0.047 * *	0.021	-0.054 * *	0.022	-0.043 * *	0.021	-0.039 *	0.021
$\ln x_3 \bullet \ln x_4$	β_{34}	-0.083 * **	0.023	-0.098 * **	0.025	-0.086 * **	0.023	-0.087 * **	0.023
ln (*year*)	β_{41}	-0.047	0.031	-0.073 * *	0.029	-0.058 *	0.031	-0.058 *	0.031
ln (*year*)	β_{42}	-0.118 * **	0.027	-0.136 * **	0.027	-0.125 * **	0.028	-0.125 * **	0.028
Usigma									
Constant	ω_0	4.076 * **	0.681	-1.442 * **	0.063	4.795 * **	0.651	4.813 * **	0.662
ln (*CDI*)	ω_1	-0.181	0.172						
ln(CDI_{-1})	ω_2	-0.989 * **	0.293						
ln(CDI_{-2})	ω_3	-0.130	0.237						
ln (*dummy of organic production*)	ω_4	0.438 * **	0.138					0.410 * **	0.136
ln (environmental subsidy)	ω_5	0.002	0.005					-0.004	0.005
ln (non-environmental subsidy)	ω_6	-0.568 * **	0.069		-0.624 * **	0.066	-0.631 * **	0.067	
dummy of shock year (2014)	ω_7	-0.010	0.094			-0.081	0.088	-0.091	0.092
Vsigma									
Constant term		-3.553 * **	0.094	-3.382 * **	0.101	-3.541 * **	0.095	-3.565 * **	0.096
E(σ_u)		0.557		0.486 * **	0.015	0.510		0.507	
σ_v		0.169 * **	0.008	0.184 * **	0.009	0.168 * **	0.008	0.170 * **	0.008
λ		3.345 * **	0.027	2.638 * **	0.022				
Statistics									
Log likelihood	-540.656	-623.9299	-568.4750	-573.288					
Number of observations	1944	1944	1944	1944					
Wald $Chi^2(14)$	14642.73	16740.43	14608.34	14647.61					
Prob. > $Chi^2(14)$	0.000	0.000	0.000	0.000					

Significant at *P < 0.10, * *P < 0.05, * **P < 0.01.

term was larger than the variance in the stochastic error term. This suggests that the one-sided random inefficiency component had a more significant impact on the measurement error and other random disturbances. Despite the first-order and second-order estimates for the land area input (x_1) having an unexpected sign, overall model quality appeared satisfactory, as evidenced by both the LR test results and associated statistics.

For Models 1–4, all first-order estimates of labor (x_2) and intermediate inputs (x_3) were statistically significant, with expected signs. The estimated first-order parameters of the Trans-log production function in Table 3 provide information on the partial production elasticities for the sample mean. The results highlight the significance of intermediate inputs and labor in crop production. The partial production elasticity of intermediate inputs was 0.894, indicating that a 1% increase in intermediate inputs leads to a 0.894% increase in crop output, which is the highest partial production elasticity in the production function. The partial production elasticity of labor was estimated to be 0.133, meaning that a 1% increase in labor increases crop output by 0.133%. This is consistent with production economics theory, underscoring the importance of agricultural labor input in agriculture and its positive contribution to production. The estimated first-order coefficients for the fixed assets input (x_4) were not significantly associated with performance, while the second-order coefficients were positively significantly associated, meaning that more fixed assets will contribute to better farm performance.

5.3. Summary of technical efficiency (TE)

Following estimation of the stochastic production function and technical inefficiency variance function using Model 1, we computed TE for each farm, as shown in Table 4. The average TE score for Swedish farms stands at 0.715, indicating that farms produced 71.5% of their potential output given the current level of technology and input usage. This suggests that there is room for improvement, and adopting the practices of the best-performing farms could potentially lead to an average increase in crop production of 28.5% in the short term. The kernel density distribution of TE is illustrated in Fig. 1. Based on the region code in the FADN database, most crop farms are situated in southern Sweden. On average, farms in southern Sweden had a higher TE score (0.726) than those in central Sweden (0.680) and northern Sweden (0.615). The average TE score for organic farms was 0.669, lower than that of non-organic farms (0.719). As discussed above in relation to the technical inefficiency determinant model, the association between TE and organic farming was negative. However, caution is needed in interpretation of this negative relationship, because there were much fewer observations for organic farms (observation number = 168) than for conventional farms (observation number = 1776) in the dataset and the representativeness and reliability of the data may differ between these groups.

Table 4
Summary of technical efficiency (TE) values.

	No. of observations	Mean	Std. Dev.
Overall TE	1944	0.715	0.161
TE in southern Sweden	1635	0.726	0.153
TE in central Sweden	195	0.680	0.161
TE in northern Sweden	114	0.615	0.223
Non-organic farms	1776	0.719	0.160
Organic farms	168	0.669	0.167
Only organic production methods for all farm products	120	0.651	0.172
Both organic and conventional production methods or in transition to organic production	48	0.714	0.145

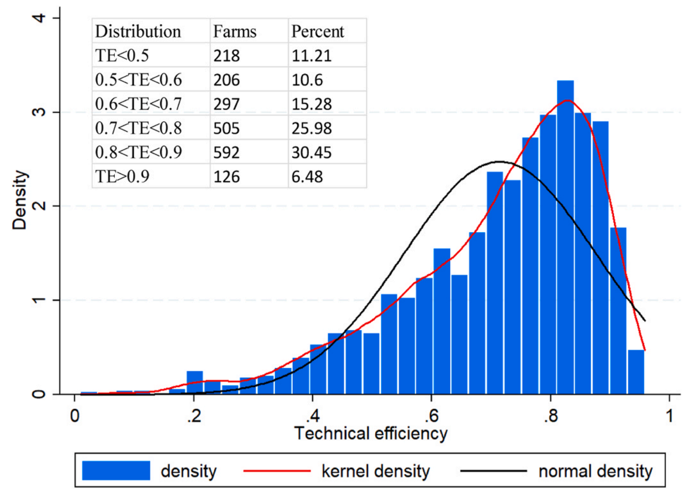

Fig. 1. Histogram of technical efficiency on Swedish arable farms.

5.4. Results of the technical inefficiency determinant model and the effects of ecologization

The technical inefficiency model was used to estimate the determinants of variation in a farm's technical inefficiency (see the lower part of Table 3). The dependent variable in this model was technical inefficiency, and thus a negative coefficient indicates a positive effect on TE. Comparing the results of Model 1 and Model 4 revealed a difference in the effects of CDI, CDI_{-1}, and CDI_{-2} on technical inefficiency. The block of CDI was estimated to be negatively correlated with technical inefficiency, supporting *hypothesis H1*. CDI, CDI_{-1}, and CDI_{-2} were positively correlated with TE, with CDI_{-2} having the highest coefficient (−0.989, statistically significant at $P < 0.05$). This is consistent with previous findings that higher crop diversity increases productivity (Cardinale et al., 2012). According to Cardinale et al. (2004), crop diversity has a "*dynamic*" effect on productivity and the effects *"grow stronger through successional time"*. Crop diversity has been found previously to be positively related to productivity in both current and lagged years (Falco and Chavas, 2008).

Comparing the results of Model 1 and Model 3 revealed differences in the effects of ecologization on TE. Interestingly, the dummy variable for organic farming was estimated to be positively correlated with technical inefficiency, meaning that organic farming decreased farm TE, confirming *hypothesis H2*. This is consistent with previous research that suggests organic farms in Finland and Sweden are linked to lower TE (Kumbhakar et al., 2009; Manevska-Tasevska et al., 2016), and indicates that complying with "environmental" requirements is output-reducing (Manevska-Tasevska et al., 2016).

The CAP environmental subsidy had no significant influence on technical inefficiency, but the non-environmental subsidy was estimated to be negatively correlated with technical inefficiency, meaning that more non-environmental subsidies will result in lower TE, confirming *hypothesis H3*. This is in line with findings by Bojnec and Fertő (2022) that Pillar I subsidies of CAP have had positive effects on farm use of paid labor in Hungary and family labor in Slovenia, and thus might be positively correlated with production performance. The policy shock introduced in 2014 was found not to be significantly related to TE, which might be explained by farmers anticipating the change in policy earlier and incorporating ecologization measures before 2014.

5.5. Policy suggestion

One of the innovative contributions of this study was to investigate the impact of ecologization on production performance. Crop diversity was found to be positively associated with TE, while organic farming and environmental subsidies showed a negative association. Non-environmental subsidies had no impact on TE. The upcoming EU CAP for 2023–2027 aims to ensure steady farm income while intensifying environmental and climate efforts, with greater emphasis on biodiversity. Our results suggest that compensation or insurance supporting crop diversity is needed to avoid crop diversity loss. Our results also suggest that compensation programs in policy should take account of the effects of ecologization on agricultural production (Koiry and Huang, 2023). The adverse impact of ecologization can probably be attributed to the distinctive traits or elements of specific ecological practices. In organic farming, for example, use of chemical fertilizers, herbicides, insecticides, or other plant protection substances is prohibited, which could impose limitations in enhancing soil fertility or addressing issues related to insect and pest infestations in crop production. While reducing the use of fertilizers and pesticides may contribute to long-term soil health improvement, it may not lead to an immediate or short-term increase in crop yield for the current year. Measures aimed at promoting crop diversification may thus need to include compensation for organic farms, which experience lower production performance, to encourage more farmers to switch to certified organic farming. Otherwise, farmers may be hesitant to make the transition.

6. Conclusions

Modern agriculture has a negative impact on climate and biodiversity, and must be transformed to align with sustainability goals while ensuring food security. Ecologization of agricultural policies is necessary to guide agricultural production towards operating within environmental constraints. A unique aspect of the present study was measurement of the influence of ecologization on TE in crop production, using indicators such as crop diversity index, certified and in-transition organic farming, and non-environmental and environmental subsidies. Land, labor, fixed costs, and variable costs were considered as the primary inputs, while the total revenue from agricultural crops in arable production in Sweden was taken as the output. The results indicated comprehensive effects of ecologization on TE. Crop diversity was identified a positive association with TE, while organic farming and environmental subsidies showed a negative association. Non-environmental subsidies had no impact on TE. The average TE of Swedish crop production was estimated to be 0.715 (ranging from 0.726 in southern Sweden to 0.615 in the north), with TE in organic farming (0.669) being lower than that in conventional farming (0.79).

There are several promising avenues for future research. First, the panel dataset used was unbalanced and it is possible that interesting information was concealed between the panels, such as the performance effects of different crop species by group, which could be further explored using panel data analysis. Second, more precise information regarding the location of crop plots/blocks, crop rotations, and diversity could improve assessment of the ecological effects of production and enable more detailed analysis of trade-offs and synergies between ecological and economic impacts, providing a comprehensive understanding of the interplay between agricultural practices and their broader environmental consequences. Third, while crop diversity is a crucial aspect of biodiversity, there are other components of ecosystem biodiversity that could be incorporated into efficiency analysis, such as wild species (e.g., semi-natural pastures, wildflower strips). This could provide a more comprehensive understanding of the interactions between biodiversity and economic values on farms.

Ethic Statement

Not applicable. This research was not performed on human/animals.

CRediT authorship contribution statement

Huang, Wei: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Manevska-Tasevska, Gordana:** Project administration, Conceptualization. **Hansson, Helena:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Availability of supporting data

This paper applies the Swedish Farm Accounting Data Network (FADN) data that authors don't have the permission to share the data.

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