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The role of green total factor productivity to farm-level performance: evidence from Norwegian dairy farms

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Abstract

In the economics literature, measuring the performance of a dairy farm with a total productivity index is common practice. Previous research, on the other hand, has been chastised for failing to account for agricultural emissions in their models when calculating resource use productivity. This study estimated green total factor productivity (GTFP) accounting for dairy farms' CH4 emission to the model. The study is based on unbalanced panel data from 692 specialized dairy farms from 1991 to 2020. To estimate GTFP and its components using multiple input–output environmental production technologies, a stochastic input distance function and a Translog model were used. The average annual growth rate of green production over the research period was 0. 032%. The main reason for the increase in GTFP was positive scale change contributions. Technological change (— 0.031% per year) and efficiency change (— 0.002% per year), on the other hand, had a detrimental effect on GTFP.

Keywords: Productivity, Emission, Panel data, Dairy management, Technology

JEL Classification: D24, M11, M21, Q12, Q51

Introduction

To maintain long-term food security while preserving the environment, policymakers encourage farm businesses to adopt sustainable choices and behaviours. While the costs of inactivity are unknown, it is widely agreed that failure to address climate change will seriously affect future generations. Livestock production accounts for approximately 40% of the gross value of agricultural production and about 11% of global GHG emissions (FAO 2020). Recent efforts, such as the Green Deal, demonstrate that the European Union's agriculture sector places a high priority on climate change mitigation. In all production systems, enhanced husbandry management and practices might cut emissions by 20–30%, resulting in increased productivity and carbon sequestration (FAO & UNSD 2020). Norwegian family farm businesses face new economic, environmental, and social challenges. As environmental concerns have grown, governments have urged farmers to adopt sustainable policies and practices to prevent environmental degradation while also assuring long-term food security and

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resource efficiency (Alem 2021). In the Global Opportunity Report for 2018 (DNV GL 2018), responsible consumption and production (Goal 12) and climate action (Goal 13) are addressed as two of the four UN Sustainable Development Goals that most likely will not be achieved by 2030 without an extraordinary effort from farmers, policymakers, and researchers.

Family farmers generally manage small and relatively vulnerable farms and, as such, operate within a decision-making environment that focuses primarily on maintaining the existence of businesses (Wilson 2008). From a global perspective, Norwegian agriculture has several advantages in achieving sustainable food production; for example, Norwegian regulations ensure that manure is used as a fertiliser and spread on arable land, many pesticides are banned, and the use of antibiotics in animal production is very low. However, Norwegian agriculture is struggling with several sustainability issues (e.g. a high percentage of emissions from livestock production). Evaluating the performance of agricultural systems while considering environmental concerns is a critical problem for the implementation of policies and practices intended to reveal sustainable development (Alem 2021; Pacini et al. 2003). As a result, farm resource efficiency and productivity must be reviewed and evaluated to pinpoint improvements that will aid agricultural policy in achieving its objectives. In economics, the term productivity refers to a wide idea; however, this research focuses on Green total factor productivity (GTFP) as a useful productivity indicator. GTFP has proven to be useful in policy initiatives aimed at promoting long-term agricultural growth (Manos et al. 2013).

Several studies, such as Koesling et al. (2008), Kumbhakar et al. (2008), Kumbhakar and Lien (2009), Kumbhakar et al. (2012), Lien et al. (2010, 2018), Alem et al. (2019), and Alem (2021), have been carried out to assess the productivity of Norwegian agriculture. Previous research on Norwegian agriculture has yielded useful information on-farm performance and food production. However, we still know relatively little about the Norwegian agricultural sector's performance. As a result, this paper contributes to the economic literature in several ways. Even though it is a critical concern for long-term agricultural development, previous studies have overlooked the dairy industry's environmental impact. We examined the performance of Norwegian dairy farms while accounting for environmental challenges, which meant that we assessed both desirable (dairy production) and undesired (environmental effect) outcomes. As a result, this article calculates Greene Total Productivity (GTFP) at the farm level contributing to the understanding of eco-performance and policy-making that improves farmers' livelihoods. We also had the benefit of working with a large dairy farm panel dataset that covered the years 1991–2020.

The remaining section of the document is structured as follows. "Agriculture and environmental policies in Norway" section discussed Norwegian agricultural and environmental policies, followed by "Theoretical framework" section which discussed the theoretical framework. "Empirical model" section provides the empirical model, and "Description of the data" section examines the data and variable definitions utilized in the empirical model. "Estimation results and discussion" section presents the empirical estimation and outcomes. Our findings and conclusions are summarized in the final section.

Agriculture and environmental policies in Norway

Norwegian agricultural policies aim to increase food production, sustain agricultural activity across the country, protect the environment, and ensure income development comparable to other groups in society. Norway is one of the countries with the least amount of arable land per capita in the world. According to recent compilations of Statistics Norway data, the arable land area per capita decreased from 1963 m^2 in 2000 to 1499 m^2 in 2020 (SSB 2021). Livestock production has become the most important agricultural product in Norway, with dairy farming accounting for nearly 30% of all farmers in the country (Alem et al. 2019). The small amount of land that is technically suitable for farming, combined with national policies to maintain and distribute production, determines the use of agricultural land in large part.

Agriculture in Norway has been and continues to be highly regulated, with some of the highest subsidies in the OECD, and farmers are still exempt from GHG emission taxes, and the EU ETS does not apply to agriculture (OECD 2022). The excess nitrogen and phosphorus levels in Norway are among the highest in the OECD, putting pressure on the quality of the soil, water, and air. It ought to shift funding away from goals of income and production in favour of stronger incentives for farmers to enhance agri-environmental outcomes and advance climate-smart agriculture. Farmers could contribute to restoring agricultural landscapes' ecological value in this way. According to the OECD 2022 Environmental Performance Review, Norway is one of the best OECD countries in terms of long-term carbon pricing. To encourage more investments in renewable energy and low-carbon technologies, it offers a strong price signal. Outside of agriculture, climate change initiatives are widespread and ought to result in proportionate reductions across all industries. Norway's focus on national GHG emissions only gives a partial picture of its global carbon footprint because of its small size and open economy.

Even if all policies and regulations are followed, Norwegian livestock farming has significant environmental consequences, including GHG emissions. Among all sources of greenhouse gases emitted into the atmosphere over the previous 40 years, methane emissions were the highest (SSB 2021). As a result, this study concentrated on dairy farms' methane emissions.

Theoretical framework

Environmental production technology

The standard producer theory's starting point is to define the technical link between inputs and outputs using production technology. Dairy farms produce both desirable (such as milk and meat) and undesirable by-products (GHG emissions). Conventional technology can manage the desired outputs. Undesired outputs, on the other hand, require special attention in efficiency analysis. The set of environmental production technologies (Ψ) is therefore defined as follows:

$$\Psi = \left\{ \left(x, y, b \right) : x \text{ can produce } \left(y, b \right) \right\} \tag{1}$$

where x, y, and b are the vectors of input, desirable output, and undesirable output, respectively. In the context of environmental production technology (Ψ)., it is crucial to mosdel the relationship between desirable and undesirable outputs. The environmental production technology set Ψ is assumed to satisfy three axioms

(a) Null jointness, i.e. if $((y, b) \in \Psi$ and $b = 0$ then $y = 0)$
(b) The set Ψ is a closed set and nonempty.
(c) If $\left(\left(y, b\right) \in \Psi \text{ and } y' \leq y \text{ then } \left(y', b\right) \in \Psi\right)$, that is, the technology set Ψ satisfies the free disposability of all inputs and outputs.

For details of other properties of the technology set, see Färe et al. (1985) and Chambers et al. (1996). An input or output possibility set can be used to illustrate environmental production technology (Färe et al. 2008). The input set (L) is then defined as follows:

$$L\left(y\right) = \left\{x : \left(x, y, b\right) \in \Psi\right\} \tag{2}$$

Following Farrell (1957), the technology boundaries (input isoquants) of the technology set $\Psi\left(x, y, b\right)$ can be defined in terms of a radical as follows:

$$\partial L\left(y\right) = \left\{x : x \in L\left(y, b\right), \theta x \notin L\left(y, b\right), \forall \theta, 0 < \theta < 1\right\} \tag{3}$$

Decision-making unit (DMU) or farms are efficient if they are within the boundaries of the input requirement set, that is, they are input efficient if $x \in \partial L\left(y\right)$. On the other hand, DMUs are input inefficient if $x \notin \partial L\left(y\right)$. Input-inefficient farms use more inputs to produce the same output compared to other input-efficient DMU. This is the case if the inefficient farms experience a slack in inputs.[1] In the directional distance function (Chambers et al. 1996), Eq. (3) can be represented as follows:

$$D_I\left(y_t, x_t, b_t, k_t; t, \omega\right) = \max\left\{\left(\lambda : {}^{x_t}/_{\lambda}\right) \in L\left(y_t, x_t, b_t, k_t, t, \omega\right)\right\} \tag{4}$$

where y_t denotes the output-level targeted by a farmer, given, a vector of undesirable output b_t, and a vector of initial capital stocks k_t, and a vector of feasible variable inputs x_t.

The feasible input set is represented by $L\left(y_t, x_t, b_t, k_t, t, \omega\right)$. λ is a scalar ($\lambda \geq 1$) assessing possible input reductions, with a minimum value of 1 corresponding to completely efficient production units. ω indicates unobserved heterogeneity like farm-effects.

Equation (4) must meet certain regularity requirements, such as being non-decreasing in inputs, linearly homogenous, and decreasing in outputs. Following Lovell et al. (1994) normalizing all inputs by one of the inputs is a straightforward technique for applying the homogeneity constraint.

$$D_I\left(y_t, x_t, b_t, k_t; t, \omega\right)/_{x_1} = L\left(y_t, \underset{t}{x}, b_t, \dot{K}_t; t, \omega\right) \tag{5}$$

where $\underset{t}{x}$ is a vector of input ratios with $\underset{kt}{x} = \frac{x_{kt}}{X_1}, \quad \forall k = 2, \ldots, K$; and $\dot{K}_t = \frac{K_t}{x_1}$.

Equation (5) can be written in logarithm and a translog functional form as in Coelli et al. (2005) as

[1] For example, Labour or capital inputs (e.g. a tractor) may not be fully used. Even if the workers put in their best effort, the farm may not use the improved technology properly because of a lack of training.

$$\ln D_I\left(y_t, x_t, b_t, k_t; t, \omega\right) - \ln x_1 = \mathrm{TL}\left(\ln y_t, \ln \underset{t}{x}, \ln b_t, \ln \dot{K}_t, t, \omega\right) \tag{6}$$

Re-arrange Eq. (6) and add the random error term (v_{it}) *to* make the distance function stochastic.

$$-\ln x_1 = \mathrm{TL}\left(\ln y_t, \ln \underset{t}{x}, \ln b_t, \ln \dot{K}_t, t, \omega\right) + v_{it} - \ln D_I\left(y_t, x_t, b_t, k_t; t, \omega\right) \tag{7}$$

where v_{it} is the noise and $\ln D_I() = u_{it} \geq 0$ D_I measures the efficiency measure that is conditional on undesirable outputs which represent the relative excess in input factors due to eco-efficiency.

GTFP measurement and decomposition approaches

Previous research on efficiency has employed various methods for calculating and decomposing TFP (for details see O'Donnell 2010; Kumbhakar et al. 2015; Alem 2018). The Divisia index is commonly used as an easy way to track TFP growth (Kumbhakar et al. 2015). A recent measure of TFP change seeks to decompose TFP change into different sources. TFP was decomposed by Kumbhakar (1996) and Kumbhakar and Lovell (2000) into technical change (TC), scale change (SC), efficiency change (EC), and pricing change components. Several publications, for example, Brümmer et al. (2002), Karagiannis et al. (2004); and Kumbhakar and Lozano-Vivas (2005), decompose the TFP change into four major components.

TFP change ($T\dot{F}P$) denotes the difference between the rate of change of an output index ($\dot{y}$) and the rate of change of the index of an input ($\dot{x}$) (see Karagiannis et al. 2004). We follow the Divisia index for the productivity change decomposed into TEC, TC, SC, and Allocative efficiency change (AEC) components. In this study, y is the net dairy output that is the difference between desirable output (Y) minus undesirable outputs (b) then estimate the Green TFP change $\left(GT\dot{F}P\right)$.

$$GT\dot{F}P = \dot{\boldsymbol{y}} - \dot{\boldsymbol{x}} \equiv \dot{\boldsymbol{y}} - \sum_j S_j \dot{x}_j \tag{8}$$

where S_j is captures the expenditure share of input $X_j\left(S_j = w_j x_j / C\right)$. C denotes the total cost ($C = \sum_j w_j x_j$); and w is the vector of input price x_j ($w = w_1 \ldots\ldots w_j$). As shown by Kumbhakar et al. (2014), by differentiating (8) totally, we get

$$GT\dot{F}P = \mathrm{TC} - \frac{\partial u}{\partial t} + \sum_j \left\{\frac{f_j x_j}{f} - S_j\right\} \dot{x}_j \tag{9}$$

$$GT\dot{F}P = \mathrm{TC} + (\mathrm{RTS} - 1) \sum_j \lambda_j \dot{x}_j + \frac{\partial u}{\partial t} + \sum_j \left\{\lambda_j - S_j\right\} \dot{x}_j \tag{10}$$

where a dot above a variable denotes the rate of change for that particular variable. $\mathrm{RTS} = \sum_j \frac{\partial \ln y}{\partial \ln x_j} = \sum_{k=1}^{4} \beta_k$ and λ_j is the elasticity of production for each input, i.e. $\lambda_j = \frac{\varepsilon_j}{\mathrm{RTS}}$, where ε_j are input elasticities defined at the input distance function $\mathrm{TL}\left(\ln y_t, \ln \underset{t}{x}, \ln b_t, \ln \dot{K}_t, t, \omega\right)$.

Green total factor productivity change is the sum of technical change (TC), efficiency change (EC), scale change (SC), and allocative efficiency change (AEC), i.e. $GT\dot{F}P = \boldsymbol{TC} + \mathbf{SC} + \mathbf{EC} + \mathrm{AEC}$. The GTFP change connected to the technology are $\boldsymbol{TC} + \boldsymbol{SC} + \boldsymbol{EC}$, which is the focus of this study.

The first source of the change in GTFP could be technical change (TC), which indicates that there is a change in the frontier. It is proof that best practices have improved because of the use of new technology. The improvement in the firm's capacity to utilise existing technology is the second factor contributing to the change in GTFP owing to efficiency change (EC). EC exhibits a move towards the frontier because of improved farm management, such as reduced resource wastage. With an intensive agricultural extension, inefficient farmers, lately adopting the currently available technology are improving efficiency (Alem 2018). The third component of GTFP is caused by a SC, which indicates movement approaching the frontier. SC illustrates how the company has evolved towards an operational size that is technologically feasible (Kumbhakar et al. 2015). The departure of input prices from the value of their marginal products in the allocation of inputs is captured by the AEC component of the GTFP change. Due to the lack of data on input prices at the farm level, AEC was not estimated for this study.

GHG emissions estimate

In the current study, the Intergovernmental Panel on Climate Change (IPCC 2006) methodology's Tier 2 approach is used, which incorporates country-specific forecasts from the Norwegian Environment Agency (NIR 2020). The basic equation to calculate the emission factor for enteric fermentation is provided in IPCC 2006 as follows.

$$\text{The CH4 emissions factors for dairy } (\mathrm{EF_D}) = \left(\frac{\mathrm{GE_D} * Y_\mathrm{m} * 365 \text{ days/year}}{55.65/\mathrm{Kg\ CH4}}\right) \tag{11}$$

$$\mathrm{GE_D} = 137.900 + (\text{Milk } 305 \times 0.0250)\ (\text{Concentrate proportion} \times 0.281)$$

$$Y_\mathrm{m} = 7.380 - (\text{Milk } 3050 * 0.00003)\ (\text{Concentrate proportion} * 0.0176)$$

where

- $\mathrm{GE_D}$ = gross energy intake for dairy farms, MJ/day
- Y_m = methane conversion rate, %
- The factor 55.65 (MJ/kg CH4) is the energy content of methane
- Milk305 = Lactation output of energy-adjusted milk at 305 days
- Concentrate proportion is the percentage of concentrates in the diet as a whole calculated using net energy. Equation (11) takes an annual emission factor into account (365 days).

Methane yearly emissions resulting from manure management of dairy cattle (CH4 emissions Dairy FARM) in each farm were derived by multiplying the farm-specific emission factor (EF_D) with the number of raised dairy cattle (N_D). Furthermore, country-specific emissions factors for non-dairy cattle (CH4 emissions, not dairy FARM) are derived by multiplying the number of non-dairy cattle (N_{notD}) by the CH4 emissions from non-dairy farms (EF_{notD}), i.e.

$$\text{CH4 emissions Dairy FARM Kg/year} = \text{EF}_\text{D} * N_\text{D} \tag{12}$$

$$\text{CH4 emissions, not Dairy FARM Kg/year} = \text{EF}_\text{notD} * N_\text{notD}. \tag{13}$$

Empirical model

Because of its flexibility, we used a translog (TL) specification of Eq. (7) in our empirical study; consequently, Eq. (7) defined as a TL input distance function in log form is:

$$\begin{aligned}
-\ln x_1 = {} & \alpha_0 + \sum_{k=1}^{K} \beta_k \ln \underset{k,it}{x} + \sum_{p=1}^{P} \beta_p \ln \dot{k}_{p,it} + \sum_{h=1}^{H} \beta_h \ln b_{h,it} + \sum_{m=1}^{M} \beta_m \ln \dot{y}_{m,it} + \beta_t D_t \\
& + \frac{1}{2} \sum_{K=1}^{K} \sum_{K=2}^{K} \beta_{kk} \ln x_{k,it} \ln x_{k,it} + \frac{1}{2} \sum_{p=1}^{P} \sum_{p=2}^{P} \beta_{pp} \ln k_{p,it} \ln k_{p,it} \\
& + \frac{1}{2} \sum_{h=1}^{H} \sum_{h=2}^{H} \beta_{hh} \ln b_{h,it} \ln b_{h,it} + \frac{1}{2} \sum_{m=1}^{M} \sum_{m=2}^{M} \beta_{mm} \ln \dot{y}_{m,it} \ln \dot{y}_{m,it} \\
& + \sum_{K=1}^{K} \sum_{p=1}^{P} \beta_{kp} \ln x_{k,it} \ln \dot{k}_{p,it} + \sum_{K=1}^{K} \sum_{h=1}^{H} \beta_{kh} \ln x_{k,it} \ln b_{h,it} \\
& + \sum_{K=1}^{K} \sum_{m=1}^{M} \beta_{km} \ln x_{k,it} \ln \dot{y}_{m,it} + \sum_{p=1}^{P} \sum_{h=1}^{H} \beta_{ph} \ln \dot{k}_{p,it} \ln b_{h,it} \\
& + \sum_{p=1}^{P} \sum_{m=m}^{M} \beta_{pm} \ln \dot{k}_{p,it} \ln \dot{y}_{m,it} + \sum_{h=1}^{H} \sum_{m=1}^{M} \beta_{hm} \ln b_{h,it} \ln \dot{y}_{m,it} \\
& + \sum_{k=1}^{K} \beta_{kt} \ln \underset{k,it}{x} D_t + \sum_{p=1}^{P} \beta_{pt} \ln \dot{k}_{p,it} D_t + \sum_{h=1}^{H} \beta_{ht} \ln b_{h,it} D_t \\
& + \sum_{m=1}^{M} \beta_{mt} \ln \dot{y}_{m,it} D_t + \frac{1}{2} \beta_{tt} D_t^2 + \omega_i + v_{it} - u_{it}
\end{aligned} \tag{14}$$

where $\ln \dot{y}_{m,it}$ is desirable outputs in log $(m = 1, \ldots, M)$. $\ln \underset{k,it}{x}$ is inputs in log divided by labour input $\left(j = 1, \ldots, J\right)$ by farms $(i = 1, \ldots, N)$ and time $(t = 1, \ldots, T)$. b_{ht} is undesirable outputs $(= 1, \ldots, H)$ and capital stocks $k_t \left(\ln \dot{k}_{p,it} = \frac{\ln I_{pt}}{X_1}, \quad \forall p = 1, \ldots, P \right)$. As discussed above $\ln \underset{kt}{x} = \frac{\ln x_{kt}}{X_1}$, $\forall k = 2, \ldots, K$. Greek letters are all variables that must be estimated, and D_t is the time variable to capture the technological change. The white noise error term (v_{it}) representing the usual statistical noise and unexpected stochastic change in a production environment and assumed $v_{it}^{iid} \sim N\left(0, \sigma_v^2\right)$. ω_i portrays unobserved heterogeneity and u_{it} is capturing the effects of technical inefficiency and assumed $u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$. Equation (14) is estimated using Greene's (2005) true fixed-effect model specifications.[2] The Battese and Coelli (1988) approach is used to calculate eco-efficiency (Eco-TE).

$$\text{Eco - TE} = E(\exp(-u_{it}|\varepsilon_{it}) \tag{15}$$

where $\boldsymbol{\varepsilon_{it}} = v_{it} - u_{it}$.

The efficiency change (EC) component is computed as $= \frac{\text{TE}_{it} - \text{TE}_{it-1}}{0.5(\text{TE}_{it} + \text{TE}_{it-1})}$.

We compute the returns to scale (RTS) component following Panzar and Willig's (1977) definition, which states that, for many outputs, the economies of scale are equal to the inverse of the sum of all partial cost elasticities, i.e. $\text{RTS} = \frac{1}{\sum \partial \ln x_{1t} / \partial \ln y_{mt}}$. Following Eq. (10) we estimate the Scale change $\text{SC} = (\text{RTS} - 1) \sum_j \lambda_j$. Where $\lambda_j = \frac{\varepsilon_j}{\text{RTS}}$, and ε_j are input elasticities estimated from Eq. (14). Additionally, we compute technical change (TC) following Caves et al. (1981) as $\text{TC} - \frac{\partial \ln x_1}{\partial t}$.

Endogeneity problems may arise during the econometric estimate of distance functions (see Sauer and Latacz-Lohmann 2015; Minviel and Sipiläinen 2018). Cuesta and Zofío (2005), on the other hand, claim that implementing the homogeneity criterion indicates that certain regressors are directly impacted by the error term, while others are inversely influenced; consequently, the ratios and product regressors can be deemed exogenous. We imposed homogeneity of degree one in inputs before estimation which implies that $\sum_{k=1}^{K} \beta_k = 1$, $\sum_{k=1}^{K} \beta_{kp} = \sum_{k=1}^{K} \beta_{kh} = \sum_{k=1}^{K} \beta_{km} = 0$ while quadratic symmetric implies $\beta_{kp} = \beta_{pk}$; $\beta_{kh} = \beta_{hk}$ $\beta_{km} = \beta_{mk}$. We impose these restrictions before the estimate. The frontier and efficiency components of Eq. 14 were computed concurrently using farm-level data and maximum likelihood estimation.

Description of the data

Every year NIBIO (Norwegian Institute of Bioeconomy Research) conducted a farm-level survey. The survey collects data on agricultural production and economics from about 1000 farms each year. An unbalanced panel of 6229 observations was selected on 692 Norwegian dairy farms participating in dairy production from 1991 to 2020. To guarantee that dairy farming is the principal farm output, we select farms where dairy product sales account for at least 80% of total farm income (see Alem 2020).

The environmental production technology is modelled by two outputs and four inputs. Desirable output is the overall farm revenue generated by dairy products. Undesirable output (CH4 emission) estimated based on Eqs. 11–13. The value of farm-level CH4 emission was calculated using data from Statistics Norway (SSB 2021). Agricultural land (x_1) is measured in hectares and labour (x_2) is calculated for all labour inputs. Feed, fuel goods, energy, animal protection fees, and other expenditures are included in the

[2] In this work, we used the 'true' fixed-effect model rather than the 'true' random-effect model. Estimates show a robust relationship between farm impacts and the regressors (not reported here).
.

Table 1 Model variables' descriptive statics used in the translog functions

Mean	Label	Unit	Mean	SD
Desirable output (*y*)	Dairy output	1000 NOK	1466.50	1167.49
Undesirable output (*b*)	CH4 emission	tonne/year	0.99	0.61
Undesirable output price	CH4 price	NOK/tonne	0.045	0.013
Inputs (x_i) x_1	Land	Hectares	3.31	2.02
x_2	Labour	100 h	35.62	10.74
x_3	Material costs	1000 NOK	480.06	453.45
x_4	Capital costs	1000 NOK	404.63	415.66
N	Observation		6229	

NOK = Norwegian Kroner and 1NOK = 10 euro

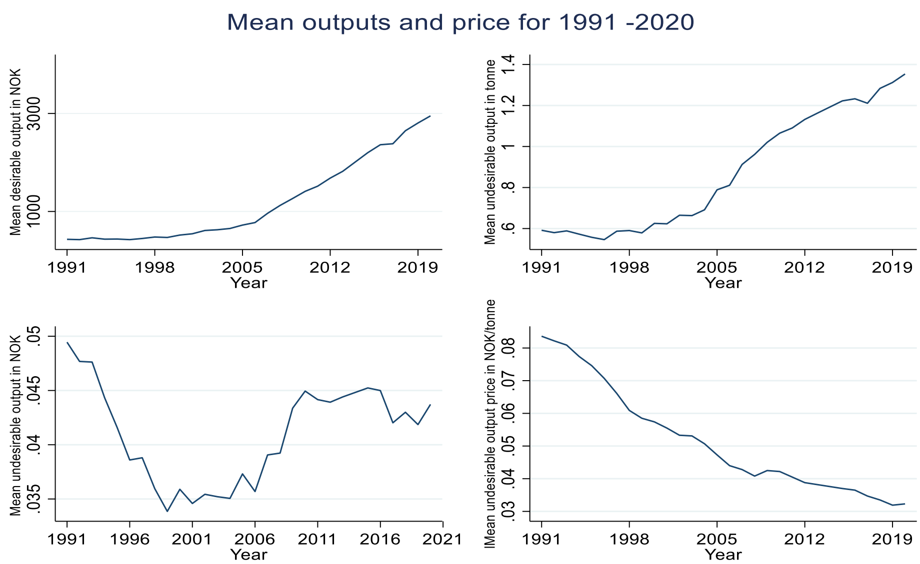

Fig. 1 Annual mean desirable and undesirable output from 1991 to 2020

materials (x_3). Capital assets (*K*) include the implicit quantity index calculated by deflating the value of machinery, buildings, and animals at the start of the year.

All values are in NOK and have been adjusted to 2015 prices using the consumer price index (CPI). The descriptive statics of the model variables used in the translog functions are shown in Table 1. Furthermore, Figs. 1 and 2 depict the progression of output-input utilization over the last 30 years.

Farms in Norway are small. The yearly average annual dairy revenue was around 1,5 million, which has been increasing over time, resulting in an average annual CH4 emission of 0.99 tonnes and increasing over time. However, because of price differences over time, the average annual CH4 emission value fluctuates (Fig. 1). All production input used in the dairy farm increase over time (Fig. 2). Table 1 shows the descriptive statics of all the input–output used for the analysis.

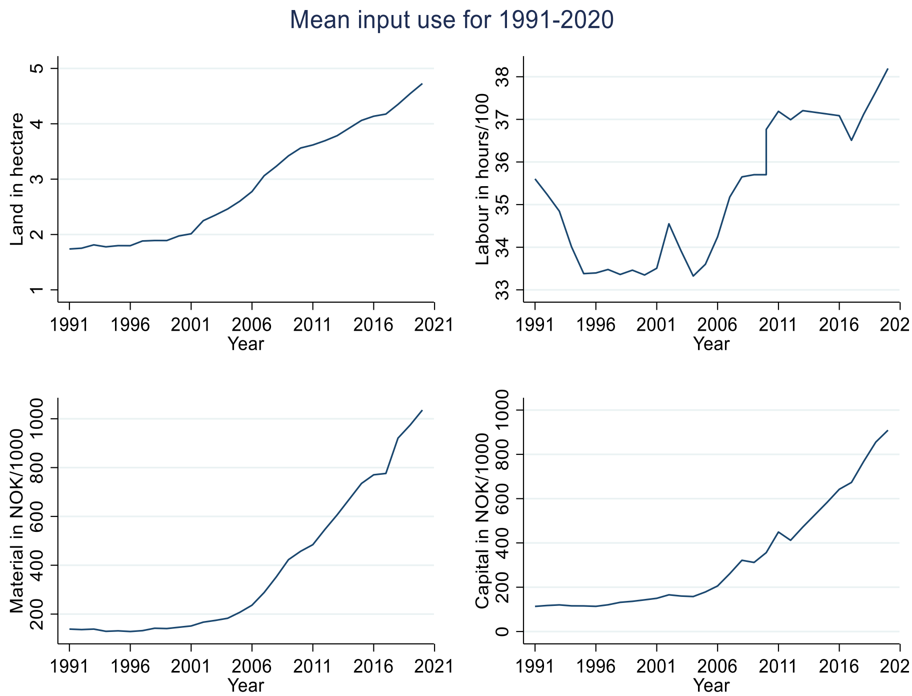

Fig. 2 Annual mean input use from 1991 to 2020

Table 2 Parameter estimates

Variable	First orders	$\ln x_2$	$\ln x_3$	$\ln x_4$	$\ln y_1$	$\ln b$	T
$\ln x_2$	0.330*** (0.029)	0.0196*** (0.001)					
$\ln x_3$	0.268*** (0.030)	− 0.082*** (0.001)	0.114*** (3.71)				
$\ln x_4$	0.148*** (0.023)	− 0.005 (0.010)	− 0.063 (0.012)	− 0.047*** (7.95)			
$\ln y_1$	− 0.211*** (0.036)	0.206*** (0.023)	− 0.041 (0.023)	0.042* (0.021)	0.038 (0.012)		
$\ln b$	− 0.438*** (0.038)	− 0.102*** (0.020)	0.055** (0.021)	0.005* (0.016)	− 0.096*** (0.024)	− 0.028 (0.033)	
Year	− 0.018*** (0.003)	− 0.005*** (0.001)	0.004** (0.001)	− 0.003** (0.001)	− 0.014*** (0.002)	0.012 (0.002)	0.001*** (0.000)
Log likelihood = 7096*** $\gamma = \frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2} = 0.94$ $N = 6229$ (0.000)							

Standard errors in parentheses; *$p<0.05$, **$p<0.01$, ***$p<0.001$; x_2 = labour/land, x_3 = material/land, x_4 = capita/land, y_1 = desirable outputs, b = undesirable output, all in logarithmic form

Estimation results and discussion

Estimation and model specification tests

The Translog function in the empirical model Eq. (14) is estimated using STATA® version 17. Table 2 shows the predicted parameters and related standard errors. A generalised likelihood ratio test (LR) using suggests the suitability of the SFA approach as opposed to OLS (see Schmidt & Lin 1984). The parameter γ ($\gamma = 0.94$) in Table 2

Table 3 Yearly GTFP and its components in percentages

Percentile	Efficiency change (EC)	Scale change (SC)	Technological change (TC)	Green TFP change	Returns of scale (RTS)
1	− 0.0023	− 1.758	− 0.055	− 0.985	1.670
5	− 0.0022	− 0.489	− 0.047	− 0.318	1.707
10	− 0.0020	− 0.239	− 0.040	− 0.202	1.732
25	− 0.0017	− 0.068	− 0.034	− 0.081	1.780
Mean	− 0.0017	0.056	− 0.029	0.032	1.839
75	− 0.0015	0.176	− 0.026	0.144	1.896
90	− 0.0014	0.338	− 0.022	0.281	1.942
95	− 0.0014	0.511	− 0.021	0.407	1.970
99	− 0.0013	1.306	− 0.017	0.965	2.023
St. Dev	0.000	0.042	0.008	0.030	0.080
Observations 6229					

illustrates the proportion of the departure from the frontier that may be attributed to inefficiency and the remainder to noise (Battese & Corra 1977; Coelli et al. 2005). An LR test rejects a TL to Cobb–Douglas simplification. First-order parameters in the estimated model are positive and significant, proving that the model used in this study satisfies the monotonicity requirement as would be anticipated for a well-behaved function.

Before estimating, all variables are normalized by setting the trend variable to zero and dividing all other variables by their respective means. As a result, the first-order parameters can be considered geometric mean elasticities. For labour, materials, and capital, the input distance elasticity (cost elasticity) was 0.33, 0.27, and 0.15, respectively. The input share of labour was the highest, while the input share of capital was the lowest. Ceteris paribus, if labour utilization in the production system rises by 1%, outputs will rise by around 0.33%. Dairy production will increase by around 0.27% if material prices go up by 1%. If the land increases by 1%, the output will increase by about 0.25%. Elasticities for desirable and undesired outputs were 0.438 and 0.018, respectively. This indicates that if dairy output grows by 1%, production costs (inputs) increase by around 0.44%, ceteris paribus.

Change in GTFP and components

We reported the estimated percentile and components of GTFP in Table 3. The table also illustrates how the farms in the sample are distributed based on their GTFP. GTFP for 1% of the farms was − 0.985 per year, while GTFP was 0.144 per year for 75% of the sample farms. During the period 1991–2020, the average yearly change in the GTFP growth rate in dairy products was 0.032%. The GTFP increases with time (Fig. 3).

Green total factor productivity (GTFP) was not quantified in previous dairy farm performance studies, so our results cannot be directly compared. Research conducted in other nations, which did not consider environmental factors, found different results regarding the change in TFP. For example, Sipiläinen et al. (2013) reported a positive TFP change for Finland and Norway dairy farms, while a survey conducted in 22 European countries reported a decline in TFP change (Madau et al. 2017).

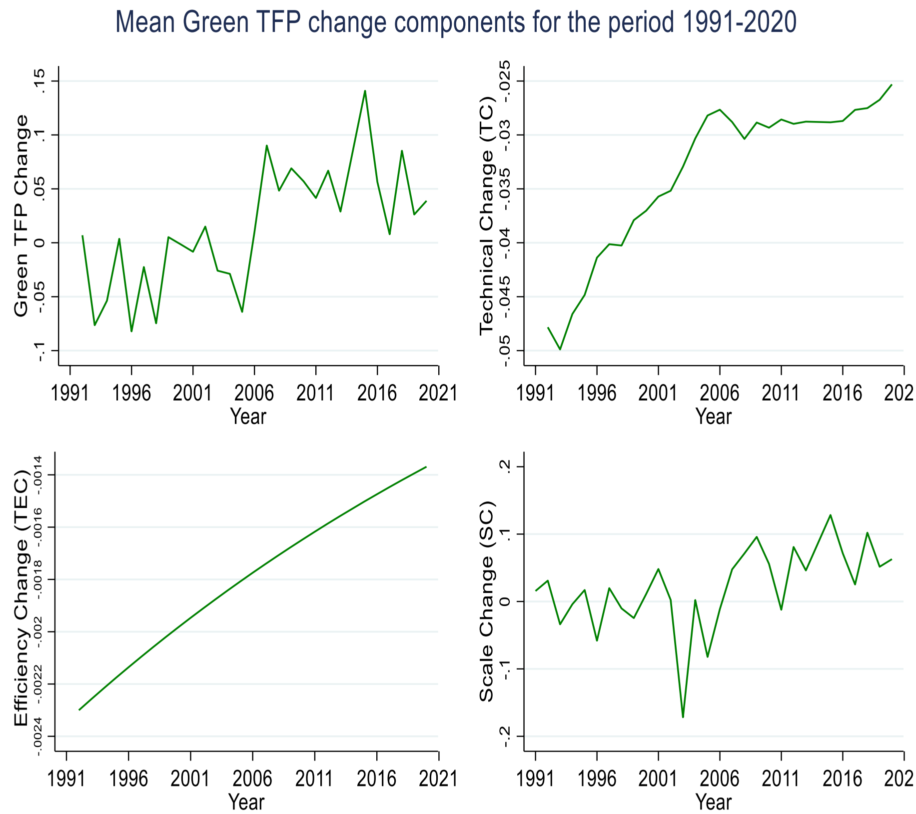

Fig. 3 Mean green TFP change components for the period 1991–2020

The component of scale change (SC) averaged 0.056% per year during the study period, demonstrating that the scale has a positive impact on the overall change in GTFP. Moreover, the Returns to scale (RTS) averaged 1.84, indicating an increasing return to scale in which output grows in proportion to input increases (Table 3). This demonstrates that Norwegian dairy farmers have not completely tapped into the benefits of scale economics. The efficiency change (EC), which measures the difference in output between observed and best-practice farmers, was − 0.002% each year, resulting in a negative GTFP growth effect. However, from 1991 to 2020, the EC is improving (see Fig. 3).

As shown in Table 3, during the sample period, the technological change (TC) on average was − 0.031% per year, with a slightly accelerating over time (see Fig. 3). Furthermore, According to Wang and Ho (2010), the first-order coefficients of the temporal trend variable provide estimates of the average yearly rate of TC (see also Alem 2018). At the 1% level of significance, the estimated parameter of the trend variable is negative and statistically distinct from zero, indicating a technological regress for Norwegian dairy output over the research period (Table 2. The major reason for regression might be because Norwegian dairy-producing farms are small-scale family farms with milk output quotas. As a result, if economies of scale exist in the manufacturing of dairy-producing technologies, there may be a shift in long-run average dairy farm costs that impacts small farms in the long run.

The non-neutrality of Hicks in technological regress is shown to be a significant interaction parameter with time (t) to input utilization (Table 2). TC has a positive impact on material costs but a negative impact on labour and capital input. As a result, during the research period, TC was not neutral. In terms of scale, the interaction parameter with time for desirable output ($t \ln y_1$) is negative and statistically significant, implying that the cost-increasing impacts of technical regress weaken as dairy production grows. According to the empirical findings, small-scale dairy farms are more affected by technical regress. The undesirable output ((tlnb) on the other hand is positive but not statistically significant. The detailed yearly mean GTFP and its component score are shown in Table 4 in "Appendix".

Concluding remarks

Existing studies on performance analysis have consequently overlooked the intertemporal element of agricultural emissions. This study varies from the previous one in that it estimates green total productivity (GTFP) and its components in Norwegian dairy farms while accounting for dairy farms' CH4 emissions in the model. We used a farm-level unbalanced panel of 6229 observations from 692 farms for the years 1991 to 2020. We employed a stochastic input distance function with multiple input–output environmental production technologies to estimate GTFP and its components. According to empirical findings, the GTFP change in dairy output grew by 0.032% every year between 1991 and 2020. The increase is mostly due to the positive impact of average scale change (0.035% each year). However, technological change (− 0.031% per year) and efficiency change (− 0.002% per year) result in a negative GTFP growth effect.

Farm green productivity would improve through interventions to improve dairy farm performance and technology use. Within the current Norwegian agricultural policy system, this paper offers two primary measures to boost GTFP in the dairy-producing sector. To begin with, technical change (TC) is the key driver of productivity growth, and it captures the technological transition, which is negative in our empirical research. As a result, for sustainable agricultural development in Norway, policymakers in Norway must prioritize dairy production research and development so that new technology can be developed to reduce dairy farm emissions and improve TC. Furthermore, the analysis shows a negative change in efficiency, showing that farmers are still trailing behind best-practice farmers. As a result, extensive agricultural extension and dissemination effort is required to assist farmers in adapting to contemporary technologies. The article only considered livestock CH4 emissions in its assessment of the GTFP of resources used to promote sustainable agricultural development. Other environmental issues, such as farm emissions of N_2O, CO_2, NH_3, and NO_3, may be explored in the future.

Appendix

See Table 4.

Table 4 Mean green TFP and components scores per year for dairy farms (1991–2020) *Source*: own calculation

Year	Mean green TFP	Mean GTFP components			Mean RTS
		EC	SC	TC	
1991	–	–	–	–	1.724
1992	0.007	− 0.0023	0.0156	− 0.0478	1.718
1993	− 0.076	− 0.0022	0.0396	− 0.0499	1.734
1994	− 0.054	− 0.0022	− 0.0338	− 0.0466	1.724
1995	0.004	− 0.0021	0.0171	− 0.0448	1.724
1996	− 0.082	− 0.0021	− 0.0581	− 0.0414	1.730
1997	− 0.022	− 0.0020	0.0199	− 0.0414	1.742
1998	− 0.075	− 0.0020	− 0.0102	− 0.0401	1.742
1999	0.005	− 0.0020	− 0.0245	− 0.0379	1.740
2000	− 0.001	− 0.0019	0.0109	− 0.0370	1.752
2001	− 0.008	− 0.0019	0.0482	− 0.0357	1.757
2002	0.015	− 0.0019	0.0023	− 0.0352	1.777
2003	− 0.026	− 0.0019	− 0.1717	− 0.0329	1.784
2004	− 0.029	− 0.0018	0.0024	− 0.0303	1.795
2005	− 0.064	− 0.0018	− 0.0822	− 0.0282	1.805
2006	0.010	− 0.0017	− 0.0113	− 0.0276	1.810
2007	0.090	− 0.0017	0.0477	− 0.0288	1.824
2008	0.048	− 0.0017	0.0713	− 0.0304	1.832
2009	0.069	− 0.0016	0.0959	− 0.0288	1.867
2010	0.057	− 0.0016	0.0558	− 0.0289	1.855
2011	0.042	− 0.0016	− 0.0122	− 0.0286	1.865
2012	0.067	− 0.0016	0.0809	− 0.0289	1.869
2013	0.029	− 0.0015	0.0461	− 0.0288	1.872
2014	0.029	− 0.0015	0.0460	− 0.0287	1.872
2015	0.141	− 0.0015	0.1283	− 0.0288	1.887
2016	0.056	− 0.0015	0.0715	− 0.0287	1.891
2017	0.008	− 0.0014	0.0253	− 0.0277	1.891
2018	0.085	− 0.0014	0.1021	− 0.0275	1.898
2019	0.026	− 0.0014	0.0515	− 0.0267	1.902
2020	0.039	− 0.0013	0.0629	− 0.0253	1.908
Total	0.032	− 0.0017	0.0560	− 0.0291	1.839
(St.Dev)	(0.030)	(0.0000)	(0.0421)	(0.008)	(0.081)

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Competing interests
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