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ORIGINAL ARTICLE

Mitigating greenhouse gas emissions on Dutch dairy farms. An efficiency analysis incorporating the circularity principle.

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Abstract

Circular agriculture is vital to achieve a substantial reduction of greenhouse gas (GHG) emissions. Optimizing resources and land use are an essential circularity principle. The objective of this article is to assess the extent to which land optimization can simultaneously reduce GHG emissions and increase production on dairy farms. In addition, we explore the potential reduction of GHG emissions under four different pathways. The empirical application combines the network Data Envelopment Analysis (DEA) with the by-production approach. This study focuses on a representative sample of Dutch dairy farms over the period of 2010–2019. Our results suggest that farms can simultaneously increase production and reduce GHG emissions by both 5.1%. However, only 0.6% can be attributed to land optimization. The land optimization results show that on average 25.3% of total farm size should be allocated to cropland, which is 6.7% more than the actual land allocation. GHG emissions could be reduced by 11.79% without changing the level of inputs and outputs. This can be achieved by catching up with the mitigation practices of the best performing peers.

KEYWORDS

By-production approach, circular agriculture, dairy farm, greenhouse gas emissions, land optimization, network data envelopment analysis

JEL CLASSIFICATION

D22, Q12, Q15, Q53

1 | INTRODUCTION

We face several major but intertwined global challenges: from climate change, to environmental degradation, global food insecurity, increasing population growth, and poverty. The dairy sector continues to generate higher absolute greenhouse gas (GHG) emissions, despite the increasing production efficiency, in response to the ever-increasing global demand for dairy products (Food and Agriculture Organization, 2019). In light of these challenges, the dairy sector needs to reduce its environmental impact, while continuing to produce high-quality animal products (Food and Agriculture Organization, 2019). The Dutch dairy sector is highly productive, but the substantial environmental cost from its production is yet to be taken into account by producers (Hou et al., 2016; van Grinsven et al., 2019; Zhu & Oude Lansink, 2022). Environmental externalities is duty-bound to be considered in production analyses. To comply with the Paris Agreement on Climate Change, the Dutch government has developed its national Climate Agreement (Klimaatakkoord) (Rijksoverheid, 2022). Dairy farmers have already taken measures to reduce emissions of greenhouse gases, but there is an urgent need to accelerate the sector's response to meet the emission reduction target (Food and Agriculture Organization, 2019; van Grinsven et al., 2019).

Current policies focus on transitioning toward a more circular agriculture, which is regarded as a cost-effective means to reduce GHG emissions (Food and Agriculture Organization, 2019; Ministerie van Landbouw Natuur en Voedselkwaliteit, 2019; Wageningen University & Research, 2022). Circular agriculture closes resource cycles by optimizing efficiency, recycling waste (e.g., manure), reducing external inputs (e.g., animal feed, artificial fertilizers, pesticides, and fossil fuels), continuous systemic improvements, cross value chain collaboration, and decreasing possible emissions and negative externalities (de Boer & van Ittersum, 2018). Intrinsic and extrinsic motivation as well as attitude predict farmers' intentions to take measures with circular agriculture (de Lauwere et al., 2022). In addition, efficient production and resource optimization are crucial for the transition toward circular agriculture. In terms of land use, feeding animal left-over crops is estimated to save 25% of global cropland compared to not keeping any livestock (van Zanten et al., 2018).

In the context of dairy farms, the circularity principle mainly refers to making optimal use of resources and land (de Boer & van Ittersum, 2018). Dutch dairy farmers have already applied the circularity principle to some degree, that is, upcycling manure for crop fertilizers and producing their own feed on the farm. However, the extent to which land optimization between cropland and grassland can contribute to reducing GHG emissions and increasing production is an empirical question. Some evidence suggests that land conversion from cropland to grassland generally reduces GHG emissions because of the carbon sequestration potential of grassroots and the lower requirement for fertilization (Castaño-Sánchez et al., 2021; Guan et al., 2020). Other factors like farm management practices and local conditions could also influence the overall GHG emissions on farms (Kløve et al., 2017). For instance, converting grassland to cropland could reduce emissions from the decreasing of peat soils in the Netherlands (Arets et al., 2020). Stetter and Sauer (2022) have studied the dynamic eco-efficiency as the ratio between economic performance and environmental damage for four different types of Bavaria farms. Eco-efficiency rewards production and penalizes pollution, but the production process is not explicitly modeled (Stetter & Sauer, 2022). Stetter and Sauer (2022) conclude that dairy farmers are on average less eco-efficient than mixed farms with livestock production and crop production.

This study aims to find the optimal land allocation between the grassland and the cropland on dairy farms to simultaneously increase production (deflated revenue) and reduce GHG emissions. Land optimization is defined as how much land should be allocated to grassland and cropland given the total land use on the farm, so as to quantify the maximum attainable efficiency gain from increasing farm production while decreasing GHG emissions.

Incorporating the circularity principle in an efficiency framework requires explicit modeling of the recycling of intermediate outputs, reallocating inputs, and reducing pollution (Rebolledo-Leiva et al., 2021). Focusing on US dairy farms, Färe and Whittaker (1995) showed how recycled crop output can be modeled as a feed input in a livestock enterprise in an efficiency framework. Färe et al. (1997) quantified potential efficiency gains from reallocating land use inputs for a sample of Illinois grain farms. Focusing on English and Welsh farms, Ang and Kerstens (2016) combined these two aspects, and characterized the inputs as joint or output-specific ones following Cherchye et al. (2013). Kahindo and Blancard (2022) investigated the reduction of pesticides use through optimal reallocation between arable farms in France.

Accounting for GHG emissions in an efficiency framework requires an accurate axiomatic representation within the production technology. The potential reduction of GHG emissions on dairy farms has been studied independently from the circularity aspect of dairy farms by Krüger and Tarach (2022), in which GHG emission is modeled as a weakly disposable input. The potential reduction of GHG emissions has also been modeled together with the circularity principle on dairy farms by Rebolledo-Leiva et al. (2022) using a non-oriented slack-based network Data Envelopment Analysis (DEA) model. A similar approach has also been applied to beekeeping by Rebolledo-Leiva et al. (2021). However, modeling the GHG emissions using the by-production approach developed by Førsund (2009) and Murty et al. (2012) is most promising presently (Ang et al., 2023). The reason is that by-production approach provides separate frontier estimations for each technology in a production system following the material balance principle (MBP), as opposed to the violation of MBP by the weakly disposability assumption (Shepard, 1970) for modeling GHG emissions (Dakpo et al., 2016). Recent

AGRICULTURAL ECONOMICS The Journal of the International Association of Agricultural Economists IAAE

applications to the agricultural sector include Dakpo et al. (2017), Serra et al. (2014), and Ang et al. (2023).

To the best of our knowledge, no study has structurally addressed these circularity aspects within one integrated multi-production technology framework that accounts for GHG emissions using the state-of-art by-production approach. The current study addresses this research gap by developing such an efficiency framework that allows to assess the potential reduction in GHG emissions. We estimate a directional distance function using network Data Envelopment Analysis. Furthermore, we explore and compare the potential reduction of GHG emissions on dairy farms versus the expansion for production, under four pathways with and without land optimization. These pathways compare the potential reduction of GHG emissions and expansion of production under four different directional orientations: contracting emissions and expanding total desirable outputs simultaneously, only contracting emissions, only expanding total desirable outputs, and only expanding dairy outputs. Overall, the insights gained from the four pathways enable policy makers to develop comprehensive and balanced policies that consider the interplay between reducing GHG emissions and expanding production. Depending on the policy objective, the four pathways provide us information on the farm-specific potential gains in economic and environmental terms.

This study contributes to the literature in three ways. First, it extends previous work from Ang and Kerstens (2016) that models upcycled crops as animal feed, by explicitly considering the manure cycle, that is, by distinguishing the upcycled manure as fertilizers for crop production and the remaining manure that is removed from the farm. In this way, we explicitly model circularity aspects of many Dutch dairy farms. Second, this is the first study that combines the work of Ang and Kerstens (2016) with the by-production approach of Førsund (2009) and Murty et al. (2012) to account for GHG emissions in an efficiency framework. Our model allows assessing the importance of land optimization decisions for mitigating GHG emissions. Third, this study provides scientific evidence on where the potential reduction of GHG emissions lies for specialized dairy farms for given input use. The Dutch agricultural policy currently focuses on reducing livestock numbers. It has implemented a program to buy out livestock farms, especially close to environmentally sensitive areas. However, this program is not successful, as only 53 livestock farms have participated by the end of 2022 (Vermaas, 2022). In this light, the quantification of efficiency gains through land optimization without reducing herd size in our study is relevant and important.

The remaining part of the article proceeds as follows. The next section describes the method. Subsequently, the sections consist of model formulation, data description, results, discussion and conclusions.

2 | METHOD

In this section, we describe the network DEA model that is used to assess the performance of dairy farms. Network DEA models opens up the traditional single-process DEA models with different subprocesses, that is, a network of interrelated processes (Färe & Grosskopf, 2000). The advantage of the network DEA model is that intermediate products generated and consumed within the production system can be modeled explicitly, which is suitable for modeling the circularity principle (Rebolledo-Leiva et al., 2021). Like single-process DEA, network DEA is sensitive to outliers and sampling bias, which could be addressed in a structural way using Stochastic Frontier Analysis (SFA) (Stetter et al., 2023). However, the network structure complicates its implementation in SFA. Our model is also used to investigate the potential for land optimization to increase production and decrease GHG emissions. We distinguish three interdependent subprocesses with their corresponding technologies. This is followed by an explanation of the axiomatic properties, model formulation and coordination inefficiency.

2.1 | Technology

This study operationalizes two sub-technologies with intended outputs: crop production and livestock production. Crop and livestock outputs are modeled separately, which allows optimizing the land allocation between both production processes. In addition, a third residual-production technology is operationalized for GHG emissions. In the by-production approach to model the pollution-generating technology, the production of intended output sets the residual-production technology in motion, which leads to the generation of by-product (Murty et al., 2012). Following the detailed explanation of Murty and Russell (2020), these three separate technologies are consistent with the original framework of Murty et al. (2012), in which all projections fall within the intersection of the conventional technologies and the pollution-generating technology.

In the Netherlands, under current cultivation conditions (grass and arable land), there is a balance between emissions and sequestration (DuurzameZuivelketen, 2018). Therefore, our model specification excludes land use from the residual GHG emission technology (see Table 1). Nevertheless, land optimization plays a role through the intended crop- and livestock-production technologies.

TABLE 1 Inputs, outputs variables for each technology.

The intended crop production technology has the following inputs and outputs:	
$x_k^C \in \mathbb{R}_+^{Nc}$	Aggregated crop-specific inputs, including crop protection products, purchased fertilizers, and seeds.
$m_k^{L,U} \in \mathbb{R}_+$	Upcycled manure used as fertilizer for crops in the same year.
$x_k^{C,l} \in \mathbb{R}_+^S$	Total cropland in hectares.
$\mathbf{q}_k \in \mathbb{R}_+^M$	Shared joint inputs by crop and livestock processes, including aggregated input set (which consists of buildings, machinery & equipment, and energy consumption); as well as water use, and labor.
$y_k^C \in \mathbb{R}_+^{OC}$	Aggregated crop output revenues from wheat, barley, potatoes, sugar beet, vegetables, grass seeds, folder crops, and other arable crops.
$z_k^C \in \mathbb{R}_+^{Oc}$	Unsold crop residuals used as animal feed: maize & grass.
The intended livestock production technology has the following inputs and outputs:	
$x_k^L \in \mathbb{R}_+^{Nl}$	Aggregated livestock-specific inputs, including animal units, purchased animal feed, animal health costs and animal water use.
$x_k^{L,l} \in \mathbb{R}_+^S$	Total grassland in hectares.
$z_k^C \in \mathbb{R}_+^{Oc}$	Unsold crop residuals used as animal feed: maize & grass.
$\mathbf{q}_k \in \mathbb{R}_+^M$	Shared joint inputs by crop and livestock processes, including aggregated input set (which consists of buildings, machinery & equipment, and energy consumption); as well as water use, and labor.
$y_k^L \in \mathbb{R}_+^{OL}$	Aggregated livestock output revenues from milk & milk products, cattle, eggs, poultry, pigs, sheep, and wool.
$m_k^{L,P} \in \mathbb{R}_+$	Surplus manure removed from the farm.
$m_k^{L,U} \in \mathbb{R}_+$	Upcycled manure used as fertilizer for crops in the same year.
The residual GHG emission technology has the following inputs and outputs:	
$x_k^{C,p} \in \mathbb{R}_+^{Npc}$	Polluting aggregated crop-specific inputs, including crop protection products, purchased fertilizers, and seeds.
$x_k^{L,p} \in \mathbb{R}_+^{Npl}$	Polluting livestock specific inputs, including animal units, purchased animal feeds, unsold crops residuals used as animal feed.
$q_k^{J,p} \in \mathbb{R}_+^{pj}$	Other polluting inputs including energy use and total manure.
$e_k \in \mathbb{R}_+$	Total GHG emissions in carbon dioxide equivalent from crop and livestock production processes.

The network DEA model structure is shown in Figure 1. Each dairy farm is denoted by subscript k. Crop production and livestock production processes are linked through (i) the use of upcycled manure from livestock production as fertilizer in crop production ($m_k^{L,U}$), and (ii) the use of unsold crop residuals (z_k^C as feed in addition to the purchased feed) in livestock production. The total on-farm GHG emissions (e_k) are generated by the polluting inputs ($x_k^{C,p}$, $x_k^{L,p}$, $q_k^{J,p}$). The detailed inputs and outputs of each production technology are described in Table 1.

We now define the three sub-technologies with their production set as follows.

The intended crop production technology is:

$$T_1 = \left\{ \left(x_k^C,\ m_k^{L,U},\ \mathbf{q}_k \right)\ produces\ \left(y_k^C,\ z_k^C \right) \right\} \tag{1}$$

The intended livestock production technology is:

$$T_2 = \left\{ \left(x_k^L,\ z_k^C,\ \mathbf{q}_k \right)\ produces\ \left(y_k^L,\ m_k^{L,P},\ m_k^{L,U} \right) \right\} \tag{2}$$

The residual GHG emission production technology is:

$$T_3 = \left\{ \left(x_k^{C,p},\ x_k^{L,p},\ q_k^{J,p} \right)\ produces\ \left(e_k \right) \right\} \tag{3}$$

The overall technology is $T = T_1 \cap T_2 \cap T_3$.

2.2 | Axiomatic properties

The free disposability axioms apply to T_1 and T_2. T_3 satisfies the costly disposability axiom (Murty et al., 2012). Costly disposability allows inefficiencies in the generation of pollution (Murty et al., 2012). For a given level of inputs and intended outputs, there is a minimum level of pollution. Pollution above this minimum level is inefficient.

T_1 is defined as:

$(x_1, y_1) \in T_1 \wedge x_1' \geq x_1 \rightarrow (x_1', y_1) \in T_1$ (Free disposability of all inputs);

$(x_1, y_1) \in T_1 \wedge y_1' \leq y_1 \rightarrow (x_1, y_1') \in T_1$ (Free disposability of all outputs).

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE

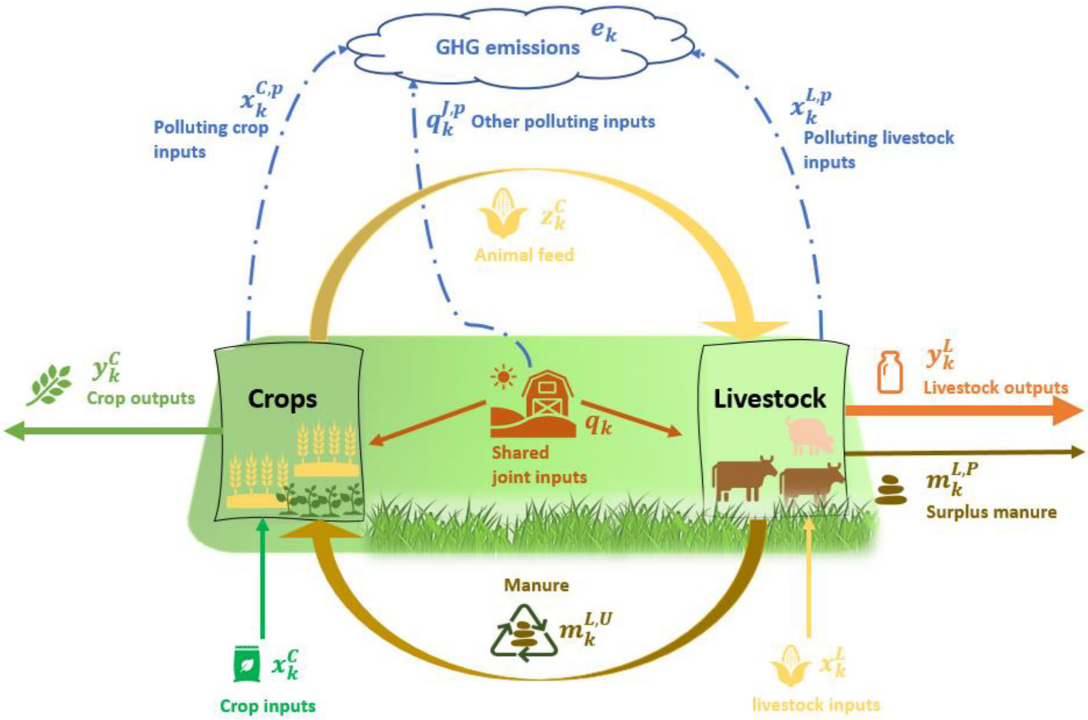

FIGURE 1 Network structure of Dutch dairy farms.

T_2 is defined as:

$(x_2, y_2, m) \in T_2 \wedge x_2' \geq x_2 \rightarrow (x_2', y_2, m) \in T_2$ (Free disposability of all inputs);
$(x_2, y_2, m) \in T_2 \wedge y_2' \leq y_2 \rightarrow (x_2, y_2', m) \in T_2$ (Free disposability of all outputs, except manure);
$(x_2, y_2, m) \in T_2 \wedge 0 < \theta < 1 \rightarrow (x_2, \theta y_2, \theta m) \in T_2$ (weak disposability of manure);
$(x_2, y_2, m) \in T_2 \wedge m = 0 \Rightarrow y_2 = 0$ (null-jointness of manure and livestock production).

The combination of weakly disposable manure and null-jointness for manure is that excess manure disposal generates costs for the farmer as manure can only be upcycled and used as crop fertilizer up to a certain amount (Shephard, 1977).

T_3 is defined as:

$(x^p, e) \in T_3 \wedge x^{p'} \leq x^p \rightarrow (x^{p'}, e) \in T_3$ (costly disposability of pollution-generating inputs);
$(x^p, e) \in T_3 \wedge e' \geq e \rightarrow (x^P, e') \in T_3$ (costly disposability of GHG emissions).

2.2.1 | Model formulation

For each individual farm (DMU) $k = 1, \ldots,$ K, the DMU under evaluation is $k = i$. The directional output distance function is given by:

$$D_k \left(x_k, y_k^C, z_k^C, y_k^L, e_k; g_k \right) = \sup \{ \beta \geq 0 : (x_k, y_k^C + \beta g_{y,k}^C, z_k^C + \beta g_{z,k}^C, y_k^L + \beta g_{y,k}^L, e_k - \beta g_{e,k}) \in T_1 \cap T_2 \cap T_3 \} \quad (3)$$

β is the overall technical inefficiency score as well as the environmental inefficiency score in Equation (3). Environmental efficiency refers to firms' ability to produce goods and services while reducing their impact on the environment (Färe et al., 2005; Silva & Magalhães, 2023). g_k is the directional vector that expands the intended outputs, y_k^C, z_k^C, and y_k^L, and contracts GHG emissions, e_k. x_k represents all inputs use. An output-oriented model is chosen as this research aims to quantify the potential of land optimization in simultaneously producing intended products and reducing residual GHG emissions, given the level of all inputs. We have selected $g_{y,k}^C = y_k^C$, $g_{z,k}^C = z_k^C$, $g_{y,k}^L = y_k^L$, $g_{e,k} = e_k$ as the directional vectors, following for instance Ang and Kerstens (2016) and Chambers et al. (1996). β indicates the maximum proportional expansion of desirable outputs and maximum proportional contraction of undesirable outputs. x_k represents all the inputs in the directional distance function. If β is zero, then the farm is fully efficient.

Land use is a non-joint input, shared by livestock production and crop production. Farmers have to decide how much land to use for livestock production and crop production. In line with Ang and Kerstens (2016) and Cherchye et al. (2017), one can simultaneously further expand production and reduce GHG emissions by optimizing land use. Let $x_k \in \mathbb{R}_+^S$ with $S \subseteq \{1, \ldots, N_C\} \cap \{1, \ldots, N_L\}$ be the process-specific inputs that have to be reallocated between the crop and livestock subprocesses, such that $x_k^{C,l} + x_k^{L,l} = x_k^l \; \forall\, l \in S$. Here, S refers to land use, common to crop and livestock that can be optimized among cropland and grassland. Land use is a reallocatable and fixed input in line with Färe et al. (1997). The total land use on the dairy farm equals the sum of cropland and grassland.

The DEA model that allows land optimization is given by Equations (4), (4a)–(4z). β_i is the reallocative technical inefficiency score for each farm i under evaluation. This model also nests the model without land optimization, that is, constraints (Equations 4a–4y) and removing the crop and grassland ($X_i^{C,l}$, $X_i^{L,l}$) from the optimization operand in Equation (4). The detailed model formulation without land optimization can be found in Appendix A. The resulting β from that model is the non-reallocative technical inefficiency score for each farm i under evaluation. Note that our model implicitly assumes that land use is immediately reallocatable among the livestock and crop enterprises on the same dairy farm.

$$\max_{\substack{\beta_i, \lambda_k, \gamma_k, \mu_k \\ X_i^{C,l} \geq 0,\; X_i^{L,l} \geq 0}} \beta_i \tag{4}$$

s.t.

$$\sum_{k=1}^{K} \lambda_k x_k^C \leq x_i^C \tag{4a}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \lambda_{\mathrm{k}} m_k^{L,u} \leq m_i^{L,u} \tag{4b}$$

$$\sum_{k=1}^{K} \lambda_k x_k^{C,l} - x_i^{C,l} \leq 0 \tag{4c}$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J1} \leq q_i^{J1} \tag{4d}$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J2} \leq q_i^{J2} \tag{4e}$$

$$\sum_{k=1}^{K} -\lambda_k y_k^C + \beta_i g_{y,k}^C \leq -y_i^C \tag{4f}$$

$$\sum_{k=1}^{K} -\lambda_k z_k^C + \beta_i g_{z,k}^C \leq -z_i^C \tag{4g}$$

$$\sum_{k=1}^{K} \lambda_k = 1 \tag{4h}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,fh} \leq x_i^{L,fh} \tag{4i}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,a} \leq x_i^{L,a} \tag{4j}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,l} - x_i^{L,l} \leq 0 \tag{4k}$$

$$\sum_{k=1}^{K} \gamma_k z_k^C \leq z_i^C \tag{4l}$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J1} \leq q_i^{J1} \tag{4m}$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J2} \leq q_i^{J2} \tag{4n}$$

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

$$\sum_{k=1}^{K} -\gamma_k y_k^L + \beta_i g_{y,k}^L \leq -y_i^L \tag{4o}$$

$$\sum_{k=1}^{K} \gamma_k = 1 \tag{4p}$$

$$\sum_{k=1}^{K} \gamma_k (m_k^{L,u} + m_k^{L,p}) = m_i^{L,u} + m_i^{L,p} \tag{4q}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{C,p} \leq -x_i^{C,p} \tag{4r}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,\,Pa} \leq -x_i^{L,\,Pa} \tag{4s}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pf} \leq -x_i^{L,Pf} \tag{4t}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pfc} \leq -x_i^{L,Pfc} \tag{4u}$$

$$\sum_{k=1}^{K} -\mu_k q_k^{J,pe} \leq -q_i^{J,pe} \tag{4v}$$

$$\sum_{k=1}^{K} -\mu_k q_k^{J,pm} \leq -q_i^{J,pm} \tag{4w}$$

$$\sum_{k=1}^{K} \mu_k e_k + \beta_i g_{e,k} \leq e_i \tag{4x}$$

$$\sum_{k=1}^{K} \mu_k = 1 \tag{4y}$$

$$x_i^{C,l} + x_i^{L,l} = x_i^l \tag{4z}$$

The coordination inefficiency (CI) is measured by

$$CI = RTIE - NRTIE \tag{5}$$

where $RTIE$ and $NRTIE$ denote reallocative technical inefficiency and non-reallocative technical inefficiency, respectively. CI is non-negative, as non-reallocation is always possible when reallocation is allowed. Any positive value for the CI indicates a possibility to further increase intended outputs and reduce GHG emissions. For each inefficient observation, the CI is the distance between the projections of it on the two frontiers (with and without land optimization). Due to the additive nature of the directional distance function, our measure of the CI is $RTIE$ minus $NRTIE$, whereas in Cherchye et al. (2017), coordination efficiency is a ratio measure as they measured efficiency using an input-oriented radial function.

Alternatively, in order to fully explore the reduction pathways of GHG emissions versus the expansion of production, we have tested three other pathways under different orientations: contracting only GHG emissions (Equation 6), expanding total desirable outputs (Equation 7), and expanding only dairy outputs (Equation 8). β in Equation (6) can be interpreted as environmental inefficiency; β in Equations (7) and (8) can be interpreted as technical inefficiency. Efficiency can be gained under different orientations, although its magnitude is unknown.

$$D_k\left(x_k,\, y_k^C,\, z_k^C,\, y_k^L,\, e_k; g_k\right) = \sup\{\beta \geq 0 : (x_k,\, y_k^C + \beta * 0,\, z_k^C + \beta * 0,\, y_k^L + \beta * 0,\, e_k - \beta g_{e,k}) \in T_1 \cap T_2 \cap T_3\} \tag{6}$$

$$D_k\left(x_k,\, y_k^C,\, z_k^C,\, y_k^L,\, e_k; g_k\right) = \sup\{\beta \geq 0 : (x_k,\, y_k^C + \beta g_{y,k}^C,\, z_k^C + \beta g_{z,k}^C,\, y_k^L + \beta g_{y,k}^L,\, e_k - \beta * 0) \in T_1 \cap T_2 \cap T_3\} \tag{7}$$

$$D_k\left(x_k,\, y_k^C,\, z_k^C,\, y_k^L,\, e_k; g_k\right) = \sup\left\{\beta \geq 0 : \left(x_k,\, y_k^C \beta * 0,\, z_k^C + \beta * 0,\, y_k^L + \beta g_{y,k}^L,\, e_k - \beta * 0\right) \in T_1 \cap T_2 \cap T_3\right\} \tag{8}$$

2.2.2 | Data description

Our empirical application focuses on a sample of Dutch dairy farms over the period of 2010–2019. We obtained data from the Dutch Farm Accountancy Data Network (FADN) supplemented with computed GHG emissions data on dairy farm from Wageningen Economic Research. Farmers participate in the FADN voluntarily. In the FADN, dairy farms are defined as those whose revenues from sales of milk, milk products, turnover and growth of cattle represent at least two thirds of their total revenue (Skevas, 2023). The sample is unbalanced as farms stay in the sample for a period of 4–7 years, and it is statistically representative for the Dutch dairy sector. In this study, there are on average 190 farms per year which apply the circularity principle. Focusing on the circularity aspect, we restrict our analysis to the dairy farms that reuse crop output on the livestock enterprise and reuse manure on the crop enterprise.

Wageningen Economic Research estimated the GHG emissions in CO_2 equivalents using emission factors of all inputs and outputs of the production process on dairy farms, following the cradle to gate life cycle assessment approach based on the calculation rules of the International Dairy Federation and the Emission Registration ("EmissieRegistratie" in Dutch). Sources of GHG emissions include energy use, purchase and use of fertilizers and feed, ruminal fermentation of cows, soil carbon conversion, use and storage of manure, as well as use of fuels from transportation (DuurzameZuivelketen, 2018). The detailed calculation method for GHG emissions can be found in appendix-1 of the report by Doornewaard et al. (2020). In this study, mixed dairy farms (main revenues are generated through a combination of livestock and crop production) are not included because corresponding data on GHG emissions is not available. This modeling framework can be applied to future studies when data on GHG emissions is available for more mixed farms.

We distinguish technology-specific inputs and outputs. For the crop production technology, we have aggregated crop-specific costs (seeds, crop protection products and fertilizers), upcycled manure, cropland use (feed crops and cash crops), aggregated crop production sold to the market in deflated revenues, and the crop residuals used for animal feed. For the livestock-specific technology, we have livestock units, aggregated livestock specific costs (animal health costs and purchased animal feed, tap water cost), feed from own crop residuals, grassland, aggregated livestock production in deflated revenues, and total manure from farm. There are joint shared inputs for the crop-production technology and the livestock-production technology: aggregated joint inputs set 1 includes energy, value of building, machinery and equipment; and joint inputs set 2 includes labor and water use irrigation. For the residual-production technology, we have included only the pollution-generating inputs and the total on-farm GHG emissions. We aggregate the monetary inputs and outputs as implicit quantities by computing the ratio of their aggregated value to their corresponding aggregated Törnqvist price index. Price indices vary over years but not over farms. This implies that the differences in the quality of inputs and outputs are reflected by implicit quantities (Cox & Wohlgenant, 1986). The separate price indices are obtained mostly from EUROSTAT (2022) and the tap water price index from the Dutch Centraal Bureau voor de Statistiek (2022). The final dataset contains 1896 observations for the period of 2010–2019. The descriptive statistics of the variables are summarized in Table 2.

3 | RESULTS

In this section, we first present the overall technical inefficiency scores, followed by land optimization results. Scenario results and a robustness check are discussed as well.

3.1 | Overall technical inefficiency scores

Table 3 depicts the yearly average results of the coordination inefficiency (*CI*), overall technical inefficiency when land is optimally chosen (*RTIE*), and the overall technical inefficiency when land optimization is not allowed between cropland and grassland (*NRTIE*). For the period 2010 to 2019, the yearly average overall technical inefficiency ranges from 3.0% to 7.2% when land is optimally chosen. This means on average farms could simultaneously expand production and reduce GHG emissions by 3.0% in 2010 and by 7.2% in 2016, *ceteris paribus*. When land is not allowed to be optimized, the yearly average overall technical inefficiency ranges from 2.3% to 6.6% for the period 2010 to 2019. This means that on average farms could gain technical and environmental efficiency by 2.3% in 2010 and by 6.6% in 2016. The difference between *RTIE* and *NRTIE*, which is the coordination inefficiency *CI*, is on average small and ranges from 0.3% to 0.8% between 2010 and 2019.

3.2 | Land optimization

We compare actual and optimal land allocation in Figure 2. Except for the year 2010, the results suggest that more land should be allocated to crop production to reduce GHG emissions and increase production simultaneously. Our results suggest that by reallocating on average 4.5 hectares from grassland to crop production on a Dutch dairy farm (total size of 66.8 hectares on average), farms can simultaneously increase production and reduce GHG emissions by 5.1%, of which only 0.6% from land optimization. Specifically, a 0.6% efficiency gain could be achieved

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TABLE 2 Descriptive statistics of model variables.

Variables	Dimensions	Average	Std dev.
Crop-specific variable inputs $x_k^C; x_k^{C,p}$	Euros	15,147.36	14,449.90
Upcycled manure $m_k^{L,u}$	Tons	3,598.76	2,494.82
Joint inputs set 1 q_k^{J1}	Euros	598,716.17	443,149.08
Joint inputs set 2 q_k^{J2}:			
Labor	Full hours	5,177.16	3,120.61
Water use irrigation	m^3	3,923.24	13,562.46
Total crop outputs as sold y_k^C	Euros	6,570.74	33,309.97
Unsold crop for animal feed (maize & grass) $z_k^C; x_k^{L,Pfc}$	kVEM	728,645.37	476,513.96
Livestock units $x_k^{L,a}; x_k^{L,Pa}$	Cow equivalents	171.42	105.28
Livestock-specific variable inputs $x_k^{L,fh}$	Euros	136,331.53	98,160.10
Total livestock production y_k^L	Euros	434,236.05	308,233.90
Animal feed expenditure $x_k^{L,Pf}$	Euros	129,869.95	95,765.49
Energy expenditure $q_k^{J,pe}$	Euros	16,469.35	12,638.89
Total manure $(m_k^{L,u} + m_k^{L,p}); q_k^{J,pm}$	Tons	4,333.93	2,937.53
Total cropland $x_k^{C,l}$	Hectares	12.40	14.19
Total grassland $x_k^{L,l}$	Hectares	54.39	33.46
Total GHG emissions e_k	Tons	1,818.44	1,238.42

Note: kVEM is the energy content of the dry matter.

TABLE 3 Average coordination inefficiency (*CI*) scores and average overall technical inefficiency scores with and without land optimization for the full model with directional vector $(g_{y,k}^C, g_{z,k}^C, g_{y,k}^L, g_{e,k})$ per year.

Inefficiency	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
CI	0.007	0.003	0.005	0.008	0.008	0.008	0.006	0.006	0.007	0.004
NRTIE	0.023	0.034	0.039	0.041	0.044	0.050	0.066	0.058	0.048	0.046
RTIE†	0.030	0.037	0.044	0.049	0.052	0.058	0.072	0.064	0.055	0.050

†Nine spearman rank correlation tests have been conducted to check the level of consistency of *RTIE* for each two consecutive years. Detailed results can be seen in Appendix C.

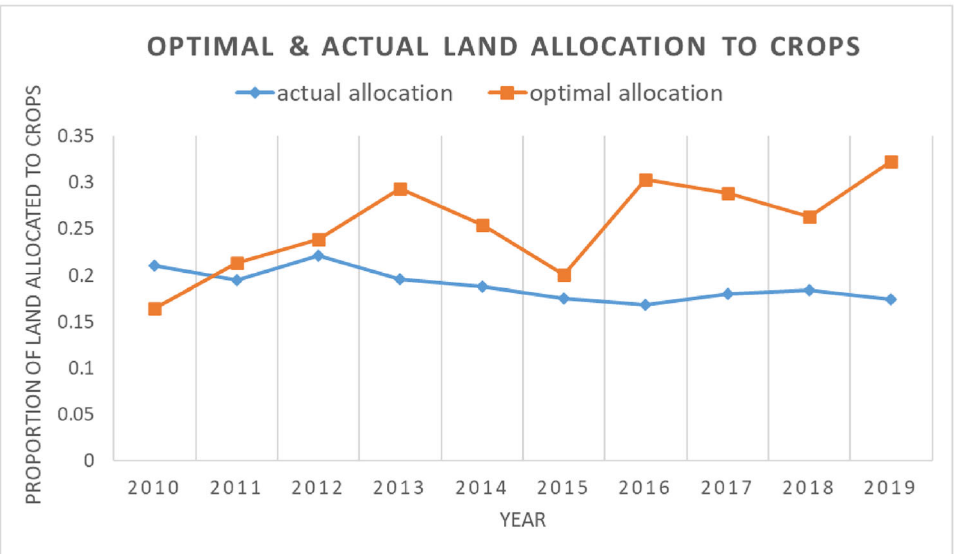

FIGURE 2 Distribution of optimal and actual proportion of land allocated for crop production per year.

TABLE 4 Average inefficiency scores and the coordination inefficiency (*CI*) scores for models with different directional vectors.

	Pathway 1	**Pathway 2**	**Pathway 3**	**Pathway 4**
Average inefficiency scores	$(\boldsymbol{y}_k^C,\ \boldsymbol{z}_k^C,\ \boldsymbol{y}_k^L,\ \boldsymbol{e}_k)$	$(0, 0, 0,\ \boldsymbol{e}_k)$	$(\boldsymbol{y}_k^C,\ \boldsymbol{z}_k^C,\ \boldsymbol{y}_k^L,\ 0)$	$(0,\ 0,\ \boldsymbol{y}_k^L,\ 0)$
CI	0.006	0.000	0.022	0.008
NRTIE	0.045	**0.118**	**0.059**	0.086
RTIE	0.051	**0.118**	**0.081**	0.094

if cropland were to take up 25.3% of the total farm size instead of 18.6% in the current situation. A 4.5% efficiency gain could be achieved if farms tried to catch up with their best performing peers.

3.3 | Comparisons of pathways to reduce GHG emissions

Besides the maximum proportional expansion of desirable outputs and contraction of undesirable outputs (denoted as pathway 1), we explore three other orientations under different directional distance vectors. The purpose is to explore the potential for further reduction of GHG emissions on dairy farms versus the potential for increased production. Table 4 illustrates the results for these four pathways. Pathway 1 shows the simultaneous results for increasing production and reducing GHG emissions, pathway 2 shows the results when only reducing GHG emissions, pathway 3 shows the results when expanding crop and livestock production, and pathway 4 shows the results when only expanding livestock production. Pathways 2, 3 and 4 capture higher efficiency improvement potential than pathway 1.

Under pathway 1 with the directional vector of ($g_{y,k}^C = y_k^C,\ g_{z,k}^C = z_k^C, g_{y,k}^L = y_k^L,\ g_{e,k} = e_k$), the average overall technical inefficiency without and with land optimization is 4.5% and 5.1%, respectively. These results show that by optimizing land use, dairy farms can expand production and reduce GHG emissions by 5.1% on average while keeping everything else constant. Optimizing land use can reduce overall inefficiency by 0.6% on average. The efficiency gain under pathway 1 with or without land optimization is the lowest among all pathways. This implies that most Dutch dairy farms are already quite efficient when it comes to proportional production expansion and GHG emissions contraction. There is only limited scope to reduce GHG emissions in this pathway.

Under pathway 2 with the directional vector of ($g_{y,k}^C = 0,\ g_{z,k}^C = 0,\ g_{y,k}^L = 0,\ g_{e,k} = e_k$), the average environmental inefficiency with/without land optimization is 11.8%, and the coordination inefficiency is 0.001% on average. These results point out that GHG emissions can be reduced by 11.79% on average among the sample dairy farms, while keeping conventional production and all inputs constant without land optimization. With land optimization, the additional efficiency gain is only 0.001%, which is very small. Land optimization does not contribute to reducing GHG emissions when inputs and conventional outputs are held constant. Nevertheless, the highest GHG reduction potential can be reached via this pathway among all pathways.

Under pathway 3 with the directional vector of ($g_{y,k}^C = y_k^C,\ g_{z,k}^C = z_k^C,\ g_{y,k}^L = y_k^L,\ g_{e,k} = 0$), the average technical inefficiency without land optimization is 5.9%, and the coordination inefficiency is on average 2.2%. Among all pathways, pathway 3 offers the highest potential to enhance both crop and livestock production, when GHG emissions and inputs are held constant. If GHG emission and all inputs are held constant, technical inefficiency can be reduced by 2.2% on average through optimizing land use across outputs. This is the highest efficiency gain from optimizing land use among all pathways.

Under pathway 4 with the directional vector of ($g_{y,k}^C = 0,\ g_{z,k}^C = 0,\ g_{y,k}^L = y_k^L,\ g_{e,k} = 0$), the average technical inefficiency without land optimization is 8.6%, and the coordination inefficiency is 0.8% on average for each farm. These results show that livestock production can be increased by 8.6% on average among sample dairy farms, while crop outputs and GHG emissions, and all inputs are held constant without land optimization. If land optimization were allowed, there would be an 0.8% additional efficiency gain for livestock outputs per farm on average. However, this efficiency gain is lower than for pathway 3, which indicates that land optimization does not contribute much to improve the efficiency in this case.

Given the importance of tackling climate change, it is more realistic to consider the implications of the results from the first two pathways. Overall, land optimization does not bring substantial efficiency gains as can be observed from the small value of *CI*. Interestingly, GHG emissions could be reduced with 11.8% on average with or without land optimization, if all inputs and conventional outputs were held constant. This reduction potential of GHGs decreases to 4.5% if producers are allowed to simultaneously expand crop and livestock outputs, holding

TABLE 5 Desirable output and GHG emission specific inefficiency with and without land optimization per year and the mean over the entire period.

Inefficiency	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean
NRTIE											
Desirable outputs											
β_i	0.041	0.051	0.053	0.057	0.065	0.076	0.107	0.082	0.072	0.083	**0.069**
GHG emissions											
α_i	0.085	0.098	0.120	0.130	0.098	0.117	0.124	0.127	0.122	0.116	**0.114**
RTIE											
Desirable outputs											
β_i	0.062	0.060	0.066	0.070	0.075	0.088	0.126	0.096	0.082	0.090	**0.082**
GHG emissions											
α_i	0.085	0.098	0.120	0.130	0.140	0.117	0.124	0.127	0.122	0.116	**0.118**

inputs and land use constant. The results have important implications for policy makers. In particular, these results point out that there is a trade-off between expanding the conventional production alone (pathway 3 or 4) and reducing the GHG emissions alone (pathway 2). However, a win-win situation (pathway 1) could be feasible if farmers make efforts to close the inefficiency gap.

3.4 | Robustness check

Our DEA model used one output-specific inefficiency score for both conventional production and residual GHG emissions. This provides us results for simultaneous expansion and contraction in the direction of corresponding directional vectors. We investigated the robustness of the results by modeling the conventional technology and residual technology using two different output-specific inefficiency scores, that is, a technical inefficiency score β for crop- and livestock-production technologies, and a technical inefficiency score α for the residual GHG emission technology. The detailled model formulation is shown in Appendix B.

Table 5 shows the separate inefficiency scores for conventional technology and residual GHG emission technology per year, with and without land optimization. The last column of Table 5 shows the average score over the entire period. It is very similar to the results listed in Table 4.

The land optimization results from the model in Appendix A are plotted in Figure 3. In general, the distribution under separate efficiency scores follows the distribution under the identical inefficiency score, with slightly lower values. In 2014 and from 2016 to 2019, more land should have been allocated to crop production than the actual land allocation. For the years 2011 to 2013, land optimization would not have brought any efficiency gains. For the year 2010 and 2015, the results suggest that more land should have been allocated to grassland use to increase efficiency. Overall, a smaller proportion of land needs to be allocated to crop production with separate inefficiency scores (on average 2.86 hectares) than considering the optimal allocation with identical inefficiency scores (on average 4.5 hectares).

4 | DISCUSSION

This study used a network DEA model with the by-production approach to quantify the technical and environmental inefficiency of dairy farms, taking GHG emissions into account. The model also enables quantification of the efficiency gains from land optimization between cropland and grassland. We found that the overall technical inefficiency is on average 4.5% at the farm level without land optimization. Land optimization could bring a small additional efficiency gain of .6% on average.

This finding is consistent with the results of Ang and Kerstens (2016), who conclude that coordination inefficient farms should in general allocate more land to crop production. However, the coordination inefficiency scores obtained in this study are lower than those estimated by Ang and Kerstens (2016), which means land optimization on Dutch dairy farms provides only minimal efficiency gains. This difference could be explained by the fact that this study focuses exclusively on dairy farms, whereas Ang and Kerstens (2016) also included mixed farms (in which livestock production and crop production covers 33%–66% of total utilized land area) and specialized crop farms (in which livestock production covers 0%–33% of total utilized land area).

Several other studies have looked into environmental efficiency on dairy farms. For French suckler cow farms, Dakpo and Oude Lansink (2019) found an average

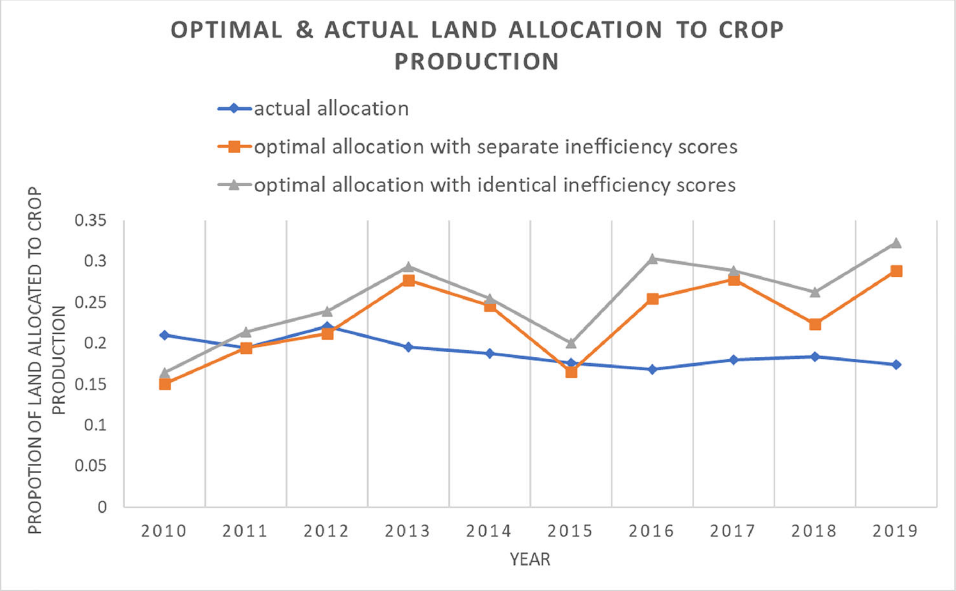

FIGURE 3 Distribution of optimal (under separate inefficiency scores and identical inefficiency scores) and actual land allocation for crop and livestock production per year.

technical inefficiency (*TIE*) for desirable output of 0.2%, while the average *TIE* for GHG emissions was 28.4%; that is, much lower and higher than for our study. For Swedish dairy farms, Martinsson and Hansson (2021) found an eco-efficiency score of 64% which means the GHG emissions can be reduced by 64% with current value added. For nitrogen use, previous studies found much higher *TIE* values for Dutch dairy farms. Reinhard et al. (1999) found a mean *TIE* of 55.9% for nitrogen whereas Lamkowsky et al. (2021) found a 50% productivity gap for nitrogen. Increasing productivity by 1% is associated with at least 0.26% decrease of GHG emission intensity for Irish dairy farms (Läpple et al., 2022). Our study shows that Dutch dairy farms can simultaneously increase production and reduce GHG emissions by 5.1%.

Our findings on the efficiency gains from land optimization in dairy farms cannot be directly generalized to other livestock or crop farming types or to mixed dairy farms. Caution is also needed while interpreting our results, as the inefficiency estimates are subject to sampling bias (Simar & Wilson, 1998). Our *RTIE* and *NRTIE* results could be biased downwards due to data limitations. However, we expect that the bias is limited for *CI*, as the downward biases of *RTIE* and *NRTIE* may be cancelled out. Additional research will be needed for assessing the potential contribution of land optimization to mitigating GHG emissions and increasing production. For that, additional data on GHG emissions should be made available for different farm types. Our study does provide an integrated efficiency modeling framework for future investigations when more data is available.

In practice, land allocation between cropland and grassland on Dutch dairy farms is allowed. Although depending on the locations of farms, farmers may need to follow specific management practices to ensure the conservation of habits and species that are subjected to the Natura 2000 area (Jacobsen et al., 2019). The land conversion in practice will come with adjustment costs for farmers, which could be an additional reason that land optimization is not a suitable strategy in reducing GHG emissions.

Our study suggests only a limited potential to reduce GHG emissions by optimizing land allocation between the grassland and the cropland. GHG emissions per farm could be reduced by 11.8% on average if the farm production were kept constant with current input and land use. However, the GHG emissions per farm could be reduced by only 4.5% on average if crop and livestock production were expanded by 4.5% with constant input and land use. This implies that there is a trade-off between reducing GHG emissions while keeping production constant, on the one hand, and reducing GHG emissions while at the same time expanding production, on the other hand. This trade-off between environmental and economic objectives has also been found for the dairy sector of other countries (Kirilova et al., 2022; Le et al., 2020).

Our findings suggest that management practices could play a pivotal role in closing the environmental inefficiency gap. By catching up with the mitigation practices of the best peers, GHG emissions could be decreased by 11.8%. Possible best management practices consist of optimizing feed rations, reducing losses, improving grazing manage-

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ment, reducing replace rate of herd by increased longevity, optimizing young stock management, using energy efficiently, applying more grazing and reduced tillage on the grassland and reducing renewal rate of grassland (Wageningen University & Research, 2019). The dissemination of the best mitigation practices is a collaborative effort involving government agencies, research institutions, agricultural organizations and industry associations in the Netherlands. Policy measures and financial incentives provided by the government are crucial, yet supporting knowledge exchange and social learning in farming communities can enhance the effectiveness of policy incentives, as suggested by Kreft et al. (2023).

Beyond the scope of this study, circular agriculture also advocates for plant-based products to be consumed by humans before feeding it to livestock animals. This calls for a dietary shift of consumers toward more plant-based products and meat from non-ruminant animals, away from milk and other dairy products. Such dietary changes could reduce the food-related GHG emissions of dairy farming (Kesse-Guyot et al., 2021) through mechanisms like a Pigouvian meat tax or green labels for consumers (Katare et al., 2020).

5 | CONCLUSIONS

This study modeled the intended production and residual GHG emissions on Dutch dairy farms with the circularity principle, by combining a network DEA model with the state-of-the-art by-production approach. The results from the directional output distance function indicate that mean inefficiency levels for Dutch dairy farms are only 4.5% on average with constant input and without land optimization. This shows that many Dutch dairy farms are already operating close to the frontier. Thus, there is only limited potential for GHG emission reduction through efficiency improvement.

Although dairy farms in the Netherlands should allocate more land to crop production according to the land optimization model, the potential efficiency gain would only be 0.6% on average. Hence, there is limited potential for reducing GHG emissions and increasing production by optimizing land use. As our sample contains dairy farms, we need to be cautious about the generality of the results. Nevertheless, we note that our study does contain dairy farms with mixed-cropping systems.

Our results suggest that the largest reduction potential for GHG emissions (11.8%) can be obtained without changing the level of inputs and outputs. The potential reduction of GHG emissions may be even higher if production (or herd size) is to be sacrificed, as shown by Le et al. (2020) and Lötjönen et al. (2020). However, this would come at a higher private cost for farmers if they were required by regulations to reduce the on-farm GHG emissions. In that case, policy instruments that pertain cost-sharing between the government and dairy producers may be needed, as suggested by Le et al. (2020).

This study is a first step to structurally incorporate the circularity principle in efficiency analysis for dairy farms. We have several recommendations for future research. In the current study, there are no interactions between individual farms, nor are waste streams from non-farm entities considered, such as urban and industry waste. Future research should consider the potential of circularity in decoupling GHG emissions from farm production at a local and/or regional level. Additionally, the behavioral and managerial determinants of high economic performance and low levels of GHG emissions will need to be investigated. Moreover, additional data on GHG emissions from mixed dairy farms should be collected to further validate the findings obtained here. Finally, adjustment costs are not taken into account in this study. We recommend to further investigate the modeling of adjustment costs in future research. Studies accounting for adjustment costs include Serra et al. (2011), Ang and Oude Lansink (2018), and Silva and Magalhães (2023).

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CONFLICT OF INTEREST STATEMENT

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A: MODEL FORMULATION WITHOUT LAND OPTIMIZATION WITH SIMULTANEOUS INEFFICIENCY

$$\max_{\beta_i,\, \lambda_k,\, \gamma_k, \mu_k} \quad \beta_i \tag{A1}$$

s.t.

$$\sum_{k=1}^{K} \lambda_k x_k^C \le x_i^C \tag{A1a}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \lambda_{\mathrm{k}} m_k^{L,u} \le m_i^{L,u} \tag{A1b}$$

$$\sum_{k=1}^{K} \lambda_k x_k^{C,l} - x_i^{C,l} \le 0 \tag{A1c}$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J1} \le q_i^{J1} \tag{A1d}$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J2} \le q_i^{J2} \tag{A1e}$$

$$\sum_{k=1}^{K} -\lambda_k y_k^C + \beta_i g_{y,k}^C \le -y_i^C \tag{A1f}$$

$$\sum_{k=1}^{K} -\lambda_k z_k^C + \beta_i g_{z,k}^C \le -z_i^C \tag{A1g}$$

$$\sum_{k=1}^{K} \lambda_k = 1. \tag{A1h}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,fh} \le x_i^{L,fh} \tag{A1i}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,a} \le x_i^{L,a} \tag{A1j}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,l} - x_i^{L,l} \le 0 \tag{A1k}$$

$$\sum_{k=1}^{K} \gamma_k z_k^C \le z_i^C \tag{A1l}$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J1} \le q_i^{J1} \tag{A1m}$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J2} \le q_i^{J2} \tag{A1n}$$

$$\sum_{k=1}^{K} -\gamma_k y_k^L + \beta_i g_{y,k}^L \le -y_i^L \tag{A1o}$$

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

s.t.

$$\sum_{k=1}^{K} \gamma_k = 1 \tag{A1p}$$

$$\sum_{k=1}^{K} \gamma_k \left(m_k^{L,u} + m_k^{L,p} \right) = m_i^{L,u} + m_i^{L,p} \tag{A1q}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{C,p} \leq -x_i^{C,p} \tag{A1r}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,\,Pa} \leq -x_i^{L,\,Pa} \tag{A1s}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pf} \leq -x_i^{L,Pf} \tag{A1t}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pfc} \leq -x_i^{L,Pfc} \tag{A1u}$$

$$\sum_{k=1}^{K} -\mu_k q_k^{J,pe} \leq -q_i^{J,pe} \tag{A1v}$$

$$\sum_{k=1}^{K} -\mu_k q_k^{J,pm} \leq -q_i^{J,pm} \tag{A1w}$$

$$\sum_{k=1}^{K} \mu_k e_k + \beta_i g_{e,k} \leq e_i \tag{A1x}$$

$$\sum_{k=1}^{K} \mu_k = 1 \tag{A1y}$$

APPENDIX B: SEPARATE INEFFICIENCIES FOR GHG EMISSIONS AND OUTPUTS

$$\max_{\substack{\beta_i, \alpha_i, \lambda_k, \gamma_k, \mu_k \\ X_i^{C,l} \geq 0, X_i^{L,l} \geq 0}} (\beta_i + \alpha_i)/2 \tag{B1}$$

$$\sum_{k=1}^{K} \lambda_k x_k^C \leq x_i^C \tag{B1a}$$

$$\sum_{k=1}^{K} \lambda_k m_k^{L,u} \leq m_i^{L,u} \tag{B1b}$$

$$\sum_{k=1}^{K} \lambda_k x_k^{C,l} - x_i^{C,l} \leq 0 \tag{B1c}$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J1} \leq q_i^{J1} \tag{B1d}$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J2} \leq q_i^{J2} \tag{B1e}$$

$$\sum_{k=1}^{K} -\lambda_k y_k^C + \beta_i g_{y,k}^C \leq -y_i^C \tag{B1f}$$

$$\sum_{k=1}^{K} -\lambda_k z_k^C + \beta_i g_{z,k}^C \leq -z_i^C \tag{B1g}$$

$$\sum_{k=1}^{K} \lambda_k = 1 \tag{B1h}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,fh} \leq x_i^{L,fh} \tag{B1i}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,a} \leq x_i^{L,a} \tag{B1j}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,l} - x_i^{L,l} \leq 0 \tag{B1k}$$

$$\sum_{k=1}^{K} \gamma_k z_k^{C} \leq z_i^{C} \tag{B1l}$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J1} \leq q_i^{J1} \tag{B1m}$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J2} \leq q_i^{J2} \tag{B1n}$$

$$\sum_{k=1}^{K} -\gamma_k y_k^{L} + \beta_i g_{y,k}^{L} \leq -y_i^{L} \tag{B1o}$$

$$\sum_{k=1}^{K} \gamma_k = 1 \tag{B1p}$$

$$\sum_{k=1}^{K} \gamma_k \left(m_k^{L,u} + m_k^{L,p}\right) = m_i^{L,u} + m_i^{L,p} \tag{B1q}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{C,p} \leq -x_i^{C,p} \tag{B1r}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,\,Pa} \leq -x_i^{L,\,Pa} \tag{B1s}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pf} \leq -x_i^{L,Pf} \tag{B1t}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pfc} \leq -x_i^{L,Pfc} \tag{B1u}$$

$$\sum_{k=1}^{K} -\mu_k q_k^{J,pe} \leq -q_i^{J,pe} \tag{B1v}$$

$$\sum_{k=1}^{K} -\mu_k q_k^{J,pm} \leq -q_i^{J,pm} \tag{B1w}$$

$$\sum_{k=1}^{K} \mu_k e_k + \alpha_i g_{e,k} \leq e_i \tag{B1x}$$

$$\sum_{k=1}^{K} \mu_k = 1 \tag{B1y}$$

$$x_i^{C,l} + x_i^{L,l} = x_i^{l} \tag{B1z}$$

$$\max_{\beta_i,\alpha_i,\,\lambda_k,\,\gamma_k,\mu_k} (\beta_i + \alpha_i)/2 \tag{B2}$$

s.t.

$$\sum_{k=1}^{K} \lambda_k x_k^{C} \leq x_i^{C} \tag{B2a}$$

$$\sum_{k=1}^{K} \lambda_k \mathrm{m}_k^{\mathrm{L,u}} \leq m_i^{L,u} \tag{B2b}$$

$$\sum_{k=1}^{K} \lambda_k x_k^{C,l} - x_i^{C,l} \leq 0 \tag{B2c}$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J1} \leq q_i^{J1} \tag{B2d}$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J2} \leq q_i^{J2} \tag{B2e}$$

$$\sum_{k=1}^{K} -\lambda_k y_k^{C} + \beta_i g_{y,k}^{C} \leq -y_i^{C} \tag{B2f}$$

$$\sum_{k=1}^{K} -\lambda_k z_k^{C} + \beta_i g_{z,k}^{C} \leq -z_i^{C} \tag{B2g}$$

$$\sum_{k=1}^{K} \lambda_k = 1 \tag{B2h}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,fh} \leq x_i^{L,fh} \tag{B2i}$$

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$$\sum_{k=1}^{K} \gamma_k x_k^{L,a} \leq x_i^{L,a} \tag{B2j}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,l} - x_i^{L,l} \leq 0 \tag{B2k}$$

$$\sum_{k=1}^{K} \gamma_k z_k^{C} \leq z_i^{C} \tag{B2l}$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J1} \leq q_i^{J1} \tag{B2m}$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J2} \leq q_i^{J2} \tag{B2n}$$

$$\sum_{k=1}^{K} -\gamma_k y_k^{L} + \beta_i g_{y,k}^{L} \leq -y_i^{L} \tag{B2o}$$

$$\sum_{k=1}^{K} \gamma_k = 1 \tag{B2p}$$

$$\sum_{k=1}^{K} \gamma_k \left(m_k^{L,u} + m_k^{L,p} \right) = m_i^{L,u} + m_i^{L,p} \tag{B2q}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{C,p} \leq -x_i^{C,p} \tag{B2r}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,\,Pa} \leq -x_i^{L,\,Pa} \tag{B2s}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pf} \leq -x_i^{L,Pf} \tag{B2t}$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pfc} \leq -x_i^{L,Pfc} \tag{B2u}$$

$$\sum_{k=1}^{K} -\mu_k q_k^{J,pe} \leq -q_i^{J,pe} \tag{B2v}$$

$$\sum_{k=1}^{K} -\mu_k q_k^{J,pm} \leq -q_i^{J,pm} \tag{B2w}$$

$$\sum_{k=1}^{K} \mu_k e_k + \alpha_i\, g_{e,k} \leq e_i \tag{B2x}$$

$$\sum_{k=1}^{K} \mu_k = 1 \tag{B2y}$$

APPENDIX C: SPEARMAN'S RANK CORRELATION RESULTS

The results from the Spearman rank correlations in Table C1 indicate that there is a generally positive relationship between inefficiency scores over two consecutive years. The range of 0.46 to 0.72 suggests that there is a moderate to strong positive monotonic relationship between inefficiency scores for each pair of two consecutive years in the unbalanced panel data. In short, there is some degree of consistency in the inefficiency scores over time.

TABLE C1 Level of consistency of *RTIE* for each two consecutive years.

Groups (number of farms)	Spearman rank correlation	P value
Year 2010–2011 (111)	0.61	1.708e-12
Year 2011–2012 (122)	0.57	8.015e-12
Year 2012–2013 (142)	**0.72**	2.2e-16
Year 2013–2014 (167)	**0.46**	5.398e-10
Year 2014–2015 (173)	0.51	1.202e-12
Year 2015–2016 (219)	0.57	2.2e-16
Year 2016–2017 (242)	0.51	2.2e-16
Year 2017–2018 (242)	0.59	2.2e-16
Year 2018–2019 (237)	0.60	2.2e-16