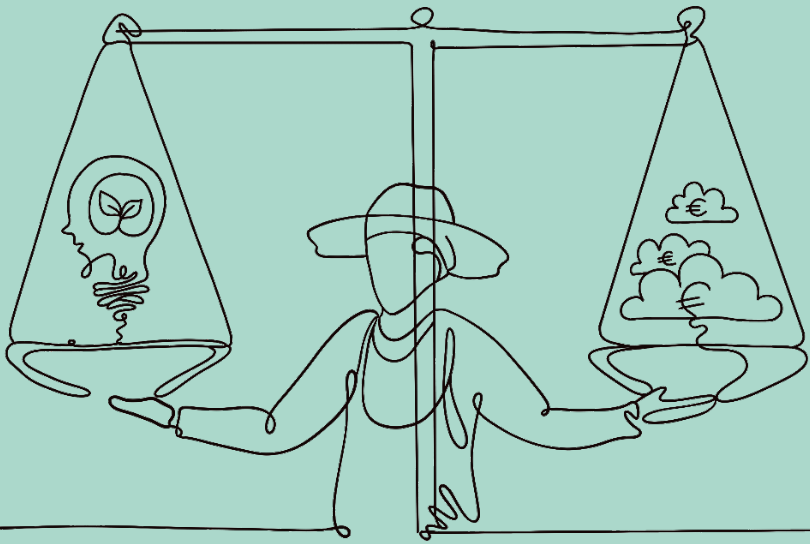
Mitigating greenhouse gas emissions on Dutch dairy farms

- integrated evidence from behavioural and efficiency models



Scarlett Wang

Propositions

1. Farmers' behavioural data are essential for better understanding their decision making.
(this thesis)

2. Stronger negative emotions of farmers are associated with lower farm environmental inefficiency.
(this thesis)

3. Emotional trust is more important than cognitive trust in decision making.

4. Overcoming geopolitical thinking is the biggest challenge to global collaboration on addressing anthropogenic climate change.

5. Effective communication starts with understanding cultural differences.

6. One only truly understands one's home country by leaving it.

Propositions belonging to the thesis, entitled

Mitigating greenhouse gas emissions on Dutch dairy farms – integrated evidence from behavioural and efficiency models

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Mitigating greenhouse gas emissions on Dutch dairy farms - integrated evidence from behavioural and efficiency models

Scarlett Wang

Thesis

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General introduction

"The truth is: the natural world is changing. And we are totally dependent on that world. It provides our food, water and air. It is the most precious thing we have and we need to defend it."

— David Attenborough

1.1 Background

The dairy sector contributes to climate change and is, concurrently, susceptible to its detrimental effects. Globally, the livestock sector is responsible for 14.5% of all anthropogenic greenhouse gas emissions (Gerber et al., 2013). In the Netherlands, dairy farming is an essential part of the characteristic landscape with a total land use of approximately 1.1 million hectares which is about 26% of the country surface (ZuilvelNL, 2023). The sector is an important part of the Dutch economy offering employment to 46,000 people, with a total of 14,729 dairy farms and 1.6 million dairy cows (ZuilvelNL, 2023). It is highly productive and has a strong global image with not only high-quality dairy products but also a commitment to innovation and sustainability (Dutch Dairy Association (NZO), 2020). The Dutch dairy sector produced around 14 billion kg of cow milk in the year 2022, with an export value of 10.8 billion euros which contributes to 7.4% of trade surplus (ZuilvelNL, 2023). The Netherlands has the highest livestock density among all European countries with 3.4 livestock units per hectare (Eurostat, 2023) and is the European Union's fourth-largest milk producer by volume (ZuilvelNL, 2023).

Globally, the demand for milk is increasing and is expected to continue increasing driven by the growing population, wealth and dietary pattern changes (Alexandratos & Bruinsma, 2012; Food and Agriculture Organization, 2023). However, the expansion of livestock production has been a major driver of land use change from native grassland and forest into agricultural land for grazing and animal feed production, leading to greenhouse gas (GHG) emissions and biodiversity loss (Steinfeld et al., 2006). Furthermore, dairy production relies on large amounts of natural resources (i.e. fresh water and arable land) and other inputs (i.e. energy, fertilisers and other materials), resulting in not only GHG emissions but also fresh water eutrophication and water depletion (Food and Agriculture Organization, 2018; Notarnicola et al., 2017).

In dairy production, GHG emissions mostly take the form of methane (CH_4) and nitrous oxide (N_2O) and to a lesser extent carbon dioxide (CO_2). The effect of the different greenhouse gases on global warming is expressed with the Global Warming Potential (GWP) of each gas. Methane is 21 times more potent and nitrous oxide is 310 times more potent in terms of the warming potential based on a 100-years horizon, than carbon dioxide (United Nations Climate Change, 2023). All dairy animals are ruminants. Methane is mainly produced in ruminants' stomachs as a result of microbial fermentation process (enteric fermentation) when digesting and emitted by eructation and flatulence. This emission rate depends on the feed intake and digestibility. Methane is also produced from the anaerobic decomposition of animal manure and its emission rate depends on the manure management by its storage and application methods. Nitrous oxide is emitted during the nitrification and denitrification process in soil and manure storage, as well as the application of fertilisers and production of fodder crops. Carbon dioxide emissions are the results of using fossil fuels during production and transportation on dairy farms (Sevenster & De jong, 2008).

1.1.1 The impact of climate change on the dairy sector

The primary driver of climate change comes from rising GHG emissions by anthropogenic activities, which leads to atmospheric warming and has serious implications for the overall health and stability of our planet (IPCC, 2022). Climate change manifests itself in various ways, encompassing shifts in average temperatures, rising sea levels, ocean warming and acidification, the melting of sea ice, the occurrence of extreme weather events (such as heatwaves, droughts, and heavy rainfall), and alterations in ecosystems (IPCC, 2022). Some of these effects threaten the dairy sector's technical and environmental efficiency (Key & Sneeringer, 2014) and create additional competition for available resources (Rojas-Downing et al., 2017).

Extreme weather events are likely to occur more frequently and this presents a challenge for the productivity of fodder crops for animal feed (Calzadilla et al., 2013) in most parts of the world. Positive impacts on crop yields have been identified for northern Europe (European Environment Agency, 2019). However, land use for fodder crops production may further face increasing competition from different land uses in the Netherlands (e.g. protected area, population growth, forest land and ecosystem services) as well as influences from policy choices in terms of long-term sustainable land management (Netherlands Environmental Assessment Agency, 2022; Smith et al., 2010). Furthermore, cow's performance and health are negatively influenced by high temperatures, having negative repercussions on their milk production, milk quality, cow mortality and fertility (European Environment Agency, 2019; Hempel et al., 2019; Maggiore et al., 2020; Misiou & Koutsoumanis, 2022). Fodor et al. (2018) projected that dairy production in north-western Europe will likely drop due to the heat stress by mid-21st century.

1.1.2 The challenge to meet the reduction target

The Dutch agriculture sector accounts for 15% of the total GHG emissions from the entire Dutch economy, while dairy cattle is responsible for the largest share among all agricultural activities accounting for 34%. In 2021, GHG emissions from Dutch agriculture were lower than those recorded in 1995, despite the higher agricultural outputs (Centraal Bureau voor de

Statistiek, 2023). This reduction of GHG emission can be largely attributed to the improvement in production efficiency over the years (Hospers et al., 2022). However, the reduction of greenhouse gas and nitrogen emissions has stagnated in recent years (Centraal Bureau voor de Statistiek, 2023). Despite the anticipated reduction in emissions, ranging from 38% to 48% by 2030, primarily stemming from the industry and transportation sectors, there is a pressing need for supplementary measures to achieve the Netherlands' national goal of a 49% emissions reduction by 2030, relative to 1990 levels, as well as the ambitious 95% reduction target by 2050 (Netherlands Environmental Assessment Agency, 2021). Especially, the challenge remains in the Dutch agriculture sector because mitigation measures can vary significantly between different farming systems, such as dairy and beef farms (Beldman, Pishgar-Komleh, et al., 2021).

The Dutch government has tasked the agricultural sector with an additional reduction of 1 Mt of GHG emissions by 2030 in order to meet the national target (Government of the Netherlands, 2019). It is important to know GHG emissions are inherent to natural production processes and at the same time, the sector can capture carbon in soils and generate renewable energy for instance. Hence, in the Dutch National Climate Agreement, the aim for the agriculture sector is to achieve an equilibrium between the unavoidable emissions of GHG, and the capture of GHG emissions and production of renewable energy and biomass by 2050 (Government of the Netherlands, 2019). To achieve this, policies emphasize not only on technical measures for reducing GHG emissions but also on further integrating circular agriculture principles (Government of the Netherlands, 2019).

To meet the national target, parties of the Dutch Climate Agreement are prioritizing innovations in reducing GHG emissions from food and non-food production as well as reducing the climate impacts of consumer choices by 2050 (Government of the Netherlands, 2019). Meanwhile, there is increasing demand from a small group of consumers for products that take into account their environmental impact and animal welfare considerations (Adams et al., 2023; Elzerman et al., 2022). Given the need to address climate change, stemming from both policy targets and consumer demands, there is an unequivocal imperative for the Dutch dairy sector to persist in reducing its GHG emissions. As a result, the Dutch dairy sector is working together with private partners and the government on Sustainable Dairy Chain for a future-proof dairy chain (Duurzamezuivelketen, 2023).

Last but not least, Dutch farmers consistently face the challenge of navigating uncertain policy measures, particularly within stringent environmental regulations regarding nitrogen and phosphates (Yanore et al., 2023). Many farmers’ protests have taken place in response to proposals to cut the nitrogen emissions in the Netherlands since October 2019. As the Dutch government seeks to cut ammonia and nitrous oxide by 50% by 2030, the Dutch government has allocated €975 million to buy out livestock farms close to the protected Natura 2000 zones, with an additional €500 million to buy out smaller-scale farms who want to quit the farming business (Darroch, 2023). However, Dutch dairy farmers are hardly interested in this buy-out scheme compared to pig and poultry farmers, with only 2% dairy farmers registered for it (Van der Boon, 2023).

1.2 Problem statement and literature gap

Currently, the biggest challenge for the Dutch dairy sector is to maintain a good income while reducing its environmental impacts on climate, water, soil and biodiversity. In this thesis, we explicitly focus on the topic of reducing the sector's environmental impacts on the climate, specifically the reduction of GHG emissions. Until now, the adoption of climate mitigation measures is largely based on farmers' voluntary behaviour in the Netherlands. Establishing clear guidelines tailored to individual farmers and their specific farming systems is essential for practical implementation at the farm level (Beldman, Pishgar-Komleh, et al., 2021). Policies targeting agri-environmental issues often fail to include behavioural factors which could potentially improve economic analysis of farmers' decision making and lead to more realistic and effective results in meeting policy targets (Dessart et al., 2019).

In order to reduce GHG emissions, best practices, innovations and policy measures must be implemented on the farm. Results from a recent survey have pointed out that it is a major challenge to motivate Dutch farmers to implement GHG mitigation measures (Beldman, Pishgar-Komleh, et al., 2021). Farmers are mostly implementing efficiency and productivity related mitigation measures, and economic benefits rather than environmental concerns are driving their adoption behaviour (Beldman, Pishgar-Komleh, et al., 2021). Exploring behavioural factors driving farmers' adoption of best mitigation practices is highly relevant and important in this light. There is a growing body of literature using behavioural approaches to investigate the drivers and barriers of farmers' adoption behaviour of climate mitigation measures (Doran et al., 2020; Gomes & Reidsma, 2021; Kreft et al., 2021; Leonhardt et al., 2022; Moerkerken et al., 2020; Niles et al., 2016). Pro-environmental behaviour has been predominantly studied using the Theory of Planned Behaviour (TPB) (Sok et al., 2021). Yet, the TPB model has been criticized for ignoring the time dimension of behavioural change and neglecting emotional or value-related determinants of behaviour (Bamberg, 2013a). Specifically, in the Dutch dairy context, the existing literature (Gomes & Reidsma, 2021; Moerkerken et al., 2020) has not investigated the effects of farmers' socio-psychological and socio-demographical factors on their adoption behaviour of climate mitigation measures by considering the time dimension.

Besides the adoption of mitigation measures, efficient production and resource optimization are essential components of the transition towards circular dairy farming (de Boer & van Ittersum, 2018). In terms of land use, feeding leftover crops to animals is estimated to reduce the global cropland requirements by 25% compared to no livestock (van Zanten et al., 2018). For English and Welsh farms, Ang and Kerstens (2016) found allocating more land to crop production on livestock farms could bring additional efficiency gains. For the GHG emissions on Dutch dairy farms, the environmental inefficiency was estimated to be 15% between 2015 to 2018 (Zhu et al., 2023). Dutch dairy farmers have already applied the circularity principle to some degree. However, the potential of land optimization to reduce GHG emissions and/or increase production under the same input levels remains unexplored. This question is relevant to current policy discussions, as it pertains no need to cut herd sizes.

Incorporating circularity in an efficiency framework requires explicit modelling of the recycling of intermediate outputs, reallocating of inputs, and reducing pollution (Rebolledo-Leiva et al., 2021). Ang and Kerstens (2016) explicitly modelled input allocation in a multi-output setting following Cherchye et al. (2013) for English and Welsh farms. In addition, Ang and Kerstens (2016) combined the modelling of recycled crop output as feed inputs following Färe and Whittaker (1995), and the efficiency gains through the reallocation of land use by Färe et al. (1997). Moreover, the potential reduction of GHG emissions has been modelled together with the circularity principle on dairy farms by Rebolledo-Leiva et al. (2022). However, Rebolledo-Leiva et al. (2022) did not apply the state-of-art by-production approach (Førsund, 2009; Murty et al., 2012) to model the GHG emissions, which results in an inaccurate measurement of technical efficiency (Ang et al., 2023; Dakpo et al., 2017; Serra et al., 2014). 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 by-production approach.

Furthermore, GHG emissions as environmental externalities are important to be considered in production analyses. The rising emissions of pollutants into the environment can, in part, be attributed to the lack of factoring the environmental costs of dairy farming in market prices and farmers' production decisions (Adenuga et al., 2019). The cost of mitigating additional undesirable outputs, like GHG emissions and nitrogen surplus, is known as the shadow price of these outputs. Reinhard et al. (1999) estimated the shadow price for nitrogen surplus on Dutch dairy farms at 1.63 euros/kg, while for Swiss dairy farms, the estimation was at 28.96 euro/kg (Mamardashvili et al., 2016). The substantial difference may arise from differences in modelling approaches, sample period and environmental conditions. Shadow price can be estimated by applying production analysis models, such as parametric Stochastic Frontier

Analysis (SFA) (Vogel et al., 2023; Zakova Kroupova et al., 2018), Deterministic Frontier Analysis (DFA) (Färe et al., 2005) or non-parametric Data Envelopment Analysis (DEA) (Baležentis et al., 2022; Berre et al., 2013; Wettemann & Latacz-Lohmann, 2017). DFA models have the property of yielding continuous frontiers as in SFA and satisfy the monotonicity conditions as in DEA. Yet, previous DFA studies (Färe et al., 2005; Hailu & Veeman, 2001) did not treat the negative externalities using the state-of-art by-production approach.

1.3 Overarching goal and research questions

The overarching goal of this thesis is to assess the potential for, and costs of reducing GHG emissions with a special reference towards the role of farmers' behavioural factors in the adoption of mitigation measures and farm environmental performance on Dutch dairy farms. To achieve this overarching goal, four research questions are addressed.

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1. *What are the roles of socio-psychological and socio-demographical factors on Dutch dairy farmers' intention to adopt climate mitigation measures?*

The first research question aims to investigate Dutch dairy farmers' adoption behaviour of climate mitigation measures. Using the self-regulated stage model of behavioural change (Bamberg, 2013b), we investigated the roles of socio-psychological and socio-demographical factors on the adoption intention of climate mitigation measures across four adoption stages. We gathered data through online questionnaires administered via the Dutch Farm Accountancy Data Network (FADN) and conducted our analysis using statistical models. Our approach helps to identify relevant socio-psychological and socio-demographical factors in each stage, enabling more effective targeting of farmers for the adoption of climate mitigation measures.

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2. *Can optimizing land use help mitigate GHG emissions on circular Dutch dairy farms?*

The second research question aims to assess the reduction potential of GHG emissions on Dutch dairy farms through the optimal land allocation between grassland and cropland under four different pathways. We incorporated circularity aspects within one integrated multi-production technology framework that accounts for GHG emissions using the by-production approach. We estimate output-oriented directional distance functions using network DEA (Ang & Kerstens, 2016; Rebolledo-Leiva et al., 2022). Our approach quantifies the efficiency gaps and provides scientific evidence on where the potential reduction of GHG emissions lies for specialized dairy farms under given input use.

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3. *What are the socio-psychological and socio-economic determinants of environmental and technical inefficiency in Dutch dairy farming?"*

The third research question aims to identify the relevant factors in improving farm efficiency by assessing the associations between socio-psychological and socio-economic factors, on the one hand, and farm inefficiency, on the other hand, for Dutch dairy farms. We employ a two-stage approach: first, a network DEA model with the by-production approach is used to calculate environmental and technical inefficiency scores for Dutch dairy farms. Then, bootstrap truncated regression models are applied to discern the statistical associations between explanatory factors and these inefficiencies. Our findings aid in pinpointing the socio-psychological and socio-economic determinants that contribute to improving farm environmental efficiency and technical efficiency individually.

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4. *What are the reduction potential and shadow prices for GHG emissions and nitrogen surplus on Dutch dairy farms?*

The fourth research question aims to assess the reduction potential and shadow prices for GHG emissions and nitrogen surplus on Dutch dairy farms. We apply the deterministic frontier analysis model with the by-production approach. We operationalize a parametric deterministic frontier analysis model using quadratic directional distance functions. Our approach offers empirical flexibility with shadow prices that can be either positive or negative. Our robustness check, using Ordinary Least Squares regression, yields estimations that closely align with existing literature compared to the deterministic frontier analysis.

1.4 Thesis outline

The thesis is structured into 6 chapters. The initial chapter serves as a general introduction, while Chapters 2-5 correspond to research articles addressing research questions 1-4, respectively. Chapter 6 provides a comprehensive discussion, synthesizing critical findings, connecting to relevant literature, emphasizing policy and business implications, acknowledging limitations, and offering recommendations. It concludes with a list of main conclusions.

2

Dutch dairy farmers’ adoption of climate mitigation measures – The role of socio-psychological and socio-demographical factors

This chapter is based on the paper: Wang, S., Höhler, J., Ang, F., & Oude Lansink, A. (2023). Dutch dairy farmers’ adoption of climate mitigation measures - the role of socio-psychological and socio-demographical factors. *Journal of Cleaner Production*, *427*. https://doi.org/10.1016/j.jclepro.2023.139187

2.1 Abstract

Mitigating greenhouse gas emissions is an essential element of climate change policies. This paper explores Dutch dairy farmers' adoption behaviour of climate change mitigation measures using a Self-regulated Stage model of Behavioural Change. It tests the statistical relationship of stage-specific socio-psychological factors with individual farmer's intentions of planning or adopting on-farm climate mitigation measures. In addition, it tests the statistical relationship of intentions on four stages (pre-decisional, pre-actional, actional, post-actional). The empirical application focuses on data from specialised Dutch dairy farmers registered with the Farm Accountancy Data Network. Our findings suggest that negative emotion, personal norm, perceived goal feasibility, action planning, and coping planning vary significantly by stage. Furthermore, personal norm, attitude, goal intention, behavioural intention, and implementation intention are found to be statistically significant and positive influencing factors on adopting climate mitigation measures. Lastly, farmers younger than 45 years old with full agricultural education and farms with high livestock density are more likely to have taken steps in adopting mitigation measures.

Key words

Pro-environmental behaviour, climate mitigation, Dutch dairy farmer, socio-psychological factors, stage model.

2.2 Introduction

Tackling climate change is a pertinent challenge for the agricultural sector. Agricultural production substantially contributes to global anthropogenic greenhouse gas emissions (IPCC, 2019). In this light, it is critical that farmers decouple production from GHG emissions (Ang et al., 2022), which can be facilitated by the adoption of climate mitigation measures. Dutch agricultural production is highly intensive and efficient. Yet, it faces various interrelated environmental and economic challenges, including climate change and manure surpluses (Jongeneel & Gonzalez-Martinez, 2021). The Dutch government has developed a national climate agreement ('Klimaatakkoord') to comply with the Paris Agreement on climate change (Rijksoverheid, 2022). With a national target of 49% reduction in GHG emissions, the Dutch agricultural sector will still need to reduce its emissions by 11% by 2030 (van Grinsven et al., 2019). Methane and nitrous oxide from livestock production and land use are important GHG emissions in agriculture. Until now, the adoption of climate mitigation measures is largely based on farmers' voluntary behaviour. The question raises as the extent to which Dutch farmers' already adopt climate mitigation measures and which factors could explain farmers' voluntary pro-environmental behaviour. Detailed insights into the factors and processes underlying farmers' adoption behaviour of climate mitigation measures are therefore crucial for devising effective policy interventions.

Psychologists and sociologists have developed several theoretical frameworks to explore the drivers and barriers of direct or indirect pro-environmental actions (Kollmuss & Agyeman, 2002; Steg & Berg, 2013). Since the early nineties, the *Theory of Planned Behaviour* has been frequently applied in explaining and predicting human behaviour (Sok et al., 2021). The TPB model postulates that an actor's intention is likely to predict new behaviour when the actor's actual control over the new behaviour is high (Ajzen, 1991). However, TPB has been criticised for ignoring the time-related dimension of behavioural changes, neglecting emotional or value-related determinants of behaviour (Bamberg, 2013a) and its inability to predict the extent to which intention translates into behavioural change (Bamberg, 2013a; Bijttebier et al., 2018; Hijbeek et al., 2018; Werner et al., 2017). Addressing this problem, Bamberg (2013b) proposes the *Self-regulated Stage model of Behavioural Change* (SSBC), a theoretical framework where (pro-environmental) behavioural change occurs in four stages: the pre-decisional, pre-actional, actional, and post-actional stage. The transition through these four stages is marked by the formation of three critical points (goal intention, behavioural intention and implementation intention) (Bamberg, 2013c). Each critical point is affected by stage-specific factors from the Norm Activation Model (NAM) and the TPB model (Bamberg, 2013c). The NAM views environmentally friendly behaviours as altruistic pro-social acts guided by the activation of personal norm (Schwartz & Howard, 1981) whereas the TPB views pro-environmental behaviours as results of rational choices which aim to maximise personal benefits (Ajzen, 1991).

Researchers are increasingly interested in studying farmers' adoption of GHG mitigation measures. Niles et al. (2016) conclude that there is a disconnection between intention and actual behaviour for New Zealand farmers. Encouraging a sense of confidence and capacity for farmers is in this sense crucial to translate intention to actual behaviour. For Swiss farmers, innovativeness is the suggested mechanism towards the adoption of GHG mitigation measures (Kreft et al., 2021). Farmers' decisions are driven by an intricate interaction of many factors and vary in different contexts (Leonhardt et al., 2022). To date, only two studies have explored Dutch farmers' adoption behaviour of climate mitigation measures. Moerkerken et al. (2020) have concluded that farmers' openness to change is the strongest predictor of Dutch farmers' willingness and actual adoption of climate mitigation measures. Gomes and Reidsma (2021) have identified drivers and barriers for the adoption of soil GHG mitigation practices by Dutch farmers. Critical barriers include economic hardship, personal resistance to change, on-farm complications and the necessity to resolve different stakeholders' rates of adoption; opportunities consist of farmers becoming able to quantify soil health, positive framing in the media, and policy tools & economic mechanisms to assist farmers (Gomes & Reidsma, 2021). Including behavioural factors enriches economic analysis of farmers' decision making and leads to a more realistic and effective policy targeting agri-environmental issues (Dessart et al., 2019). However, in the Dutch context, both Moerkerken et al. (2020) and Gomes and Reidsma (2021) did not explore the effects of farmers' socio-psychological factors on their adoption behaviour.

We bridge this research gap by exploring Dutch dairy farmers' adoption behaviour of climate mitigation measures using the SSBC model. The SSBC model is a suitable framework for investigating the role of farmers' socio-psychological factors on their adoption behaviour, especially with its emphasis on the temporal dynamics as well as the rich set of socio-psychological factors. The objectives of this empirical study are (1) to estimate farmers' current adoption level of climate mitigation measures, (2) to test the statistical relationship between stage-specific socio-psychological factors and the matching intentions, (3) to test the statistical associations between intention types and stage membership, and (4) to explore farmers' socio-demographical characteristics in each stage.

This paper has three contributions to the literature. First, this paper investigates the role of a rich set of socio-psychological factors in farmers' adoption of climate mitigation measures based on the SSBC model. To do so, we match a unique dataset of socio-psychological factors with the commonly used Farm Accountancy Data Network dataset. Second, this study is the first in applying the SSBC model in the context of agricultural production. Thus far, the SSBC has only been applied in the context of consumption (Keller et al., 2019). Lastly, this paper is the first empirical study that measures and tests all the main theoretical constructs of the SSBC model. All the previous studies using SSBC model has not measured the four constructs in the last two stages (Keller et al., 2019).

The remainder is organised as follows. Section 2.3 describes the theoretical model, which is followed by the conceptual framework and hypotheses in section 2.4. Section 2.5 describes the method. Results are reported in section 2.6. The discussion and conclusion follow in section 2.7 and 2.8.

2.3 Theoretical model

Various factors influence the transition to a more environmentally friendly behaviour. Transition is a complex process that involves various activities and tasks over time (Keller et al., 2019). In this light, environmental psychologists increasingly conceptualise behavioural change as subsequent phases in a stage model (Bamberg, 2013b; Keller et al., 2019; Schwarzer, 2008).

2.3.1 The self-regulated stage model of behavioural change

Bamberg (2013b) introduced the SSBC model, which makes the temporal aspect of behavioural change explicit as action phases (Gollwitzer, 1990). The main assumption in the SSBC model is that people may change their current behaviour (which has negative impacts on the environment) if they have the motivation to do so, despite their everyday routines and habits. This process of behavioural change involves several stages from abstract motivation to goal setting and concrete behavioural change, potentially involving the volitional stage (Klöckner, 2017). People do not consciously think about which stage they are in. However, they face different tasks which are represented by stage-specific socio-psychological factors if they want to change certain behaviours. The completion of these different tasks is signalled by the formation of matching intentions (Bamberg, 2013c). The formation of goal intention indicates the transition from the pre-decisional to the pre-actional stage; the formation of a behaviour intention indicates the transition from the pre-actional to the actional stage; and the formation of an implementation intention marks the transition into the post-actional stage (Table 2.1).

The transition between these four time-ordered stages is reflected in a person's increasing readiness for change (Bamberg, 2013c). Bamberg (2013a) integrated socio-psychological constructs from the TPB and NAM as well as four other theory-based constructs to create a comprehensive set of explanatory variables for these transition points underlying behavioural changes. This is in line with the conclusions from two meta-analyses, which both indicate that TPB and NAM constructs are significant predictors of pro-environmental behaviours (Bamberg & Möser, 2007; Gardner, 2008). One strength of the SSBC model is the detailed tasks that a person has to solve in each stage which is captured by those matching stage-specific socio-psychological factors (Bamberg, 2013c). In addition, the SSBC model offers the possibility to elicit systematic interventions (Keller et al., 2019). A limitation of the SSBC model is that the differentiation of these four stages may appear to be more ambiguous and arbitrary in empirical studies than stated in the model (Keller et al., 2019).

Table 2.1: Stage model with transition points and psychological tasks.

Stage	Transition point	Psychological task
Pre-decisional	Goal intention ('be' goal)	Re-evaluation of actual behaviour
Pre-actional	Behaviour intention ('do' goal)	Selection of new behavioural alternative
Actional	Implementation intention ('control' goal)	Implementation of new behaviour
Post-actional		Habitualisation of new behaviour

Based on (Bamberg, 2013a, 2013b; Ohnmacht et al., 2018)

2.3.2 Socio-psychological factors related to stages

In the pre-decisional stage, the SSBC aims to explain the motivation of individuals to re-evaluate their current behaviour. The NAM addresses precisely this aspect. The NAM assumes that individuals may have negative emotions when they are aware of the negative environmental impacts of their current behaviour and when they accept their responsibility for causing the damage (Schwartz & Howard, 1981). Negative feelings may trigger their personal norms, that is, the obligation to behave more in line with personally important moral standards. Simultaneously, the perceived social norms, which is what important social reference persons expect the individuals to do, may contribute to activating personal norms. The activation of personal norms leads to anticipated positive emotions when individuals behave more in line with their personal norms. The personal norms and the anticipated positive emotions serve as direct predictors of goal intention. In addition, perceived goal feasibility plays a vital role in determining whether individuals will actually commit to the new goal. For instance, if individuals perceive their goal feasibility as low, they may forgo commitment to a new goal to decrease negative emotions (Bamberg, 2013b; Schwartz & Howard, 1981).

In the pre-actional stage, an individual is assumed to actively compare the advantages and disadvantages of different behaviour alternatives, resulting in a behavioural intention that reflects an individual's self-commitment to the chosen behaviour (Bamberg, 2013b). The SSBC model suggests that attitude towards, perceived behavioural control over the chosen behaviour (Ajzen, 1991) and the goal intention are the predictors of the behavioural intention (Bamberg, 2013a).

In the actional stage, the model explains what factors determine an implementation intention. Gollwitzer and Sheeran (2006) suggest that engagement in mental planning might be one factor. Schwarzer (2008) further suggests separating mental planning into action planning and coping planning: the former focuses on planning the 'how to' of implementing the selected behaviour, while the latter refers to plans to solve potential obstacles during the implementation stage. He also points out that maintenance of self-efficacy, that is, the confidence in maintaining one's chosen behaviour, may also impact the implementation intention. Bamberg (2013b) therefore combined these three constructs and the behavioural intention as predictors for the implementation intention.

In the post-actional stage, the model assesses the determinants of habituating the new behaviour. Forming a new behaviour needs not only a strong implementation intention, but also skills and strategies in resisting temptations to relapse to previous behaviour or recovering from potential set-backs (Bamberg, 2013b; Lewin et al., 1944). The recovery self-efficacy, defined as a person's confidence in resuming a difficult behaviour after a set-back, may increase the chance of consolidating a new behaviour (Bamberg, 2013b; Schwarzer, 2008). Bamberg (2013b) therefore combined recovery self-efficacy and the implementation intention as predictors for forming the new behaviour.

2.3.3 Socio-demographical factors related to stages

We further explore the statistical associations between socio-demographical factors and adoption stages (Kreft et al., 2021; Liu et al., 2022; Moerkerken et al., 2020). The literature provides little guidance on the selection of socio-economic variables and shows mixed results of their impacts on farmers adoption behaviour (Knowler & Bradshaw, 2007; Lastra-Bravo et al., 2015; Mozzato et al., 2018). However, these factors usually consist of farmer demographic characteristics and farm financial and structural features (Knowler & Bradshaw, 2007; Kreft et al., 2021; Mozzato et al., 2018; Serebrennikov et al., 2020). In this study, we select farmer's age and education level, annual farm income, and livestock density.

The age of the farmer approximates the farming experience and planning horizon. Chatzimichael et al. (2014) hypothesised and demonstrated that age has an inverted U-shaped relation with adoption of organic farming. This means that the chance of farmers adopting new technologies increases up to a certain age, after which the chance decreases again. The lower adoption rate among young farmers could be explained by a lack of farming experience, and for older farmers by increasing risk aversion when approaching retirement (Chatzimichael et al., 2014; Foguesatto et al., 2020). The education level of the farmer is a proxy for more environmental awareness and knowledge about the challenges of climate change. Previous studies have found a positive association between education level and farmers' inclination to adopt environmentally friendly farming practices (Foguesatto et al., 2020; Mozzato et al., 2018).

Farm financial features refer to farm economic size. In northern and southern Europe, a higher farming income has been associated with early adoption of environmentally friendly farming practices (Mozzato et al., 2018), explained by larger investment abilities that allow for a shorter adoption period (Rogers, 2003). Farm structural characteristics generally include farm size (in ha), farm type, and livestock density (Kreft et al., 2021; Mozzato et al., 2018; Serebrennikov et al., 2020). For this study, we only focus on livestock density among the common structural factors as there is only one farm type in the sample and farm size is partially reflected in the livestock density measure. Livestock density is hypothesised to be positively associated with the adoption of manure treatment technologies (Case et al., 2017; Gebrezgabher et al., 2015).

2.4 Conceptual framework and hypotheses

The conceptual framework can be seen in Figure 2.1. In the pre-decisional stage, farmers re-evaluate their actual behaviour; in the pre-actional stage, the farmers select a potential climate mitigation measure; in the actional stage, the farmers implement the selected mitigation measure; and in the post-actional stage, the farmers continue to implement the selected mitigation measure in a habitual way. Stage-specific factors explaining matching intentions can be seen in Figure 2.1. Following the SSBC model, we test two sets of hypotheses. The first set of hypotheses concerns the associations of stage specific socio-psychological factors on the matching intentions (Table 2.2); the second set of hypotheses relates to the associations of the intentions on the matching stages (Table 2.3). We tested these two sets of hypotheses in a step-wise fashion.

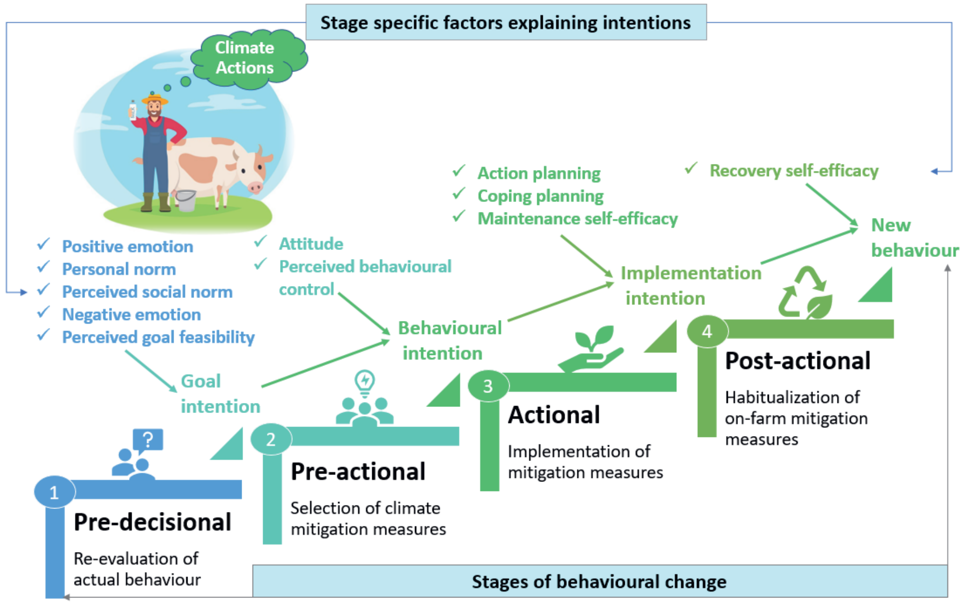

Figure 2.1: Conceptual framework of farmers' adoption behaviour of climate mitigation measures (adapted from Bamberg (2013b)).

Table 2.2 contains fourteen hypotheses. There are four separate multiple regression tests for each intention. Multiple hypotheses testing becomes an issue when there are several hypotheses tests simultaneously, because the chance of making type I error (falsely reject null hypotheses) will increase. To address this issue, we apply both the Bonferroni correction and the Benjamini-Hochberg procedure. In general, the Bonferroni is more stringent than the Benjamini-Hochberg procedure, due to the increasing chance of making type II error (falsely not rejecting null hypotheses) (James et al., 2023). We report the results for H1-H14 under both a stringent

Bonferroni correction and a less stringent Benjamini-Hochberg procedure in the results section. An overview of previous empirical results on the SSBC model can be found in the review of Keller et al. (2019).

Table 2.2: First set of hypotheses testing the explanatory power of stage-specific socio-psychological factors on matching intentions.

No.	Independent variable	Dependent variable	Expected sign
H1	Positive emotion from successfully reducing the GHG emissions		+
H2	Personal norm for reducing farming related GHG emissions		+
H3	Perceived social norm for reducing farming related GHG emissions	Goal intention	+
H4	Negative emotion from not taking any mitigation measures		+
H5	Perceived goal feasibility of reducing on-farm emissions		+
H6	Attitude of adopting climate mitigation measures		+
H7	Perceived behavioural control of the selected mitigation measure	Behavioural intention	+
H8	Goal intention		+
H9	Action planning undertaken in implementing the mitigation measure		+
H10	Coping planning undertaken in implementing the mitigation measure	Implementation intention	+
H11	Maintenance self-efficacy		+
H12	Behavioural intention		+
H13	Recovery self-efficacy	New behaviour	+
H14	Implementation intention		+

(These 14 hypotheses can be read in the same way: independent variable is positively associated with the dependent variable.)

Table 2.3: Second set of hypotheses testing the explanatory power of intentions on the matching stages.

No.	Independent variable	Dependent variable	Expected sign
H15	Goal intention	Pre-actional stage	+
H16	Behavioural intention	Actional stage	+
H17	Implementation intention	Post-actional stage	+

(These 3 hypotheses can be read in the same way: independent variable is most strongly associated with the dependent variable.)

2.5 Method

This chapter presents the questionnaire design, statistical analysis, and sample statistics.

2.5.1 Questionnaire design

An online questionnaire based on the SSBC model was developed and disseminated to specialised dairy farmers participating in the Dutch Farm Accountancy Data Network (FADN) between 28 July 2021 and 16 September 2021. The FADN is an European instrument to evaluate farm income and the impact of the Common Agricultural Policy (van der Meer, 2019). Farmers participate in the FADN voluntarily, but the sample is drawn to be representative of the sector. In FADN, specialised dairy farms are defined as those whose revenues from milk, milk products and turnover and growth of cattle represent at least two thirds of the total revenue (Skevas, 2023). In total, 300 farmers received the survey; 122 farmers voluntarily replied of which 100 complete records could be used for data analysis. This represents a survey response rate of 40.67% and a completion rate of 33%. As this online survey provides no compensation or other direct incentive, the obtained response rate is relatively high compared to similar survey studies (Leonhardt et al., 2022; Sauermann & Roach, 2013).

The socio-demographical data were not part of the questionnaire, but provided by Wageningen Economic Research, which is responsible for FADN data collection. As the latest matching socio-demographical data for survey participants were for the year 2020, we adjusted farmer age to their age in the year 2021. Agricultural education level in 2021 was assumed to be the same as that in 2020. After merging the survey results and matching socio-demographical data, 93 complete observations were available for data analysis. Seven observations were removed because those farmers had entered the survey twice. We have kept their responses from the later attempt.

Survey questions were formulated based on previous literature (Bamberg, 2013a, 2013b; Ohnmacht et al., 2018) and adapted to the context of climate mitigation in the Dutch dairy sector. Participants were asked at what stage they would place themselves when it comes to their current adoption level of climate mitigation measures. In addition, their agreement with eleven socio-psychological factors and three transition points were measured in statement questions using five-point Likert scales (1 = strongly disagree to 5 = strongly agree). Questions about the pre-decisional stage were asked in relation to the reduction of farming-related GHGs emissions. These factors included negative emotion, positive emotion, social norm, personal norm, goal intention, and perceived goal feasibility. Once the goal intention is formed, several actions could normally be used to achieve the intended goal (Bamberg, 2013b). Hence, farmers were asked to select one climate mitigation option for preferential adoption at the pre-actional stage. Questions about the second, third, and fourth stage were asked in relation to the chosen most preferred mitigation measure in our study, which is in line with the original design of Bamberg (2013b) for the most suitable behavioural strategy in achieving the desired goal.

A pilot questionnaire was tested for clarity, plausibility, and acceptability, both internally and among three professional dairy farmers. Their feedback was included in the final version of the online survey (see Appendix 2A – Table A1). The list of climate mitigation measures presented to survey respondents was based on Zijlstra et al. (2019), who selected measures based on experts' estimates on their suitability for the Dutch dairy context, and their impact on mitigating GHG emission and farm profitability (Zijlstra et al., 2019). The results of farmers' chosen measure can be seen next to the list of measures in Appendix 2A – Table A1. The study was approved in an *ex-post* review by the social science ethics committee of Wageningen University & Research.

Appendix 2A – Table A1 presents the operationalisation of the theoretical constructs and the measurement type and level. Cronbach's alpha and average inter-item correlation were used to estimate the reliability of the latent variables with two indicators, consisting of social norm, personal norm, attitude, and perceived behavioural control. A Cronbach's alpha value > 0.7 is considered acceptable according to Nunnally (1978). In our sample, only personal norm met this criteria (alpha of 0.738; Appendix 2A – Table A1). However, alpha is largely dependent on the total number of indicators per latent variable. With only two indicators per latent construct, we also check the inter-item correlation for the indicators, as recommended by Pallant (2013). The acceptable range for inter-item correlation is 0.2 to 0.4. Three latent constructs (social norm, personal norm, and attitude) measured with two indicators were reliable according to this standard (Appendix 2A – Table A1), with only the inter-item correlation for perceived behavioural control slightly under 0.2. As a result, the answers to the question "Adopting my chosen GHG emissions mitigation option would be [1 very difficult...5 very easy] for me" were used to represent the construct perceived behavioural control and the other question was dropped for the data analysis.

2.5.2 Statistical analysis

There are three steps in the statistical analysis. First, we checked the differences of the socio-psychological factors across different stages by using an ANOVA analysis. The stage-dependent coefficients capture the piecewise linear aspects across stages, in line with the SSBC model. Second, four multiple linear regression models were applied to test the statistical relationship between stage-specific socio-psychological factors and the matching intentions (first set of hypotheses). Structural equation modelling (SEM) and non-proportional odds model are alternative approaches to test the SSBC model (Keller et al., 2019). SEM was not feasible for this study as we did not measure each latent construct with more than one item. The reason is that the survey design was requested to be short as we did not want to overburden the participating FADN farmers. The non-proportional odds model would be a good approach to test the varying effects of socio-psychological factors across different stages, however it is infeasible for this study due to the small sample size. According to the SSBC model, different factors are at play at different stages. Four multiple regression models are the most suitable approaches allowing us to test the SSBC model in our case. For controlling the multiply hypotheses testing issue, the family-wise error rate is fixed at 0.05 for the Bonferroni correction and the false discovery rate is fixed at 0.05 for the Benjamini-Hochberg procedure based on James et al. (2023).

Third, a multinomial logistic regression (MLR) model was applied to test the statistical relationship between intentions and the stages (second set of hypotheses). We chose this model as we interpreted stage membership as a nominal variable. Behavioural changes are dynamic processes, which implies that individuals may jump over stages and fall back again. There is no intrinsic meaning in the ordering of stages. Multinomial logistic regression is a method of classification modelling with more than two possible discrete outcomes (Greene, 2003). It provides the effects in log odds of explanatory variables in being in a higher stage relative to the reference category, that is, the first stage. Additionally, the MLR model allows prediction of the probabilities of stage membership over the probabilities of the baseline category based on explanatory variables. The formulation of the MLR model for testing intentions on stages can be seen as below:

$$\log\left(\frac{P(k=2,\ldots,4)}{P(k=1)}\right) = \beta_{0k} + \beta_{1k}X_1 + \beta_{2k}X_2 + \beta_{3k}X_3 \tag{1}$$

On the right hand side of the equation, β_{1k}, β_{2k} and β_{3k} are the coefficients for goal intention, behavioural intention and implementation intention respectively. β_{0k} is the stage-specific constant. On the left hand side of the equation, it is the log odds of being in the stage 2 or 3 or 4 versus being in the first stage (baseline).

Lastly, we tested the association between socio-demographic factors and stage membership using the MLR model as below:

$$\log\left(\frac{P(k=2,\ldots,4)}{P(k=1)}\right) = \beta_{0k} + \beta_{1k}A + \beta_{2k}A^2 + \beta_{3k}E_b + \beta_{4k}E_f + \beta_{5k}I + \beta_{6k}LD \tag{2}$$

On the right hand side of the equation, β_{1k} is the coefficient for age and β_{2k} is the coefficient for age square. β_{3k} is the coefficient for basic agricultural education and β_{4k} is the coefficient for full agricultural education. β_{5k} is the coefficient for yearly farm income and the β_{6k} is the coefficient for livestock density. β_{0k} is the stage-specific constant. On the left hand side of the equation, it is the log odds of being in the stage 2 or 3 or 4 versus being in the first stage.

2.5.3 Descriptive analysis and sample characteristics

Sample characteristics are summarised in Table 2.4. On average, farmers were about 57 years old. The farms had an average livestock density of 2.1 heads per hectare of cultivated area and farmers had an average yearly farm income of 70,500 EUR. For the entire population of Dutch dairy farms, the respective averages are 2.2 heads per hectare of cultivated area and 42,400 EUR (BINternet, 2022). Dairy farmers participating in the FADN have a higher income on average compared to the entire Dutch dairy farmer population. The sample is representative, as indicated by a comparison of key farm structural factors (e.g. livestock density). We divided the values of farm family income by 10,000 to facilitate computation in the multinomial logistic regression model. In terms of education level, 83 farmers had a full agricultural education (a Bachelor's or Master's degree in agriculture), four farmers had basic agricultural education (full time professional education or any other agricultural courses/internships), and six only had practical expertise in farming (no agricultural education, but any other type of non-agricultural education). The bar chart with error bar plot using standard deviation for the socio-psychological variables in the survey can be found in Appendix 2A – Figure A1.

Table 2.4: Sample characteristics.

Variable	Min	Mean	Standard deviation	Max	Note
Age	35.99	56.70	8.70	79.15	Years
Livestock density	0.62	2.11	0.80	5.35	Livestock unit/hectare
Annual farm income	−6.75	7.05	10.94	70.59	10,000 euros
Basic agricultural education	0	0.04	NA	1	Dummy variable
Full agricultural education	0	0.89	NA	1	Dummy variable

NA: not applicable.

2.6 Results

Farmers self-reported their current adoption stage of climate mitigation measures as follows: 6 farmers assigned themselves to pre-decisional stage, 31 farmers assigned themselves to the pre-actional stage, 8 farmers assigned themselves to actional stage and 48 farmers assigned themselves to the post-actional stage. ANOVA results,. multiple regression results and MLR results are presented below.

2.6.1 ANOVA results

Table 2.5 presents the means and standard deviations of socio-psychological factors in different stages. Differences of the means among stages reflect the piecewise linear relations of those factors with stage membership. ANOVA tests were used to determine the statistical significance of the differences between the stages. Based on p-values, negative emotion, personal norm, perceived goal feasibility, action planning, and coping planning vary significantly between different stages. These ANOVA results provide empirical support for the piecewise linear relations of some socio-psychological factors across stages. Contrary to the linear relations postulated by the TPB model, the SSBC model is able to show that different factors are important at different stages.

Table 2.5: ANOVA tests of socio-psychological factors across the stages of behavioural change (M = Mean; SD = standard deviation.).

Independent variable (ANOVA)	Stage 1	Stage 2	Stage 3	Stage 4
	M(SD)	M(SD)	M(SD)	M(SD)
Negative emotion (F = 5.885, p = 0.001)	2.2 (1.2)	2.6 (0.8)	2.4 (0.7)	3.3 (1.0)
Positive emotion (F = 0.884, p = 0.453)	3.5 (1.0)	3.8 (0.7)	3.6 (0.7)	3.9 (0.7)
Perceived social norm (F = 2.686, p = 0.051)	2.2 (1.1)	2.5 (0.7)	2.8 (0.9)	2.9 (0.7)
Personal norm (F = 4.097, p = 0.009)	2.6 (1.2)	3.3 (0.7)	3.4 (0.6)	3.6 (0.7)
Perceived goal feasibility (F = 3.166, p = 0.028)	1.7 (0.8)	2.6 (0.7)	2.8 (1.2)	2.8 (0.9)
Attitude (F = 2.632, p = 0.055)	2.9 (0.7)	3.5 (0.6)	3.9 (0.4)	3.5 (0.7)
Perceived behavioural control (F = 1.242, p = 0.299)	2.5 (0.8)	2.9 (0.8)	3.2 (0.7)	3.1 (0.8)
Action planning (F = 5.208, p = 0.002)	2.8 (0.8)	3.6 (0.7)	4.0 (0.0)	3.9 (0.7)
Coping planning (F = 3.317, p = 0.024)	2.7 (0.8)	3.3 (0.8)	3.5 (0.8)	3.6 (0.7)
Maintenance self-efficacy (F = 0.354, p = 0.786)	3.0 (0.9)	3.4 (1.0)	3.5 (0.8)	3.3 (1.0)
Recovery self-efficacy (F = 1.878, p = 0.139)	3.0 (0.6)	3.5 (0.8)	3.9 (0.4)	3.5 (0.7)

2.6.2 Multiple regression results

Four multiple regression models were conducted to test the hypotheses H1-H5, H6-H8, H9-H12, H13-H14 respectively using the ordinary least squares technique. Correlations between independent variables in each regression model were checked to verify whether multicollinearity may be problematic. The correlation matrices (see Appendix 2B) indicate that there is no correlation greater than Spearman r = 0.7, suggesting that multicollinearity is unlikely to be problematic. We have reported the results for the multiple regression models under both the Bonferroni correction and the Benjamini-Hochberg procedure (Table 2.6, 2.7, 2.8 & 2.9). Hypotheses (H1-H14) will be rejected if the p-value is larger than the corrected Bonferroni threshold (James et al., 2023). The estimation results based on the Benjamini-Hochberg procedure can be seen in Appendix 2C. Our results are the same under both the Bonferroni correction and the Benjamini-Hochberg procedure.

Table 2.6 shows the results of the multiple linear regression model for explaining goal intention. Positive emotion, personal norm, perceived social norm, negative emotion, and perceived goal feasibility are all positively associated with goal intention. Only personal norm is significantly associated with goal intention ($\beta = 0.395$, $p = 0.00085$) under both correction methods. A one unit increase in personal norm is expected to increase the goal intention by 0.395, *ceteris paribus*. Therefore, we fail to reject H2: Personal norm for reducing farming related GHG emissions is positively associated with goal intention. We reject hypotheses H1, H3, H4 and H5. R^2 measures the proportion of the variation in the dependent variable explained by the independent variables for a linear regression model. Adjusted R^2 adjusts the statistic based on the number of independent variables in the model. Adjusted R^2 is 0.31 in Table 2.6 which means 31% of variance in goal intention can be explained by these independent variables.

Table 2.7 shows the multiple linear regression results for explaining behavioural intention. Attitude and goal intention are both statistically significantly and positively associated with behavioural intention under both correction methods. A one unit increase of attitude is associated with an increase in behavioural intention with 0.487, *ceteris paribus*. We fail to reject H6: Attitude of adopting climate mitigation measures is positively associated with behavioural intention. A one unit increase of goal intention is expected to increase behavioural intention by 0.303, *ceteris paribus*. We fail to reject H8: Goal intention is positively associated with the behavioural intention. Since perceived behavioural control is not significantly associated with behavioural intention, we reject H7. Adjusted R^2 is 0.418 in Table 2.7 which means 41.8% of variance in behavioural intention can be explained by these independent variables.

Table 2.8 shows the multiple linear regression results for explaining implementation intention. Action and coping planning are negatively associated with implementation intention which are not as expected. Maintenance self-efficacy and behavioural intention are positively associated with implementation intention. Behavioural intention is significantly associated with implementation intention ($\beta = 0.55$, $p = 0.00032$) under both correction methods. A one unit increase of goal intention is expected to increase behavioural intention by 0.55, *ceteris paribus*. Therefore, we fail to reject H12: Behavioural intention is positively associated with implementation intention. We reject hypotheses H9, H10 and H11. Adjusted R^2 is 0.176 in Table 2.8 which means 17.6% of variance in implementation intention can be explained by these independent variables.

Table 2.9 shows the multiple linear regression results for explaining new behaviour. Recovery self-efficacy is positively associated with new behaviour. We reject H13. Implementation intention is positively and significantly associated with new behaviour ($\beta = 0.305$, $p = 0.0175$) under both correction methods. A one unit increase of implementation intention is expected to increase new behaviour by 0.305, *ceteris paribus*. Therefore we fail to reject hypothesis H14: Implementation intention is positively associated with new behaviour. The adjusted R^2 is 0.073 in Table 2.9, which means 7.3% of variance in implementation intention can be explained by these independent variables.

Table 2.6: Multiple linear regression results for explaining goal intention.

	Dependent variable: Goal intention			
	Coefficients (SE)	P value	Bonferroni Threshold: $\alpha/5 = 0.01$	The Benjamini-Hochberg procedure
Positive emotion	0.169 (0.113)	0.13814	Reject H1	Reject H1
Personal norm	0.395 (0.114)	0.00085	Fail to reject H2	Fail to reject H2
Perceived social norm	0.024 (0.120)	0.84340	Reject H3	Reject H3
Negative emotion	0.104 (0.098)	0.29137	Reject H4	Reject H4
Perceived goal feasibility	0.116 (0.082)	0.15988	Reject H5	Reject H5
Constant	0.623 (0.462)	0.18076		
Observations				93
R^2				0.348
Adjusted R^2				0.310
Residual Std. Error				0.668 (df = 87)
F Statistic				9.284 (df = 5; 87, p<0.01)

Table 2.7: Multiple linear regression results for explaining behavioural intention.

	Dependent variable: Behavioural intention			
	Coefficients (SE)	P value	Bonferroni Threshold: $\alpha/3 = 0.0167$	The Benjamini-Hochberg procedure
Attitude	0.487 (0.104)	0.00001	Fail to reject H6	Fail to reject H6
Perceived behavioural control	0.066 (0.075)	0.38519	Reject H7	Reject H7
Goal intention	0.303 (0.084)	0.00048	Fail to reject H8	Fail to reject H8
Constant	0.912 (0.378)	0.01786		
Observations				93
R^2				0.437
Adjusted R^2				0.418
Residual Std. Error				0.573 (df = 89)
F Statistic				23.044 (df = 3; 89, p<0.01)

Table 2.8: Multiple linear regression results for explaining implementation intention.

	Dependent variable: Implementation intention			
	Coefficients (SE)	P value	Bonferroni Threshold: α/4 = 0.0125	The Benjamini-Hochberg procedure
Action planning	-0.103 (0.170)	0.54612	Reject H9	Reject H9
Coping planning	-0.036 (0.140)	0.79858	Reject H10	Reject H10
Maintenance self-efficacy	0.087 (0.097)	0.37009	Reject H11	Reject H11
Behavioural intention	0.550 (0.147)	0.00032	Fail to reject H12	Fail to reject H12
Constant	1.592 (0.469)	0.00103		
Observations				93
R^2				0.212
Adjusted R^2				0.176
Residual Std. Error				0.764 (df = 88)
F Statistic				5.902 (df = 4; 88, p<0.01)

Table 2.9: Multiple linear regression model results for explaining new behaviour.

	Dependent variable: New behaviour			
	Coefficients (SE)	P value	Bonferroni Threshold: α/2 = 0.025	The Benjamini-Hochberg procedure
Recovery self-efficacy	0.267 (0.151)	0.0802	Reject H13	Reject H13
Implementation intention	0.305 (0.126)	0.0175	Fail to reject H14	Fail to reject H14
Constant	0.680 (0.688)	0.3257		
Observations				93
R^2				0.093
Adjusted R^2				0.073
Residual Std. Error				1.016 (df = 90)
F Statistic				4.598(df = 2; 90, p<0.05)

2.6.3 Multinominal logistic regression results

Multinominal logistic regression results for testing hypotheses H15-H17 are shown in Table 2.10. Goal intention has a statistically significant and positive impact on all stage membership. A one unit increase in the goal intention variable is associated with an increase in the log odds of being in stage 2 versus stage 1 in the amount of 1.734 ($p < 0.05$). A one unit increase in the goal intention variable is associated with an increase in the log odds of being in stage 3 versus stage 1 in the amount of 2.35 ($p < 0.05$). A one unit increase in the goal intention variable is associated with an increase in the log odds of being in stage 4 versus stage 1 in the amount of 2.205 ($p < 0.01$). H15 postulates the goal intention is most strongly associated with a person's assignment to the pre-actional stage. We reject H15, as goal intention is most strongly associated with actional stage.

Behavioural intention has a positive yet non-significant relationship with membership of all stages. According to H16, the behavioural intention is expected to be most strongly associated with a person's assignment to the actional stage. Behavioural intention has the largest coefficient with actional stage. However, it is not statistically significant. Therefore, H16 is rejected. Implementation intention is negatively associated with stage 2 and 4 and positively associated with stage 3. However, none of the associations is statistically significant. Therefore, we reject H17 that the implementation intention is most strongly associated with a person's assignment to the post-actional stage.

Table 2.10: Multinomial logistic regression model results between intentions and stage membership (Coeff. = Coefficient; SE = standard error.).

	Dependent variable: Stage membership		
	Stage 2 Coeff. (SE)	Stage 3 Coeff. (SE)	Stage 4 Coeff. (SE)
Goal intention	1.734** (0.756)	2.350** (0.954)	2.205*** (0.771)
Behavioural intention	0.206 (0.751)	0.657 (1.070)	0.523 (0.773)
Implementation intention	-0.184 (0.727)	0.104 (0.927)	-0.631 (0.729)
Constant	-3.080 (2.415)	-9.406** (3.837)	-3.873 (2.514)
			Pseudo-R2 (McFadden): 0.108 Residual Deviance: 181.769; AIC: 205.767
Note:			*p**p***p<0.01

Multinominal logistic regression results for testing the associations between socio-demographical factors and stage membership are shown in Table 2.11. Age, agricultural education level, and livestock density have significant associations with stage membership. Age has a statistically significant inverted-U relationship with membership of stages 2, 3 and 4 ($p < 0.01$). This is because the coefficients for age are all positive and the coefficients for age squared are all negative in Table 2.11. From the inverted U relationship of age with stage membership, an optimal age can be computed which maximises *ceteris paribus* the likelihood of membership per stage. The calculated optimal age of farmers is 64 in stage 2, 45 in stage 3, and 31 in stage 4. We conclude that younger farmers are *ceteris paribus* more likely in later adoption stages than older farmers for climate mitigation measures.

Farmers with basic agricultural education versus only practical farming experiences are more likely to be in stage 2 ($\beta = 19.93$, $p < 0.01$) and 4 ($\beta = 11.06$, $p < 0.01$) rather than stage 1. However, it is the opposite for stage 3 compared with stage 1 as the $\beta = -12.28$ ($p < 0.01$). Farmers with full agricultural education versus only practical farming experiences are more likely in stage 2 ($\beta = 9.99$, $p < 0.01$), 3 ($\beta = 0.15$, $p < 0.01$), and 4 ($\beta = 0.67$, $p < 0.01$) rather than stage 1. Therefore, we conclude that farmers with full agricultural education are more likely in later stages of adoption than farmers with only practical farming experience. Farmers with basic agricultural education are more likely in stage 2 and 4 than stage 1 when compared to farmers without agricultural education.

Livestock density has a positive and significant association with stage 2, 3 and 4 versus stage 1. A one unit increase in the livestock density is associated with an increase in the log odds of being in stage 2 versus stage 1 in the amount of 0.67 ($p < 0.01$). A one unit increase in the livestock density is associated with an increase in the log odds of being in stage 3 versus stage 1 in the amount of 0.54 ($p < 0.01$). A one unit increase in the livestock density is associated with an increase in the log odds of being in stage 4 versus stage 1 in the amount of 0.74 ($p < 0.01$). We conclude that farms with higher livestock density are more likely in adoption stages 2, 3 and 4 than the first stage. Yearly farm income has a non-significant association with stage membership. The associations are both positive for stage 2 and 4 versus stage 1, and the association is negative for stage 3 versus 1.

McFadden pseudo-R^2 is the ratio of the likelihoods of the full model to the intercept model. McFadden pseudo-R^2 is 0.108 in Table 2.10 and 0.1 in Table 2.11. The Akaike information criterion (AIC) and residual deviance are mathematical methods for evaluating how well a model fits the data it was generated from. They are usually used to compare different models. Lower score indicates better model fit. Comparing the AIC and residual deviance of Table 2.10 and 2.11, the multinomial logistic model between intentions and stage membership fits better than the model between socio-demographic factors and stage membership. Lastly, the calculated model prediction accuracy score is 55% for intentions on stage membership and 53%

for socio-demographical factors on stage membership, compared to the actual stage membership reported by survey respondents.

Table 2.11: Multinomial logistic regression model results between socio-demographic factors and stage membership (Coeff. = Coefficient; SE = standard error.).

	Dependent variable: Stage membership		
	Stage 2 Coeff. (SE)	Stage 3 Coeff. (SE)	Stage 4 Coeff. (SE)
Age	1.28^{***} (0.06)	0.27^{***} (0.06)	0.61^{***} (0.05)
Age squared	-0.01^{***} (0.001)	-0.003^{***} (0.001)	-0.01^{***} (0.001)
Basic agricultural education	19.93^{***} (0.001)	-12.28^{***} (0.00)	11.06^{***} (0.001)
Full agricultural education	9.99^{***} (0.002)	0.15^{***} (0.003)	0.67^{***} (0.003)
Yearly family farm income	0.01 (0.06)	-0.06 (0.08)	0.01 (0.06)
Livestock density	0.67^{***} (0.14)	0.54^{***} (0.02)	0.74^{***} (0.17)
Constant	-45.24^{***} (0.002)	-7.35^{***} (0.002)	-17.09^{***} (0.002)
			Pseudo-R2 (McFadden): 0.10
			Residual Deviance: 184.42 ; AIC: 226.42
Note:			*p**p***p<0.01

2.7 Discussion

This study explored Dutch dairy farmers' adoption behaviour of climate mitigation measures using the SSBC model. Our empirical results show that most of the socio-psychological factors have a positive association with intention, which is in line with the prior expectations from the SSBC model.

Our approach helps to identify relevant socio-psychological factors in each stage, which can be used for targeting farmers' adoption of climate mitigation measures. Our results suggest that, in the pre-decisional stage, the personal norm should be the target to strengthen farmers' goal intention in reducing GHG emissions. A stronger personal norm was found to be associated with more pro-environmental behaviour regardless of social norm by de Groot et al. (2021) in diet choices. Similarly, a positive personal norm as measured in risk and innovation norms was found to promote pro-environmental land management by Price and Leviston (2014). Emotions are not significant influencing factors for goal intention in our study. However, a positive association between negative emotions and pro-environmental behaviour have been found in similar studies before (N Harth et al., 2013; Mallett, 2012). Rees et al. (2015) demonstrated empirically that negative moral emotions (e.g. guilt and shame related to human-caused environmental damages) strongly predict actual pro-environmental behaviour with an experimental approach with students from a German university.

In the pre-actional stage, attitude and goal intention are suggested to be the targets for steering the farmers' selection of climate mitigation measures based on our results. Intrinsically motivated farmers usually think it is important to mitigate GHG emissions. Facilitating farmers to evaluate the advantages and disadvantages of certain climate mitigation measures may increase farmers' attitude towards certain measures. This can be achieved through learning from peers (Lamkowsky et al., 2021), using farm extension services (Farstad et al., 2022) and smart applications in calculating the mitigation potential and trade-offs with other farming goals (FrieslandCampina, 2020). In order to strengthen farmers' goal intention in mitigating emissions, Dutch government and the dairy sector can collaborate in promoting the long-term benefits of mitigating GHG emissions and compensate the short-term costs that farmers may encounter. Farstad et al. (2022) also suggest that a combination of a structural approach (like subsidy schemes) and behavioural approach is important to promote more adoption of climate mitigation measures for Norwegian agriculture.

In the actional stage, our results suggest behavioural intention should be the target in order to influence the implementation intention. Behavioural intention is influenced by attitude and goal intention as suggested from our results in Table 2.7. Action, coping planning and maintenance self-efficacy had an insignificant association with implementation intention. However, self-efficacy has been found to be a positive and significant influencing factor in other studies (Kreft et al., 2021; Niles et al., 2016). Action and coping planning are negatively associated with implementation intention. These negative associations contradict prior expectations based on the SSBC model. However, these associations are not statistically significant.

In the post-actional stage, the targets shall be the implementation intention in order to influence the continuation of the adopted mitigation measures based on our results. Implementation intention is influenced by behavioural intention as shown from our results in Table 2.8. Farmers' own confidence in dealing with potential setbacks when implementing mitigation measures is highly important for recovery self-efficacy. This confidence comes mostly likely from farmers' positive experiences with certain measures and learning from peers as suggested by Farstad et al. (2022).

Regarding socio-demographical factors, the expected inverted U relationship of age and stage membership is supported by our data. The optimal age of adopting mitigation measures is lower when transiting to later stages. The calculated optimal age of farmers is 64, 45 and 31 for stage 2, 3, and 4, respectively. In addition, farmers with a higher livestock density are more likely to have adopted climate mitigation measures, i.e. be in a later stage of the SSBC model. Interestingly, the results on education level are not entirely in line with prior expectations. Our survey shows that farmers with full agricultural education versus those with only practical farming experiences are more likely to be in later stages comparing to the first stage. Farmers with basic agricultural education level versus those with only practical farming experience are more likely in stage 2 and 4 rather than stage 1.

This is the first empirical study which applied the SSBC model in the context of agricultural production. The SSBC model is partially supported by our empirical study. We find some empirical support for H1-H14, but not for H15-17. H15-17 (2^{nd} set of hypotheses) is independent from H1-14 based on the theory of the SSBC model. The fact that we have to reject H15-H17 could lie in the cross-sectional study design and the limitation of the SSBC model in distinguishing the time-ordered four stages, in addition to the limitation of a small sample size. The distinction of the four stages is rather arbitrary, which is often found in other empirical studies which applied the SSBC model (Keller et al., 2019). In practice, people do not think in stages and people may jump back and forth in these four stages while changing their behaviour. This makes the elicitation of the relationship between intentions and stages difficult in a cross-sectional study. This finding does not outright invalidate the entire model, but this warrants further investigation by future studies, especially with larger sample sizes. Moreover, we advise future studies reflect well the nature of the behaviour before applying the SSBC model. The list of mitigation measures in Appendix 2A – Table A1 is a mixture of day-to-day repeated farming managing practices (e.g. animal feeding related measures) as well as investment decisions (e.g. energy saving technologies, and emission reduction floor). The SSBC model has been mostly applied to repetitive behavioural change settings with few applications to high-cost investment decisions (Keller et al., 2019).

This study has several limitations. First, unlike previous studies on consumer behaviour (Ohnmacht et al., 2018; Weibel et al., 2019), this study has relatively small pseudo-R^2s. This may be due to the small sample size. We could only reach 300 farmers registered in the FADN and there was no incentives provided due to limited resources. Disseminating surveys to Dutch FADN farmers was cost-efficient to reach a representative pool of dairy farmers, for which matching socio-demographical data were available. Obtaining actual farm income data in our survey would otherwise be practically challenging. Nonetheless, we should be cautious in generalizing our findings given the small sample size.

We did not have a sample size justification nor a-priori power analysis to determine a minimum sample size. This is because the expected effect sizes are very difficult to estimate as there is no previous study which has tested the SSBC stage model in the context of dairy production. In this case, as suggested by Lakens et al. (2018), we carried out minimal statistically detectable effect analyses for the multiple regression models. These analyses estimate the smallest effect size that can be statistically significant under a given family wise alpha level (5%) and sample size (Lakens, 2022). The analyses were done in GPower software (version 3.1.9.7) (Faul et al., 2009). The description and outputs of the minimal statistically detectable effect analyses can be found in Appendix 2D. Based on the criterion for Cohen's f^2 (Cohen, 1988), the given sample size and level of power (95%), we are able to detect medium and large effects.

Second, although we encouraged farmers to provide honest answers in the introduction of the online questionnaire, survey results may still suffer from response bias as some farmers may not want to appear unwilling to take up climate mitigation measures. Overall, 37 farmers allocated themselves to the first two stages based on their current adoption level, and 56 farmers allocated themselves to the last two stages. The number of farmers belonging to the first two stages was lower than the number in the last two stages. This stage distribution is somewhat unusual in the domain of behavioural change studies using SSBC stage model (Keller et al., 2019). The outcome for our case the Netherlands may be explained by the programme: 'on the way to climate neutral dairy' from the largest dairy cooperative in the Netherlands (FrieslandCampina), which has been in place since 2015 (FrieslandCampina, 2023). As a result, many Dutch dairy farmers have already implemented some climate mitigation measures. We have also asked our participating farmers in the survey to select climate mitigation measures that they adopted in the past three years (no measure is also an option) from the same list as in Appendix 2A – Table A1. The results showed that all 93 sample farmers had adopted some mitigation measures in the past three years. However, some of the energy-related and efficiency-improving mitigation measures are also cost-saving for farmers. This could potentially explain why 37 out of these 93 farmers allocate themselves to the first two stages when reflecting upon their current adoption level of mitigation measures.

It is important to point out that we relied on the stated stage membership. Revealed stage membership could in theory validate our model estimation, but is in practice difficult to implement. The fact that the sampled farmers are used to FADN surveys and all answers are treated confidentially, reduces the problem of inaccurate responses about the adopted mitigation measures.

Third, this study focused on individual farmer's actions, whereas the role of collective factors (e.g. collective emotion, motivation, norms, goals and identification) on pro-environmental actions is left unexplored (Barth et al., 2021). Although the SSBC model aims to depict the temporal aspects of the decision-making process, complex interdependencies and feedback loops between different model variables along time are left undetectable due to the cross-sectional design of this study.

2.8 Conclusion

This paper explored the adoption behaviour of Dutch dairy farmers for climate change mitigation measures using a self-regulated stage model of behavioural change. For the current adoption level in the year 2021, 51.6% of the farmers in our sample assigned themselves to the post-actional stage, while 33.3% claimed to be in the pre-actional stage. Another 8.6% of them were in the actional stage and 6.5% were in the pre-decisional stage. Our regression results show that personal norm, attitude, goal intention, behavioural intention, and implementation intentions are significant and positive influencing factors on adopting climate mitigation measures. Intentions as transition points did not associate with the matching stages as expected. Furthermore, younger farmers with full agricultural education and farms with high livestock density are found to be significantly and positively associated with later stages in the SSBC model.

Our results show that negative emotion, personal norm, perceived goal feasibility, action planning, and coping planning vary significantly between different stages. This means certain interventions will have different impacts across stages. Our empirical study provides evidence for the piecewise linear relations of several socio-psychological factors across stages, comparing to the linear relations postulated by the TPB model. Hence, the choice of which factor to target depends on the stage at which individuals find themselves within the change process. The temporal dimension integrated into the SSBC model provides a more authentic portrayal of people's behavioural change process. In practical terms, these factors may also correspond to various mitigation strategies. However, it is important to note that in our study, we did not differentiate between specific mitigation measures when assessing the SSBC model.

Our study offers a step forward in understanding the impact of socio-psychological factors on farmers' adoption of climate mitigation practices through the examination of the SSBC model. Nevertheless, it should be reminded that, like the TPB model, the SSBC model relies on self-reported behaviour primarily and that intentions do not directly translate into behavioural change.

We suggest future research to further explore the causal role of personal norm, attitude, goal intention, behavioural intention, and implementation intentions on farmers’ adoption of climate mitigation measures, in experimental settings using stage-tailored intervention. Firstly, the stage distribution can be assessed through self-reporting measures, such as interviews, and/or through revealed measures, such as investments in reducing GHG emissions. One way to collect these investment data would be through the national farm accountancy data networks. Besides, it could be useful to develop a model which predicts stage membership based on commonly available data, such as size, labour force, crop acreages and livestock activities. Based on the stage distribution, tailored intervention shall be delivered to respective individuals at each stage. An online tool[1] is available for systematically designing and evaluating theory based interventions. The final step is to evaluate the effectiveness of the intervention between the treatment and control groups. Recruiting large numbers of farmers can be a practical challenge due to the costs and contact availability, yet it is not impossible as showcased by Thomas et al. (2019). Bamberg (2013a) has utilized social marketing campaigns via phone calls to study the effectiveness of interventions on car use reduction. Web-based intervention studies based on the SSBC model have been applied in changing dietary behaviour (Klöckner, 2017) and car use (Sunio et al., 2018). Once the causal factors are known, intervention strategies based on tailored stages can be deployed to target on desired behavioural changes (Steg & Vlek, 2009). For the policy advice, if policy makers want to increase the adoption rate of climate mitigation measures in the short-term, it may be useful to target farmers younger than 45 years old, with full agricultural education level and farms with high livestock density. An important precondition for our policy recommendations relates to the fact that the GHG emission mitigation measures in our survey are cost-effective for Dutch dairy farmers (Zijlstra et al., 2019).

[1] https://theoryandtechniquetool.humanbehaviourchange.org/

Acknowledgement

This work received funding from the European Union's research and innovation programme under grant agreement No. 817566 – MIND STEP. We want to thank Professor Sebastian Bamberg for his invaluable assistance with our survey design and guidance in selecting appropriate statistical tests for our study. Your expertise in the field has given us a deeper understanding of the intricacies and nuances associated with applying the SSBC framework to our research. We want to thank Dr. Jaap Sok for sharing his experiences and insights regarding studies based on the Theory of Planned Behaviour which has been instrumental in helping us carefully design our study. Our thanks are also due to anonymous reviewers for their constructive comments on an earlier draft.

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Appendix 2A: Survey questions & measurement.

Table A1: Online questionnaire questions & measurement.

Focus	Survey questions and Measurement type & level
Dependent variable	
Stage Model	**Ordered – 4 Stages (participants choose the statement that fits their current adoption level of on-farm GHG mitigation measures the most)**
1. Pre-decisional	*a- I am not planning to take any on-farm GHGs emissions mitigation measure and also see no reason why I should do it.*
	b- I am not planning to take any on-farm GHGs emissions mitigation measure because it *would be impossible for me to do so currently.*
2. Pre-actional	*c- I would like to reduce my on-farm GHGs emissions, but now I am not sure about how I can reduce it, or when I should do so.*
3. Actional	*d- I already know which mitigation measures I want to use for my farm, but, I have not put this into practice yet.*
4. Post-actional	*e- I have already taken measures to reduce GHGs emissions on my farm via mitigation measures. I shall maintain or further reduce my already low level of on-farm GHGs emissions for the coming 3 years.*
Socio-psychological variables (Independent Variables)	
Negative emotion	Q1: I feel bad if I take no measures to reduce my farming related GHGs emissions. *(1 strongly disagree... 5 strongly agree)*
	1 ordinal five-point Likert scale treated as equidistant
Positive emotion	Q1: I feel happy if I succeed in reducing my on-farm GHGs emissions. *(1 strongly disagree... 5 strongly agree)*
	1 ordinal five-point Likert scale treated as equidistant
Social norm	Q1 (SNB): People in my professional environment (e.g. fellow farmers and business partners) expect me to reduce my on-fam GHGs emissions. *(1 strongly disagree... 5 strongly agree)*
	Q2 (SNF): People who are important to me (e.g. family/friends), think that I should take measures to reduce my on-farm GHGs emissions. *(1 strongly disagree... 5 strongly agree)*
	mean-index consisting of 2 ordinal five-point Likert scales treated as equidistant, Cronbach's alpha = 0.614, average inter-item correlation = 0.210.
Personal norm	Q1 (PN1): Regardless of what other people do, my values and principles oblige me to reduce farming related GHGs emissions.

	(1 strongly disagree... 5 strongly agree)
	Q2 (PN2): I think that reducing GHG emissions is the right thing to do for me. *(1 strongly disagree... 5 strongly agree)*
	mean-index consisting of 2 ordinal five-point Likert scales treated as equidistant, Cronbach's alpha = 0.738, average inter-item correlation = 0.300.
Goal intention	Q1: My goal to reduce on-farm GHGs emissions within the coming 3 years is... *(1 very weak...5 very strong)*
	1 ordinal five-point Likert scale treated as equidistant
Perceived goal feasibility	Q1: How feasible is it for you to reach your future goal in reducing on-farm GHGs emissions within the coming 3 years? *(1 strongly disagree... 5 strongly agree)*
	1 ordinal five-point Likert scale treated as equidistant

Here we present you a list of on-farm GHGs mitigation options**.** We would like you to **tick the option you prefer the most** for reaching your **future** on-farm emission reduction goal. *You can tick one option.*

Mitigation option	**Number of ticks/total**
Less young stock	1/93
Higher milk production per cow	4/93
Increase feed efficiency (less losses, more frequent feeding)	16/93
Decrease artificial N-fertiliser	12/93
Increase legumes in grass	15/93
Renewable energy production (solar, biogas, wind)	13/93
Increase maize share in ration	1/93
Decrease concentration share in ration	8/93
Use of renewable energy	2/93
Reduce renewal rate of grassland	3/93
Energy saving technologies	6/93
Emission-reducing floor	3/93
Any other measures than the ones mentioned above	9/93
No measures	0/93

Keep the on-farm GHGs mitigation option you have selected in mind, we would like to know to what extent do you agree or disagree with the following three statements.

Behavioural intention	Q1: I plan to adopt my chosen GHGs mitigation option within the coming 3 years. *(1 strongly disagree... 5 strongly agree)*
	1 ordinal five-point Likert scale treated as equidistant
Implementation Intention	Q1: I have already informed myself about the necessary details to get started on my chosen GHGs mitigation option. *(1 strongly disagree... 5 strongly agree)*
	1 ordinal five-point Likert scale treated as equidistant
Attitude	Q1 (AT_bene): Adopting my chosen GHGs mitigation option on my farm is advantageous for me. *(1 strongly disagree... 5 strongly agree)*
	Q2 (AT_imp): It is important to me that the measure I have chosen to reduce greenhouse gas emissions is applied to my company *(1 strongly disagree... 5 strongly agree)*
	mean-index consisting of 2 ordinal five-point Likert scales treated as equidistant, Cronbach's alpha = 0.628, average inter-item correlation = 0.235.
Perceived behaviour control	Q1 (PBC_easy): Adopting my chosen GHGs mitigation option would be ... for me. *(1 very difficult...5 very easy)*
	Q2 (PBC_high): I do not depend on anyone to implement the measure I have chosen to reduce greenhouse gas emissions. *(1 strongly disagree... 5 strongly agree)*
	mean-index consisting of 2 ordinal five-point Likert scales treated as equidistant, Cronbach's alpha = 0.484, average inter-item correlation = 0.172.
Action planning	Q1: I have already run through my head on how to best carry out my plan of implementing my chosen GHGs mitigation option. *(1 strongly disagree... 5 strongly agree)*
	1 ordinal five-point Likert scale treated as equidistant
Coping planning	Q1: I have already figured out how I will solve potential problems and obstacles during the implementation of my chosen measure to reduce greenhouse gas emissions. *(1 strongly disagree... 5 strongly agree)*
	1 ordinal five-point Likert scale treated as equidistant

Maintenance self-efficacy	Q1: I am capable of maintaining implementation of my chosen GHGs mitigation option despite potential barriers. *(1 strongly disagree... 5 strongly agree)*
	1 ordinal five-point Likert scale treated as equidistant
Recovery self-efficacy	Q1: I rely on my ability to successfully implement measures to reduce greenhouse gas emissions in the event of setbacks. *(1 strongly disagree... 5 strongly agree)*
	1 ordinal five-point Likert scale treated as equidistant

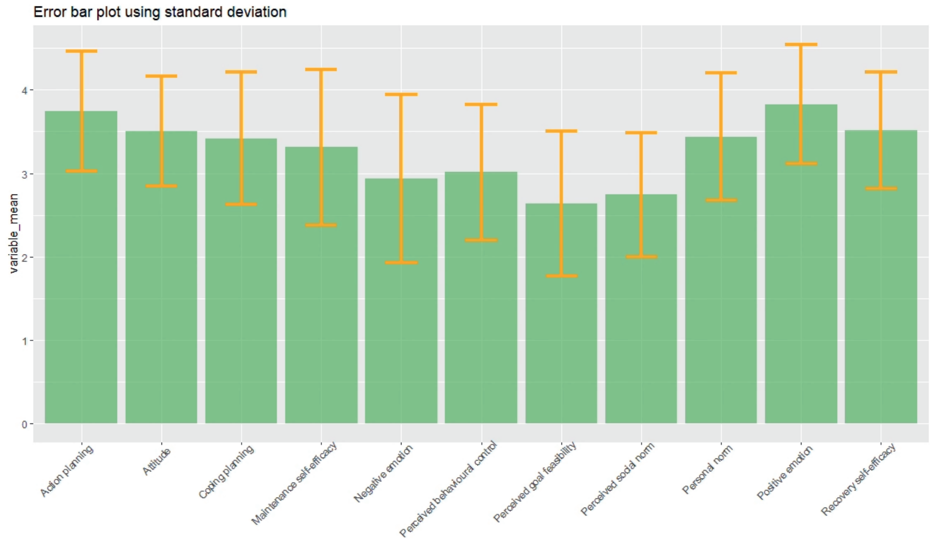

Figure A1: Mean survey scores for socio-psychological variables (error bars show standard deviation).

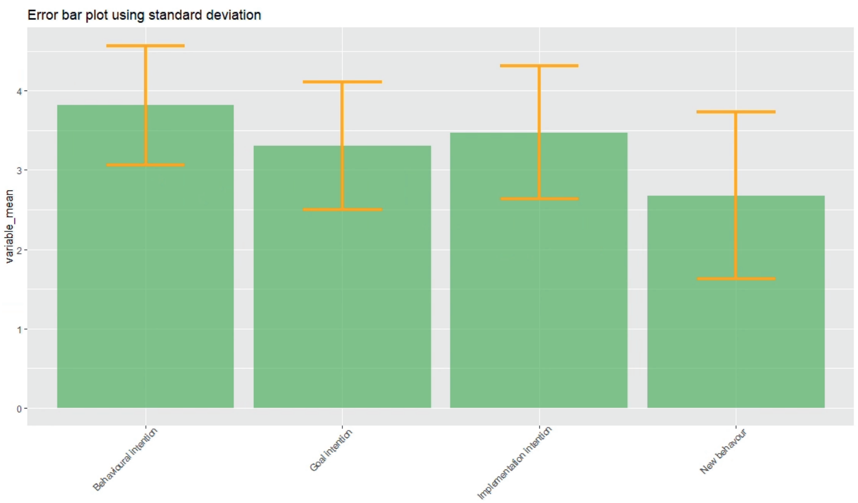

Figure A2: Mean survey scores for intentions and new behaviour (error bars show standard deviation).

Appendix 2B: Correlation matrices.

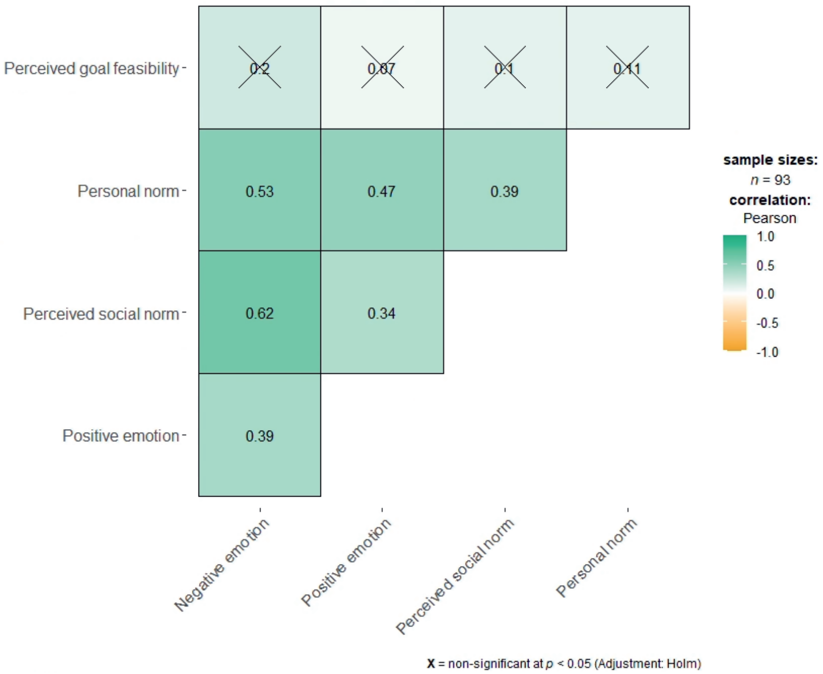

Figure B1: Correlation matrix for all the independent variables for goal intention.

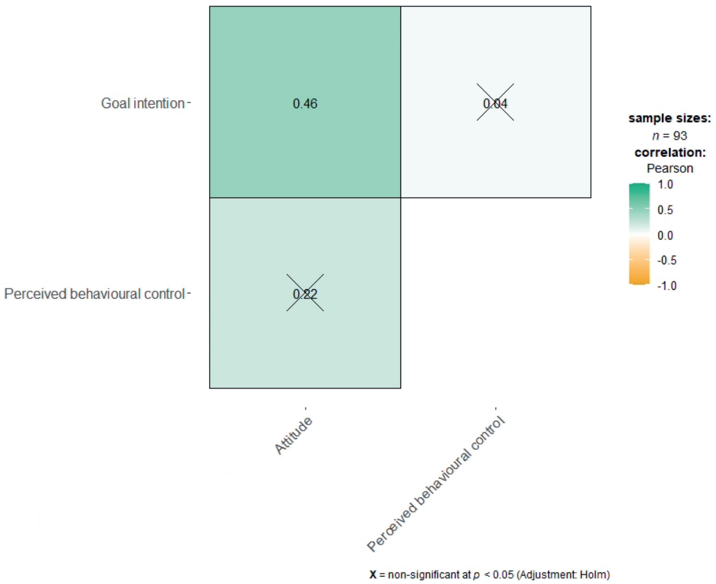

Figure B2: Correlation matrix for all the independent variables for behavioural intention.

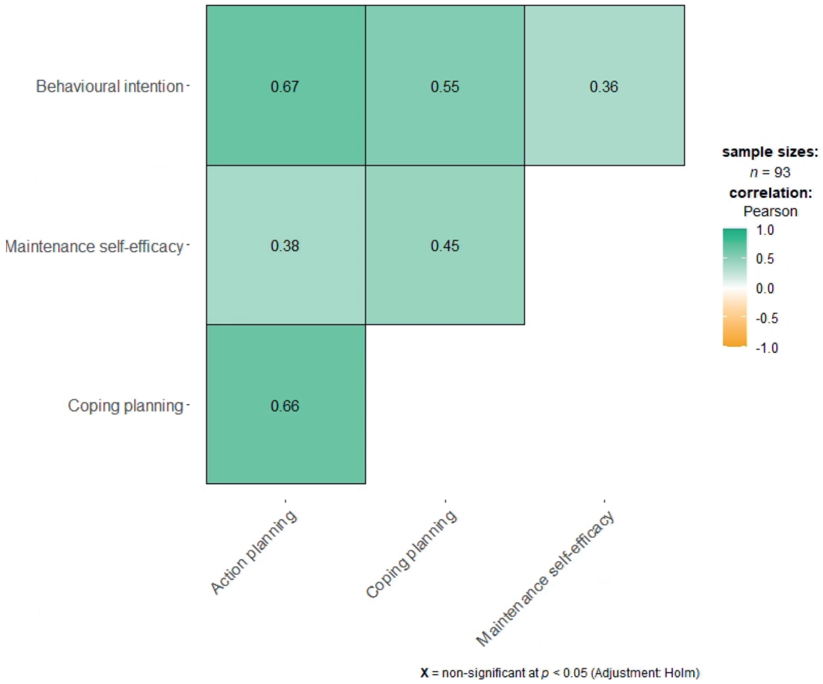

Figure B3: Correlation matrix for all the independent variables for implementation intention.

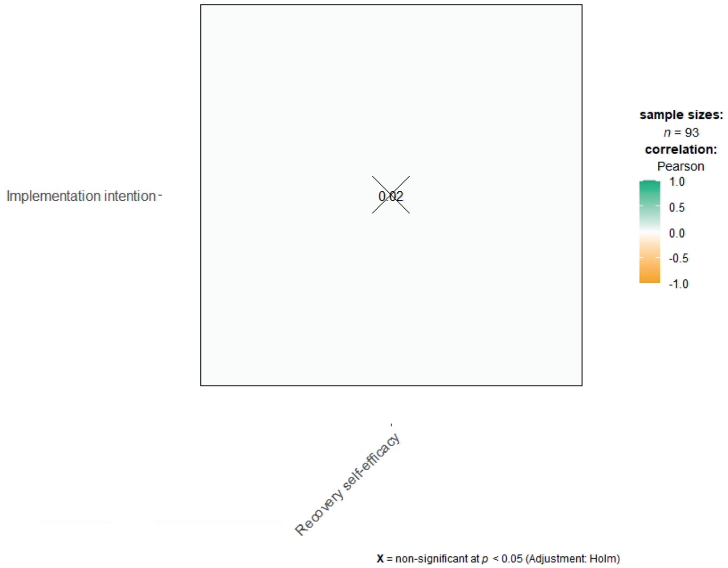

Figure B4: Correlation matrix for all the independent variables for new behaviour.

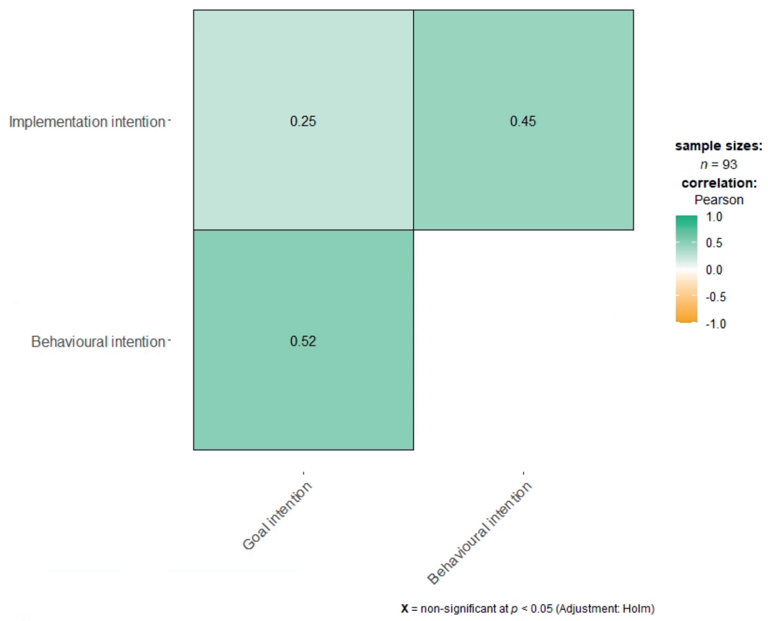

Figure B5: Correlation matrix for all the independent variables for stage membership.

Appendix 2C: The estimation results based on the Benjamini-Hochberg procedure.

Below, there are four tables showing the estimation results based on the Benjamini-Hochberg procedure. The Benjamini-Hochberg critical value is calculated using the formula: α * j / m. α is the false discovery rate which is fixed at 0.05; j is the rank, and m is the total number of variables.

Table C1: Benjamini-Hochberg procedure for Table 2.6.

Variable	p-value	Rank	Benjamini-Hochberg critical value	Significant if p-value < BH critical value
Personal norm	0.00085	1	0.01	Significant
Positive emotion	0.13814	2	0.02	Non-significant
Perceived goal feasibility	0.15988	3	0.03	Non-significant
Negative emotion	0.29137	4	0.04	Non-significant
perceived social norm	0.8434	5	0.05	Non-significant

Table C2: Benjamini-Hochberg procedure for Table 2.7.

Variable	p-value	Rank	Benjamini-Hochberg critical value	Significant if p-value < BH critical value
Attitude	0.00001	1	0.017	Significant
Goal intention	0.00048	2	0.033	Significant
Perceived behavioural control	0.38519	3	0.05	Non-significant

Table C3: Benjamini-Hochberg procedure for Table 2.8.

Variable	p-value	Rank	Benjamini-Hochberg critical value	Significant if p-value < BH critical value
Behavioural intention	0.00032	1	0.0125	Significant
Maintenance self-efficacy	0.37009	2	0.025	Non-significant
Action planning	0.54612	3	0.0375	Non-significant
Coping planning	0.79858	4	0.05	Non-significant

Table C4: Benjamini-Hochberg procedure for Table 2.9.

Variable	p-value	Rank	Benjamini-Hochberg critical value	Significant if p-value < BH critical value
Implementation intention	0.0175	1	0.025	Significant
Recovery self-efficacy	0.0802	2	0.05	Non-significant

Appendix 2D: Minimum detectable effect size analyses based on G-power.

We have selected the exact test family, with linear multiple regression statistical test and sensitivity power analysis to compute the minimum detectable effect size. Effects can only be statistically significant if R^2 does not lie within the critical interval (Lakens, 2022). All the R^2s from Table 2.6, 2.7, 2.8 & 2.9 are larger than the matching calculated upper critical R^2s from Figure D1-D4. Hence, we are able to detect statistically significant effects with our sample size.

ρ^2 under H1 is the squared multiple correlation coefficient. The effect size f^2 is calculated from ρ^2 as follows: $f^2 = \rho^2/(1-\rho^2)$ (Cohen, 1988). Since the ρ^2s under H1 are 0.22, 0.19, and 0.20 and 0.17 in Figure D1-D4, the minimum detectable effect sizes for the multiple regression models in Table 2.6-2.9 can be calculated as 0.28, 0.23, 0.25, and 0.20 respectively.

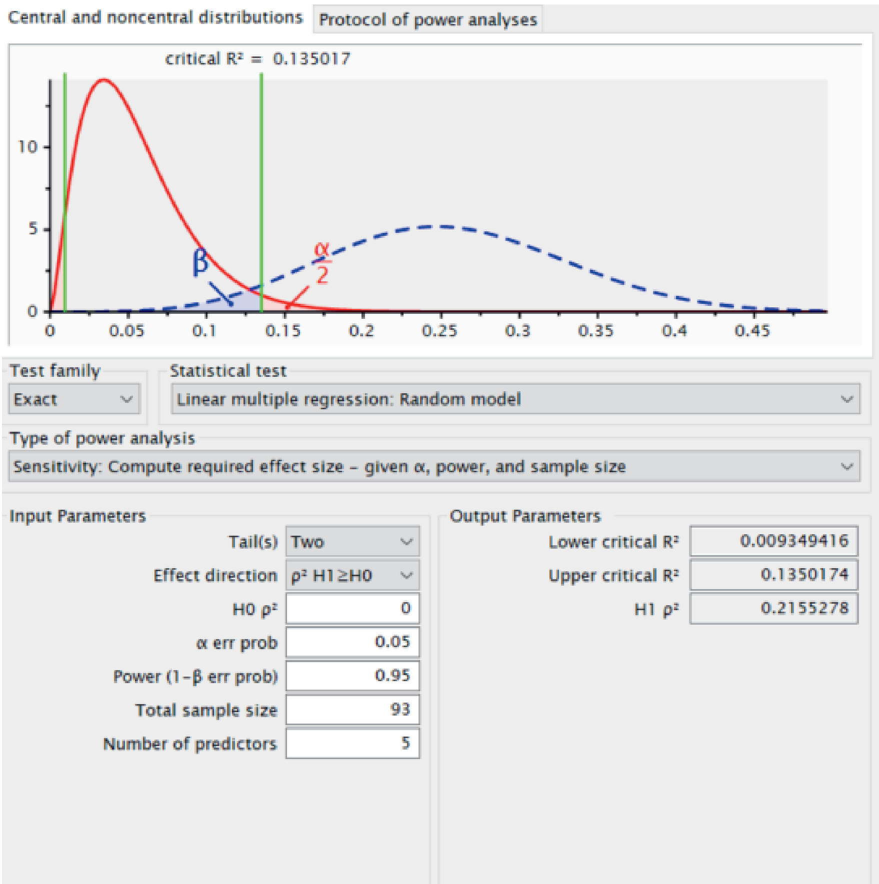

Figure D1: The minimal statistically detectable effect for the multiple regression model in Table 2.6.

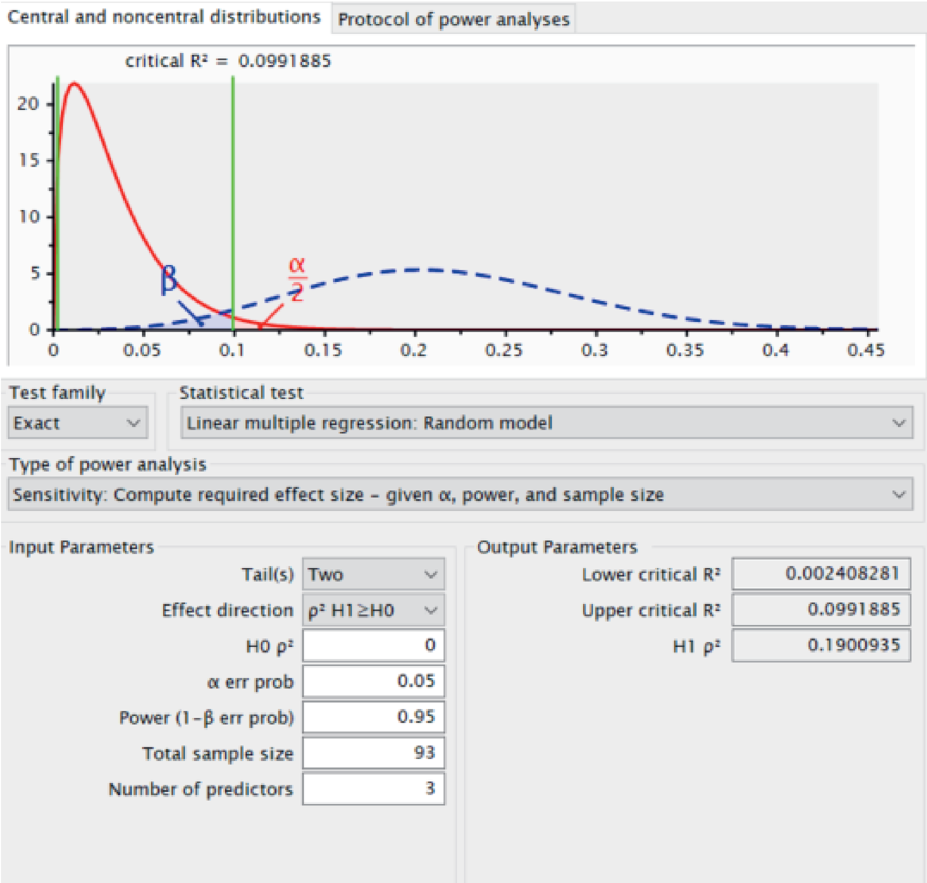

Figure D2: The minimal statistically detectable effect for the multiple regression model in Table 2.7.

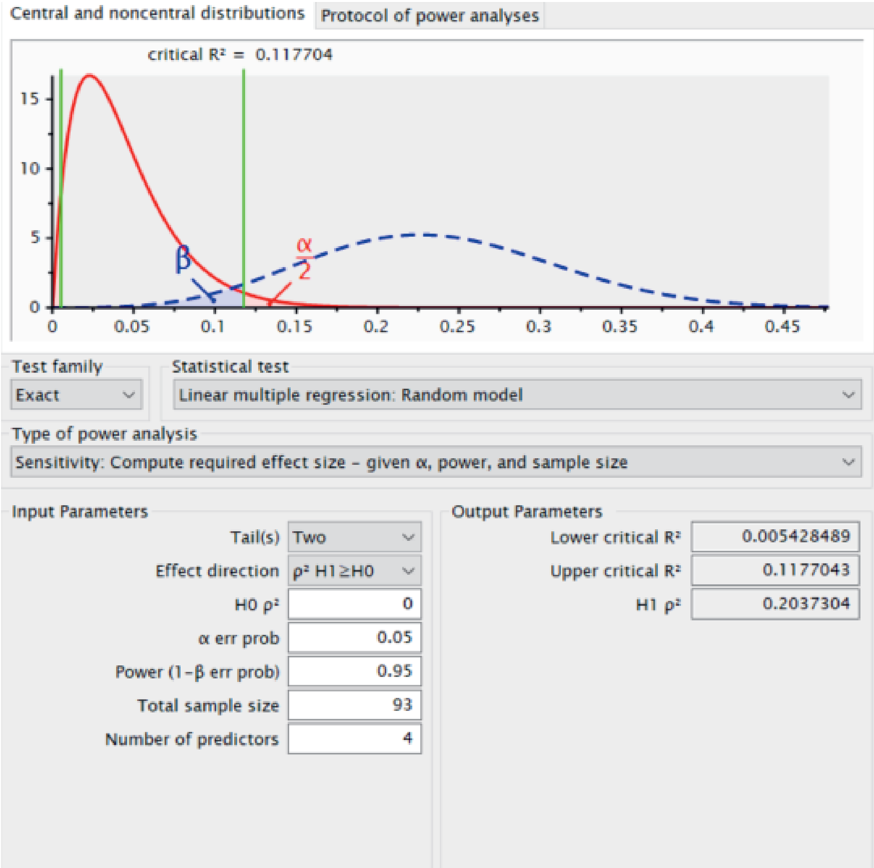

Figure D3: The minimal statistically detectable effect for the multiple regression model in Table 2.8.

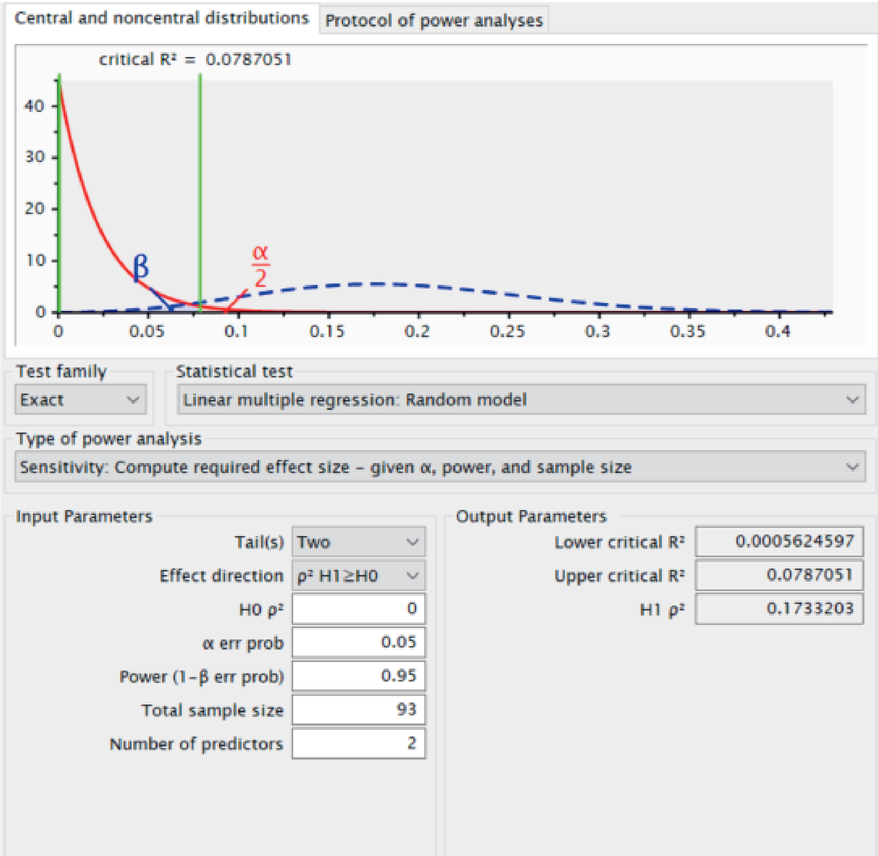

Figure D4: The minimal statistically detectable effect for the multiple regression model in Table 2.9.

Supplementary information

As part of the survey questions, participants were asked for their opinions on seven possible incentives for reducing GHG emissions. The two most favoured incentives are 'receiving financial compensation' and 'getting a price premium', followed by 'law enforcement', 'emission trading scheme for agriculture sector', and 'free practical advice'. The two least preferred incentives are societal wishes, and monitoring farm GHG emissions via a smart app.

Note: this supplementary information was not published with the research paper. It is however documented in the project deliverable for the MINDSTEP consortium.

3

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

This chapter is based on the paper: Wang, S., Ang, F., & Oude Lansink, A. (2023). Mitigating greenhouse gas emissions on Dutch dairy farms. an efficiency analysis incorporating the circularity principle. *Agricultural Economics*, *54(6)*, 819–837.
https://doi.org/10.1111/agec.12804

3.1 Abstract

Circular agriculture is vital to achieve a substantial reduction of greenhouse gas 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 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.

Key words

Land optimization, greenhouse gas emissions, dairy farm, circular agriculture, network data envelopment analysis, by-production approach.

3.2 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 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 towards 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 fertilisers, 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 towards 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, i.e. upcycling manure for crop fertilisers 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 modelled (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 modelling of the recycling of intermediate outputs, reallocating inputs, and reducing pollution (Rebolledo-Leiva et al., 2021). Focusing on U.S. dairy farms, Färe and Whittaker (1995) showed how recycled crop output can be modelled 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 modelled as a weakly disposable input. The potential reduction of GHG emissions has also been modelled together with the circularity principle on dairy farms by Rebolledo-Leiva et al. (2022) using a non-oriented slack-based network Data Envelopment Analysis model. A similar approach has also been applied to beekeeping by Rebolledo-Leiva et al. (2021). However, modelling 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 modelling GHG emissions (Dakpo et al., 2016). Recent 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 fertilisers 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 paper proceeds as follows. The next section describes the method. Subsequently, the sections consist of model formulation, data description, results, discussion and conclusion.

3.3 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 modelled explicitly, which is suitable for modelling 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 (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.

3.3.1 Technology

This study operationalizes two sub-technologies with intended outputs: crop production and livestock production. Crop and livestock outputs are modelled 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 & Russell, 2020b), 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 3.1). Nevertheless, land optimization plays a role through the intended crop- and livestock-production technologies.

Table 3.1: 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 fertilisers, and seeds.
$m_k^{L,U} \in \mathbb{R}_+$	Upcycled manure used as fertiliser for crops in the same year.
$x_k^{C,l} \in \mathbb{R}_+^S$	Total cropland in hectares.
$q_k \in \mathbb{R}_+^M$	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 labour.
$y_k^C \in \mathbb{R}_+^{OC}$	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.
$q_k \in \mathbb{R}_+^M$	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 labour.
$y_k^L \in \mathbb{R}_+^{OL}$	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 fertiliser 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 fertilisers, 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 3.1. 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 fertiliser 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.

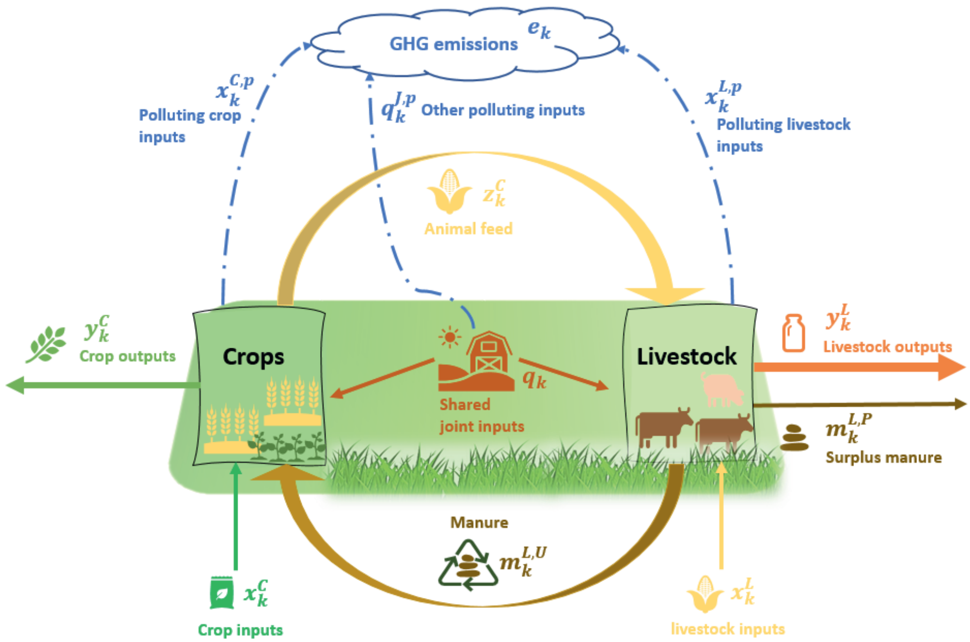

Figure 3.1: Network structure of Dutch dairy farms.

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

The intended crop production technology is:

$$T_1 = \{(x_k^C, m_k^{L,U}, q_k) \; produces \; (y_k^C, z_k^C)\} \tag{1a}$$

The intended livestock production technology is:

$$T_2 = \{(x_k^L, z_k^C, q_k) \; produces \; (y_k^L, m_k^{L,P}, m_k^{L,U})\} \tag{1b}$$

The residual GHG emission production technology is:

$$T_3 = \{(x_k^{C,p}, x_k^{L,p}, q_k^{J,p}) \; produces \; (e_k)\} \tag{2}$$

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

3.3.2 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).

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 fertiliser up to a certain amount (Shephard, 1977).

T_3 is defined as:

$(x^p, e) \ \in T_3 \ \wedge \ x^{p'} \leq \ x^p \ \rightarrow \ (x^{p\prime}, e) \ \in T_3$ (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).

3.4 Model formulation

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

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

β is the overall technical inefficiency score as well as the environmental inefficiency score in (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. 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 $S \subseteq \{1, \dots, N_C\} \cap \{1, \dots, N_L\}$ 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 re-allocatable 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, i.e. constraints (4a) – (4y) and removing the crop and grassland ($X_i^{C,l}$, $X_i^{L,l}$) from the optimization operand in (4). The detailed model formulation without land optimization can be found in Appendix 3A. 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 re-allocatable 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.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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 (6), expanding total desirable outputs (7), and expanding only dairy outputs (8). β in (6) can be interpreted as environmental inefficiency; β in (7) and (8) can be interpreted as technical inefficiency. Efficiency can be gained under different orientations, although its magnitude is unknown.

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

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

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

3.5 Data description

Our empirical application focuses on a sample of Dutch dairy farms over the period of 2010 to 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 fertilisers 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 modelling 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 fertilisers), 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 labour 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 1,896 observations for the period of 2010 to 2019. The descriptive statistics of the variables are summarized in Table 3.2.

Table 3.2: 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}**:**			
Labour	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.

3.6 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.

3.6.1 Overall technical inefficiency scores

Table 3.3 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.

Table 3.3: 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
$RTIE$[1]	0.030	0.037	0.044	0.049	0.052	0.058	0.072	0.064	0.055	0.050

([1]: 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 3C.)

3.6.2 Land optimization

We compare actual and optimal land allocation in Figure 3.2. 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 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.

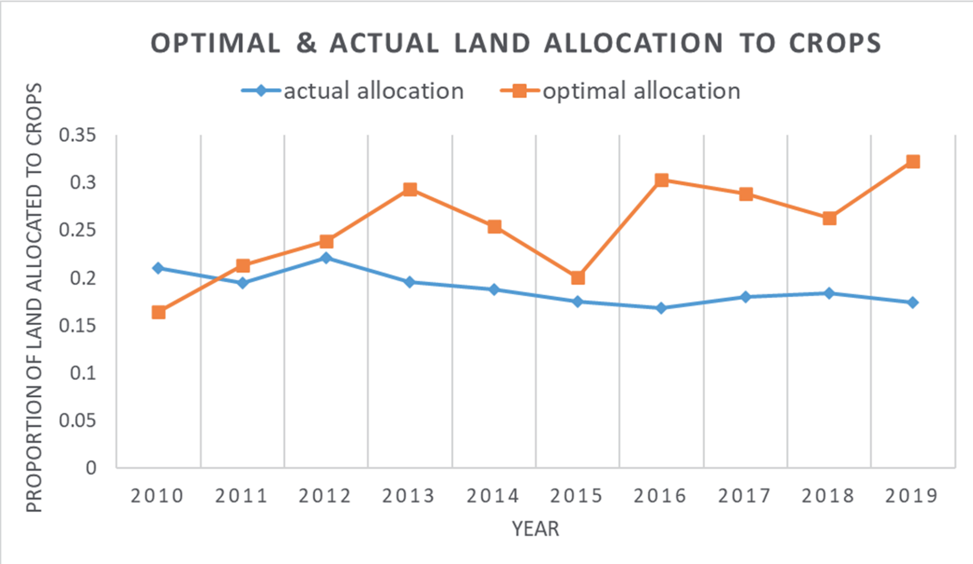

Figure 3.2: Distribution of optimal and actual proportion of land allocated for crop production per year.

3.6.3 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 3.4 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.

Table 3.4: 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	$(\boldsymbol{y_k^C, z_k^C, y_k^L, e_k})$	$(\boldsymbol{0, 0, 0, e_k})$	$(\boldsymbol{y_k^C, z_k^C, y_k^L, 0})$	$(\boldsymbol{0, 0, y_k^L, 0})$
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

3

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 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.

3.6.4 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 modelling 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 3B.

Table 3.5 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 3.5 shows the average score over the entire period. It is very similar to the results listed in Table 3.4.

Table 3.5: 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**

The land optimization results from the model in Appendix 3B are plotted in Figure 3.3. 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).

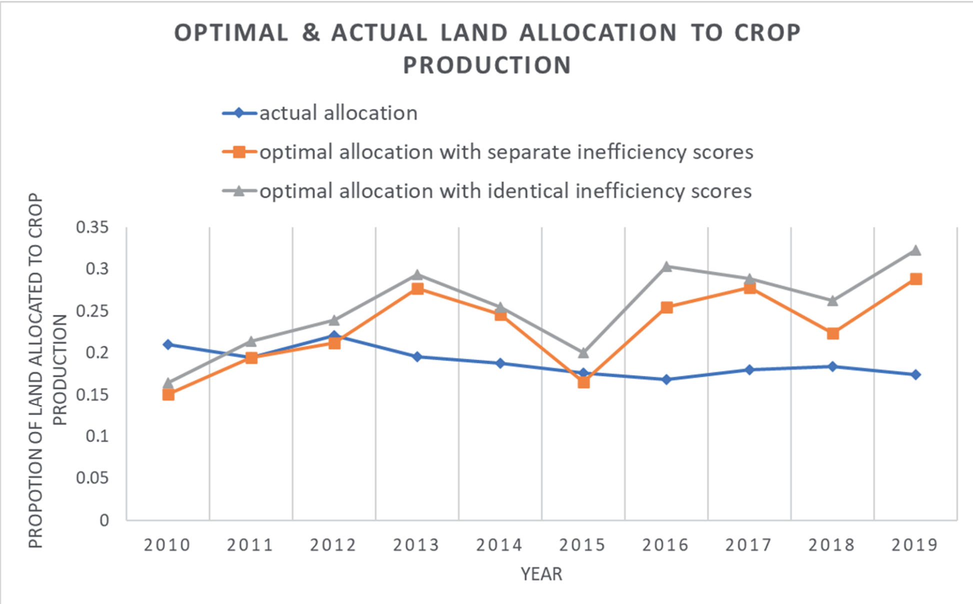

Figure 3.3: Distribution of optimal (under separate inefficiency scores and identical inefficiency scores) and actual land allocation for crop and livestock production per year.

3.7 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 0.6% 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 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 modelling 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 management, 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 towards 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).

3.8 Conclusion

This study modelled 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 behavioural 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 modelling 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).

Acknowledgement

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Appendix 3A: Model formulation without land optimization with simultaneous inefficiency.

$$\max_{\beta_i,\, \lambda_k, \gamma_k, \mu_k} \beta_i \qquad (A)$$

s.t.

$$\sum_{k=1}^{K} \lambda_k x_k^C \;\leq\; x_i^C \qquad (Aa)$$

$$\sum_{k=1}^{K} \lambda_k m_k^{L,u} \;\leq\; m_i^{L,u} \qquad (Ab)$$

$$\sum_{k=1}^{K} \lambda_k\, x_k^{C,l} - x_i^{C,l} \leq 0 \qquad (Ac)$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J1} \;\leq\; q_i^{J1} \qquad (Ad)$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J2} \;\leq\; q_i^{J2} \qquad (Ae)$$

$$\sum_{k=1}^{K} -\lambda_k y_k^C + \beta_i g_{y,k}^C \leq -y_i^C \qquad (Af)$$

$$\sum_{k=1}^{K} -\lambda_k z_k^C + \beta_i g_{z,k}^C \leq -z_i^C \qquad (Ag)$$

$$\sum_{k=1}^{K} \lambda_k = 1 \qquad (Ah)$$

$$\sum_{k=1}^{K} \gamma_k\, x_k^{L,fh} \;\leq\; x_i^{L,fh} \qquad (Ai)$$

$$\sum_{k=1}^{K} \gamma_k\, x_k^{L,a} \;\leq\; x_i^{L,a} \qquad (Aj)$$

$$\sum_{k=1}^{K} \gamma_k\, x_k^{L,l} - x_i^{L,l} \;\leq\; 0 \qquad (Ak)$$

$$\sum_{k=1}^{K} \gamma_k z_k^C \;\leq\; z_i^C \qquad (Al)$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J1} \;\leq\; q_i^{J1} \qquad (Am)$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J2} \;\leq\; q_i^{J2} \qquad (An)$$

$$\sum_{k=1}^{K} -\gamma_k y_k^L + \beta_i g_{y,k}^L \leq -y_i^L \qquad (Ao)$$

$$\sum_{k=1}^{K} \gamma_k = 1 \qquad (Ap)$$

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

$$\sum_{k=1}^{K} -\mu_k x_k^{C,p} \leq -x_i^{C,p} \qquad (Ar)$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pa} \leq -x_i^{L,Pa} \qquad (As)$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pf} \leq -x_i^{L,Pf} \qquad (At)$$

$$\sum_{k=1}^{K} -\mu_k x_k^{L,Pfc} \leq -x_i^{L,Pfc} \qquad (Au)$$

$$\sum_{k=1}^{K} -\mu_k q_k^{J,pe} \leq -q_i^{J,pe} \qquad (Av)$$

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

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

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

3

Appendix 3B: Separate inefficiencies for GHG emissions and outputs.

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

s.t.

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

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

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

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

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

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

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

$$\sum_{k=1}^{K} \lambda_k = 1 \quad (B1h)$$

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

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

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

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

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

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

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

$$\sum_{k=1}^{K} \gamma_k = 1 \quad (B1p)$$

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

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

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

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

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

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

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

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

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

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

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

s.t.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Appendix 3C: 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

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Socio-psychological and socio-economic determinants of environmental and technical inefficiency for Dutch dairy farming

4.1 Abstract

The Dutch dairy sector still needs to reduce its greenhouse gas emissions in order to contribute to the GHG emission reduction targets for the Netherlands. In this article, we aim to explore the influence of socio-psychological and socio-economic factors on environmental inefficiency of farming related GHG emissions, as well as the associations of these factors with farm technical inefficiency. We investigate this by utilizing a two-stage approach. First, a network Data Envelopment Analysis model with the by-production approach is used to assess the environmental and technical inefficiency scores of Dutch dairy farms. Second, a bootstrap truncated regression model is used to identify the statistical associations between the explanatory factors and environmental and technical inefficiencies. Perceived social norm and short term debt ratio have statistically positive associations with technical inefficiency. Negative emotions from not taking climate mitigation measures are negatively associated with farm environmental inefficiency. When promoting GHG mitigation measures, communication campaigns should take into account farmers' negative emotions related to not taking climate mitigation measures.

Key words

Greenhouse gas emissions, network data envelopment analysis, by-production, Dutch dairy farms, socio-psychological factors, socio-economic factors, bootstrap-truncated regression.

4.2 Introduction

The Dutch dairy sector has a high production per cow and per hectare (van Grinsven et al., 2019). It is committed to deliver high quality food with a lower climate impact (FrieslandCampina, 2022). The average milk production per cow per year has increased from 6 tonnes in the year of 1990 to 8.8 tonnes in 2019. During the same time period, the total amount of greenhouse gas emissions from the Dutch dairy sector has reduced by 15%, with a higher reduction per kilogram of milk by 35% (Hospers et al., 2022). Assessing the reduction potential of GHG emissions is highly relevant for determining the contribution of the Dutch dairy sector to meeting the national reduction targets, especially in the light of the growing global demand for dairy products. The Dutch dairy sector still needs to reduce GHG emissions with a special focus on emissions from enteric fermentation and manure storage to meet the national reduction targets (Hospers et al., 2022). The current paper addresses the question of how to further reduce GHG emissions.

The implementation of appropriate mitigation measures plays an essential role for achieving further reduction of GHG emissions. Two aspects are crucial in this light. First, a portfolio of best practices for each dairy farm's specific situation is needed. Second, incentives and interventions to ensure the implementation of these best practices are necessary (Beldman, Pishgar-Komleh, et al., 2021). Beldman, Pishgar-Komleh, et al. (2021) found that Dutch dairy farmers tend to adopt productivity-enhancing mitigation measures, which is driven by economic benefits rather than environmental concerns. Lack of motivation is identified as a main barrier for the low uptake of climate mitigation measures (Beldman, Pishgar-Komleh, et al., 2021).

Motivation for adopting climate mitigation measures can be understood from the perspective of socio-psychological factors. The desire to comply with social and personal norms could act as motivational factors in taking up mitigation measures (Wang, Höhler, et al., 2023). In addition, people's emotions, attitude, perceived goal feasibility and perceived behavioural control can all influence ones' motivation in adopting climate mitigation measures (Wang, Höhler, et al., 2023). Analysing the relationship between socio-psychological factors and adoption decisions on best mitigation practices is relevant and important in this light (Gomes & Reidsma, 2021; Moerkerken et al., 2020).

Efficiency analysis is a suitable tool to gauge the untapped potential to reduce GHG emissions. Appropriately modelling the technological relationship between inputs, outputs, and GHG emissions, "environmental efficiency" indicates a firm's ability to produce goods and services while minimising GHG emissions (Färe et al., 2005; Silva & Magalhães, 2023). Studies in the field of efficiency analysis have predominantly focused on farm characteristics and farmers' socio-economic attributes as determinants of technical and environmental inefficiency (Guesmi & Serra, 2015; Zhu et al., 2023). For the Dutch dairy sector, Zhu et al. (2023) concluded that farm size is associated with higher economic efficiency yet lower environmental efficiency; government support is associated with higher social efficiency yet lower environmental efficiency; intensity of advisory services are associated with higher environmental efficiency yet lower economic efficiency. These detailed findings are relevant, but challenging for practical implementation as there are trade-offs on different sustainability dimensions. For instance, strengthening advisory services brings higher environmental efficiency but lower economic efficiency.

Socio-psychological factors could be associated with lower environmental inefficiency from generating GHG emissions. Yet, little is known about the role of socio-psychological factors in the environmental performance of dairy farms. Likewise, the role of socio-psychological factors in the technical inefficiency has also not been explored previously. This literature gap underscores the need to incorporate behavioural data to gain a more comprehensive understanding of these factors. Therefore, the objective of this study is to explore the role of socio-psychological factors in the inefficiency in the emission of greenhouse gases as well as their role in the overall technical efficiency. We focus on farmers' socio-psychological factors, in addition to the customary farmer characteristics and farm economic factors (i.e. farmers' age, debt ratio and subsides) which have been included in many previous studies (Ahovi et al., 2021; Guesmi & Serra, 2015; K. Schneider et al., 2021; Singbo et al., 2014; Zhu et al., 2023).

In this article, we apply a commonly used two-stage approach. First, we assess the environmental and technical inefficiency of Dutch dairy farms by combining the network Data Envelopment Analysis model (Ray et al., 2015) with the by-production approach (Førsund, 2009; Murty et al., 2012). Second, the estimated environmental and technical inefficiency scores are regressed on a set of socio-psychological and socio-economic factors. The relationship between environmental inefficiency scores and explanatory factors is grounded in the SSBC model, with well-defined hypotheses. In contrast, the estimation for technical inefficiency scores and socio-psychological factors is exploratory in nature. Our analysis provides suggestions on possible behaviour-related incentives to further mitigate GHG emissions and improve farm production.

The remainder of this paper is organized as follows: the next section outlines the methodology. Section 4.4 describes the socio-psychological factors. Section 4.5 explains data used. Section 4.6 presents results and section 4.7 contains discussion and conclusion.

4.3 Methodology

In this paper, we use the two-stage approach for explaining the determinants of environmental and technical inefficiency. In this section, we first describe the network DEA model formulation, followed by the estimation procedure of the second stage truncated bootstrap regression model.

4.3.1 Assessing environmental and technical inefficiency

We estimated the environmental and technical inefficiency by combing the network DEA model and by-production approach.

In the model, we explicitly accounted for the circular material flows, i.e. (i) the use of upcycled manure from livestock production as fertiliser 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. In addition, the model optimized the land use to find the maximum efficiency improvement potential across dairy farms with circularity principles. More details about the theoretical background of this network DEA model can be found in Wang, Ang, et al. (2023). Below, we explain the model formulation.

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

$$D_k(x_k, y_k^C, z_k^C, y_k^L, e_k; g_k) = \sup \{ \beta \geq 0, \alpha \geq 0 : \left(x_k, y_k^C + \beta g_{y,k}^C, z_k^C + \beta g_{z,k}^C, y_k^L + \beta g_{y,k}^L, e_k - \alpha g_{e,k}\right) \in T_1 \cap T_2 \cap T_3 \quad (1)$$

β is the technical inefficiency score in (1) and α is the environmental inefficiency score in (1). We estimate the technical and environmental inefficiency separately. 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. An output-oriented model is chosen as this model aims to quantify the potential of land optimization in increasing intended products and reducing residual GHG, 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 expansion of desirable outputs and α indicates the maximum contraction of undesirable outputs. x_k represents all the inputs in the directional distance function. If β or α is zero, then the farm is fully efficient either in producing total desirable outputs or reducing GHG emissions.

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 $S \subseteq \{1, \dots, N_C\} \cap \{1, \dots, N_L\}$ 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 re-allocatable 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, and excludes the unutilized (set-aside) land.

The DEA model that allows land optimization is given by equations (2), (2a) – (2z):

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

s.t.

$$\sum_{k=1}^{K} \lambda_k x_k^C \leq x_i^C \tag{2a}$$

$$\sum_{k=1}^{K} \lambda_k m_k^{L,u} \leq m_i^{L,u} \tag{2b}$$

$$\sum_{k=1}^{K} \lambda_k x_k^{C,l} - x_i^{C,l} \leq 0 \tag{2c}$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J1} \leq q_i^{J1} \tag{2d}$$

$$\sum_{k=1}^{K} \lambda_k q_k^{J2} \leq q_i^{J2} \tag{2e}$$

$$\sum_{k=1}^{K} -\lambda_k y_k^C + \beta_i g_{y,k}^C \leq -y_i^C \tag{2f}$$

$$\sum_{k=1}^{K} -\lambda_k z_k^C + \beta_i g_{z,k}^C \leq -z_i^C \tag{2g}$$

$$\sum_{k=1}^{K} \lambda_k = 1 \tag{2h}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,fh} \leq x_i^{L,fh} \tag{2i}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,a} \leq x_i^{L,a} \tag{2j}$$

$$\sum_{k=1}^{K} \gamma_k x_k^{L,l} - x_i^{L,l} \leq 0 \tag{2k}$$

$$\sum_{k=1}^{K} \gamma_k z_k^C \leq z_i^C \tag{2l}$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J1} \leq q_i^{J1} \tag{2m}$$

$$\sum_{k=1}^{K} \gamma_k q_k^{J2} \leq q_i^{J2} \tag{2n}$$

$$\sum_{k=1}^{K} - \gamma_k y_k^{L} + \beta_i g_{y,k}^{L} \leq -y_i^{L} \tag{2o}$$

$$\sum_{k=1}^{K} \gamma_k = 1 \tag{2p}$$

$$\sum_{k=1}^{K} \gamma_k (m_k^{L,u} + m_k^{L,p}) = m_i^{L,u} + m_i^{L,p} \tag{2q}$$

$$\sum_{k=1}^{K} - \mu_k x_k^{C,p} \leq - x_i^{C,p} \tag{2r}$$

$$\sum_{k=1}^{K} - \mu_k x_k^{L,Pa} \leq - x_i^{L,Pa} \tag{2s}$$

$$\sum_{k=1}^{K} - \mu_k x_k^{L,Pf} \leq - x_i^{L,Pf} \tag{2t}$$

$$\sum_{k=1}^{K} - \mu_k x_k^{L,Pfc} \leq - x_i^{L,Pfc} \tag{2u}$$

$$\sum_{k=1}^{K} - \mu_k q_k^{J,pe} \leq - q_i^{J,pe} \tag{2v}$$

$$\sum_{k=1}^{K} - \mu_k q_k^{J,pm} \leq - q_i^{J,pm} \tag{2w}$$

$$\sum_{k=1}^{K} \mu_k e_k + \alpha_i \, g_{e,k} \leq e_i \tag{2x}$$

$$\sum_{k=1}^{K} \mu_k = 1 \tag{2y}$$

$$x_i^{C,l} + x_i^{L,l} = x_i^{l} \tag{2z}$$

4.3.2 Second stage truncated bootstrap regression model

The bootstrap truncated regression model by Simar and Wilson (2007) addresses the serially correlated inefficiency scores obtained from the DEA model, so to meet the independence assumption of standard regression models. To identify the determinants of inefficiency in the second stage, this study applies the widely applied bootstrap truncated regression model developed by Simar and Wilson (2007). This procedure has been proven to yield consistent estimates (Simar & Wilson, 2011). The bootstrap truncated regression model is specified as follows for the environmental inefficiency α_i:

$$\widehat{\alpha_i} = Z_i\theta + \varepsilon_i \tag{3}$$

The estimation based on the algorithm #1 proposed by Simar and Wilson (2007) goes in four steps:

[1]. Compute the environmental inefficiency score α_i using (2).

[2]. Use the method of maximum likelihood to obtain an estimate $\hat{\theta}$ of θ and an estimate of $\widehat{\sigma_\varepsilon}$ of σ_ε in the truncated regression of $\widehat{\alpha_i}$ on Z_i in (3) using only inefficient observations. Z_i is a vector of socio-psychological and socio-economic factors, and θ refers to a vector of parameters to be estimated, σ_ε denotes the standard deviation of the error term, and the ε_i is the error term.

[3]. Loop over the next three steps 1000 times to obtain a set of bootstrap estimates.

[3.1.]. For each $i = 1, \cdots, m$, draw ε_i from the N (0, $\widehat{\sigma_\varepsilon}^2$) distribution with left-truncation at (0-$Z_i\hat{\theta}$).

[3.2.]. Again for each $i = 1, \cdots, m$, compute $\widehat{\alpha_i}^* = Z_i\hat{\theta} + \varepsilon_i$. (uses draw from step 3.1).

[3.3.]. Use the maximum likelihood method to estimate the truncated regression of $\widehat{\alpha_i}^*$ on Z_i, yielding estimates $\left(\hat{\theta}^*, \hat{\sigma}_\varepsilon{}^*\right)$.

[4]. Use the bootstrap values and the original estimates $\hat{\theta}$, $\hat{\sigma}_\varepsilon$ to construct estimated confidence intervals for each element of θ and σ_ε.

The parameter estimates of $\hat{\theta}$ only indicate directions of statistical associations between variables Z_i and overall inefficiency scores. Therefore, marginal effects are computed at the variables' mean to enable interpretation of the association. Marginal effects indicate the effect on the predicted inefficiency scores from one unit change in a particular explanatory variable. In this study, the marginal effects of a variable that is left-truncated at 0 is defined as follows, following Cameron and Trivedi (2010):

$$\frac{\partial E(\widehat{\alpha_i}|Z_i,\widehat{\alpha_i}>0)}{\partial Z_i} = \left\{1 - \frac{Z_i{}'\hat{\theta}^*}{\hat{\sigma}_\varepsilon{}^*} * \frac{\phi\left(\frac{Z_i'\hat{\theta}^*}{\hat{\sigma}_\varepsilon{}^*}\right)}{\Phi\left(\frac{Z_i'\hat{\theta}^*}{\hat{\sigma}_\varepsilon{}^*}\right)} - \left[\frac{\phi\left(\frac{Z_i'\hat{\theta}^*}{\hat{\sigma}_\varepsilon{}^*}\right)}{\Phi\left(\frac{Z_i'\hat{\theta}^*}{\hat{\sigma}_\varepsilon{}^*}\right)}\right]^2\right\}\hat{\theta}^* \tag{4}$$

where $\widehat{\alpha_i}$ is the environmental inefficiency score, Z_i is the mean of an explanatory variable, $\hat{\theta}^*$ are the bootstrapped coefficients of the explanatory variables, $\hat{\sigma}_\varepsilon{}^*$ is the estimated variance of the error term. $\phi(\cdot)$ is the standard normal distribution and $\Phi(\cdot)$ is the standard normal cumulative distribution function.

The bootstrap truncated regression model for technical inefficiency β_i follows the same steps as described above after replacing α_i in (3) by β_i estimated in (2).

Although we argue that there are some direct or indirect relationships between these seven socio-psychological factors (Bamberg, 2013b), we remain cautious about the potential multicollinearity issue among these socio-psychological factors in the 2^{nd} stage truncated bootstrapping regression model. It is not uncommon to have independent variables that are interrelated to a certain extent especially when survey data is collected (Forthofer et al., 2007). We use the Variance Inflation Factor (VIF) to check for multicollinearity. The VIF of an explanatory variable indicates the strength of the linear relationship between the variable and the remaining explanatory variables (Thompson et al., 2017).

4.4 Socio-psychological factors

In this section, we explain the rationale for including the explanatory variables in the second stage bootstrap truncated regression model. We collected a set of socio-psychological factors based on the *self-regulated Stage model of Behavioural Change* (Bamberg, 2013b). More information about the survey that was used in the data collection can be found in (Wang, Höhler, et al., 2023). These socio-psychological factors are stage-specific based on the SSBC model, and these factors are mainly taken from the Norm Activation Model (Schwartz & Howard, 1981) and the Theory of Planned Behaviour Model (Ajzen, 1991). According to the SSBC model, seven key socio-psychological factors come into play before the implementation of climate mitigation measures. These factors are negative emotion, personal norm, positive emotion, social norm, perceived goal feasibility, attitude, and perceived behavioural control.

Following the implementation of climate mitigation measures, a different set of factors becomes prominent. These factors are action planning, coping planning, maintenance self-efficacy, and recovery self-efficacy. These four factors affect the implementation and maintenance of climate mitigation measures. Thus, these factors have a direct impact on the use of farm inputs. The socio-psychological factors ought to be considered independently from the inputs uses in the network DEA model estimated in the first stage. Consequently, we focus on the seven socio-psychological factors that help us understand farmers' intentions when it comes to planning and adopting on-farm climate mitigation measures.

Below we explain these seven socio-psychological factors, their expected relationships with environmental inefficiency and the related hypotheses.

Negative emotion. According to the Norm Activation Model (Schwartz & Howard, 1981), when decision makers are aware of the negative environmental impacts from their current behaviour and accept their responsibility, they may have negative emotions associated with not doing anything to reduce the negative environmental impacts. Rees et al. (2015) have demonstrated that negative moral emotions strongly predict actual pro-environmental behaviour. The more intense the negative emotions tied to the lack of GHG mitigation, the greater the likelihood that farmers will be motivated to take action, whether they have already done so or plan to do so in the future. As farmers score higher on negative emotion associated with not mitigating GHG emissions, there is a higher chance that the environmental inefficiency in generating GHG emissions on their farm is lower.

Hypothesis 1: negative emotion from not taking any mitigation measures is negatively associated with farm-level environmental inefficiency.

Personal norm. Negative emotions may trigger a decision maker's personal norm which refers to behaving in line with personal moral standards (Schwartz & Howard, 1981). Some studies have found positive associations between personal norm and pro-environmental behaviour (de Groot et al., 2021). The stronger ones' personal norm in reducing farming-related emissions, the more likely a farmer will act on it or have already take actions. As farmers score higher on personal norm, there is a higher chance that the environmental inefficiency in generating GHG emissions is lower.

Hypothesis 2: personal norm is negatively associated with farm-level environmental inefficiency.

Positive emotion. When individuals behave more in line with their personal norms, they will experience positive emotions (Schwartz & Howard, 1981). C. R. Schneider et al. (2021) found that positive emotions are positively linked to engagement with climate change actions. The stronger the positive emotions from successfully reducing farming-related emissions, the more likely a farmer will continue mitigating GHG emissions. As farmers score higher on positive emotion, there is a higher chance that the environmental inefficiency in generating GHG emissions on their farm is lower.

Hypothesis 3: positive emotion is negatively associated with farm-level environmental inefficiency.

Perceived social norm. Perceived social norm refers to individuals' perceptions about what important social reference persons expect them to do in terms of reducing farming related GHG emissions. Bolsen et al. (2014) have found empirical support that social norms strongly affect individuals' behavioural intentions to take voluntary climate actions, using web-based survey-experiments. The stronger the perceived social norm, the higher the probability that farmers will either commit to reducing GHG emissions or have already made such commitments. As farmers score higher on perceived social norm, there is a higher chance that the environmental inefficiency in generating GHG emissions on their farm is lower.

Hypothesis 4: perceived social norm is negatively associated with farm-level environmental inefficiency.

Perceived goal feasibility. The stronger individuals' perceived feasibility of reducing GHG emissions, the higher the chance they will commit to this goal. The lower the perceived goal feasibility, the more likely one may give up on the new goal (Schwartz & Howard, 1981). As farmers score higher on perceived goal feasibility, their likelihood of reducing GHG emission increases, either already or in the future. Consequently, this leads to a decrease in environmental inefficiency in terms of GHG emissions on their farms.

Hypothesis 5: perceived goal feasibility is negatively associated with farm-level environmental inefficiency.

Attitude. The more positive the attitude held by farmers about mitigation measures, the higher the likelihood a farmer is committed to taking mitigation actions. Masud et al. (2016) found that attitude has a positive influence on behavioural intention of mitigating GHG emissions. As farmers score higher on attitude, there is a higher chance that they have already reduced GHG emissions or will do so. As a result, this contributes to a reduction in environmental inefficiency concerning the generation of GHG emissions on their farms.

Hypothesis 6: attitude is negatively associated with farm-level environmental inefficiency.

Perceived behavioural control. Perceived behaviour control reflects individuals' perception of how much control they have on their own actions and their confidence in successfully implementing those actions. Masud et al. (2016) have found that perceived behavioural control has a positive influence on behavioural intention of mitigating GHG emissions. The higher the perceived behavioural control of implementing certain mitigation measures, the more likely that a farmer will implement them. The question we used for the perceived behavioural control was: "Adopting my chosen GHGs mitigation option would be … for me. (1 very difficult … 5 very easy)" (Wang, Höhler, et al., 2023). As farmers score higher on this question, there is a higher chance that they will take the mitigation option or have already done so. Therefore, the environmental inefficiency in generating GHG emissions on their farm is likely lower.

Hypothesis 7: perceived behavioural control is negatively associated with farm-level environmental inefficiency.

Additionally, our investigation between these socio-psychological factors and farm technical inefficiency is exploratory in nature. Therefore, we provide our conjectures and interpretations in the Discussion and Conclusion section.

Except the seven socio-psychological factors, we have also selected four socio-economic factors as control variables.

Age. The effect of age on efficiency has been shown with mixed evidence (K. Schneider et al., 2021; Zhu et al., 2023). Age could positively explain efficiency as accumulated experience contributes to better farm management (Zhengfei & Oude Lansink, 2006). However, decreased motivation or lack of successor could explain the lower efficiency when the farmer gets older (Tauer, 1995).

Short-term debt ratio. Short-term debt ratio is measured through the ratio of short-term debt to the total asset value. Farmers with a low short-term debt ratio can easily adjust to changes in their environment, therefore they can increase the efficiency according to the adjustment theory of Paul et al. (2000). Gadanakis et al. (2020) have provided empirical support for this adjustment theory. While others have found that high short-term debt ratio is positively associated with high efficiency (Zhengfei & Oude Lansink, 2006), as technically efficient farms can easily borrow more credit as they are more likely to repay the debt (Berger & Bonaccorsi di Patti, 2006).

Long-term debt ratio. Long-term debt ratio is measured through the ratio of long-term debt to the total asset value. Long-term debt is expected to improve farm efficiency when the debt is invested in the farm business. When a farm specializes in a single activity, it is anticipated that it will accumulate in-depth knowledge over time, leading to increased efficiency in that specific activity (Zhu & Oude Lansink, 2010).

Total subsides per hectare. The literature is very divided when it comes to the role of subsides in farm efficiency (Minviel & Latruffe, 2017). Subsidies could improve farmers' ability to invest in new technology in reducing GHG emissions or enhancing production. Alternatively, subsides could deter farmers to make economically rational decisions (Zhu et al., 2012). In this study, we use total subsides per hectare of total land use to avoid measuring farm-size effects (Minviel & Latruffe, 2017). Total subsides include the government subsidies and EU payments in this study.

4.5 Data description

This study uses the data from a sample of Dutch dairy farms in the year of 2021. We obtained data from the Dutch Farm Accountancy Data Network (FADN) supplemented with computed GHG emissions data on dairy farms based on the KringloopWijzer tool from Wageningen Economic Research. The detailed calculation rules of the KringloopWijzer can be found in the report provided by Dijk et al. (2020). 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 socio-psychological variables were measured using five-point Likert scales (1 = strongly disagree to 5 = strongly agree) in a survey that was conducted in 2021 (see Appendix 2A of Wang, Höhler, et al. (2023)).

We distinguish technology-specific inputs and outputs. For the crop production technology, we have aggregated crop-specific costs (seeds, crop protection products and fertilisers), upcycled manure, cropland use (feed crops and cash crops), total crop yields that are sold to the market, 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), feed from own crop residuals, grassland, total livestock production in revenue, and total manure from farm. Joint inputs are found in the crop-production technology and the livestock-production technology: joint inputs set 1 includes energy use, depreciation of building, depreciation of machinery and equipment; and joint inputs set 2 includes labour and water use irrigation. For the residual-production technology, we have included only the pollution-generating inputs and the total on-farm GHG emissions. The detailed inputs and outputs of each production technology are described in Table 4.1.

The descriptive statistics of the network DEA model variables are summarized in Table 4.2. The sample consists of 74 observations for the year 2021 after merging the FADN data and survey data from Wang, Höhler, et al. (2023). The descriptive statistics of the explanatory variables for the 2nd stage truncated bootstrapping regression can be seen in Table 4.3. The farms in our sample have an average livestock density of 2.17 heads per hectare of cultivated area, which closely aligns with the national average livestock density of 2.2 heads per hectare of cultivated area, as reported by BINternet (2022).

Table 4.1: 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 fertilisers, and seeds.
$m_k^{L,U} \in \mathbb{R}_+$	Upcycled manure used as fertiliser for crops in the same year.
$x_k^{C,l} \in \mathbb{R}_+^S$	Total cropland in hectares.
$q_k \in \mathbb{R}_+^M$	Shared joint inputs by crop and livestock processes, including aggregated input set (which consists of depreciation of buildings, depreciation of machinery & equipment, and energy consumption); as well as water irrigation, and labour.
$y_k^C \in \mathbb{R}_+^{OC}$	Total crop revenues.
$z_k^C \in \mathbb{R}_+^{Oc}$	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, and animal health costs.
$x_k^{L,l} \in \mathbb{R}_+^S$	Total grassland in hectares.
$z_k^C \in \mathbb{R}_+^{Oc}$	Unsold crop residuals used as animal feed: maize & grass.
$q_k \in \mathbb{R}_+^M$	Shared joint inputs by crop and livestock processes, including aggregated input set (which consists of depreciation of buildings, depreciation of machinery & equipment, and energy consumption); as well as water irrigation, and labour.
$y_k^L \in \mathbb{R}_+^{OL}$	Total livestock revenues.
$m_k^{L,P} \in \mathbb{R}_+$	Surplus manure removed from the farm.
$m_k^{L,U} \in \mathbb{R}_+$	Upcycled manure used as fertiliser 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 fertilisers, 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.

Table 4.2: Descriptive statistics of model variables for the network DEA model.

Variables	Dimensions	Average	Std dev.
Crop-specific variable inputs x_k^C ; $x_k^{C,p}$	Euros	14,892.94	10,888.84
Upcycled manure $m_k^{L,u}$	Kg	16,788.38	11,626.24
Joint inputs set 1 q_k^{J1}	Euros	80,263.16	54,316.60
Joint inputs set 2 q_k^{J2}**:**			
Labour	Full hours	5,235.53	2,483.46
Water use irrigation	M^3	683.11	2,601.18
Total crop outputs as sold y_k^C	Euros	5,292.25	17,213.53
Unsold crop for animal feed (maize & grass) z_k^C ; $x_k^{L,Pfc}$	kVEM	844,594.70	623,205.10
Livestock units $x_k^{L,a}$; $x_k^{L,Pa}$	Cow equivalents	167.81	112.26
Livestock-specific variable inputs $x_k^{L,fh}$	Euros	165,316.80	122,341.60
Total livestock production y_k^L	Euros	533,524.10	353,714.80
Animal feed expenditure $x_k^{L,Pf}$	Euros	150,275.10	113,525.10
Energy expenditure $q_k^{J,pe}$	Euros	10,576.41	7,586.44
Total manure $(m_k^{L,u} + m_k^{L,p})$; $q_k^{J,pm}$	Kg	80,947.59	12,688.34
Total cropland $x_k^{C,l}$	Hectares	11.25	11.24
Total grassland $x_k^{L,l}$	Hectares	65.94	47.19
Total GHG emissions e_k	Kg	1,727,006.00	1,173,801.00

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

Table 4.3: Descriptive statistics of explanatory variables for the truncated bootstrapping regression model.

Variables	Dimensions	Average	Std dev.
Negative emotion	-	2.93	0.97
Personal norm	-	3.33	0.80
Perceived social norm	-	2.66	0.77
Positive emotion	-	3.81	0.68
Perceived goal feasibility	-	2.69	0.89
Attitude	-	3.46	0.70
Perceived behavioural control	-	3.04	0.78
Age	10 years	5.70	0.85
Short term debt ratio	-	0.01	0.02
Long term debt ratio	-	0.24	0.12
Total subsides per hectare	100 euros/hectare	4.68	1.94

4.6 Results

The average environmental inefficiency for the year of 2021 is 10.19%. This means on average farms could reduce GHG emissions by 10.19 % in 2021, *ceteris paribus*, which is 175.98 tons of CO_2 equivalent. The average technical inefficiency for the year 2021 is 5%. This means on average farms could increase total farm crop and livestock outputs by 5%, *ceteris paribus*. This translates to an increase of 26,676 euros in total livestock production and 265 euros in crop production. The results from the second-stage bootstrapping regression model, which focuses on the influence of socio-psychological and socio-economic factors on environmental inefficiency, are presented in Table 4.4. Meanwhile, the results of the bootstrap regression model that addresses technical inefficiency are presented in Table 4.5. If VIF scores are above 10, then the parameter estimates are less reliable due to the multicollinearity (Forthofer et al., 2007). All the VIF scores listed in Table 4.4 and 4.5 indicate that multicollinearity does not pose a problem.

Among the entire set of determinants in Table 4.4, only the negative emotion associated with the absence of action in reducing GHG emissions demonstrates statistical significance. The more intense a farmer's negative feelings about not taking action to mitigate GHG emissions, the lower the inefficiency score that their farm exhibits in terms of farm-level environmental inefficiency related to GHG emissions. One unit increase in negative emotion will decrease the overall inefficiency by 0.5% to 9.69%, that would lead to a total reduction of 167.35 tons of GHG emissions in CO_2 equivalent, *ceteris paribus*. Specifically, a one unit increase in negative emotion contributes to an additional reduction of 8.63 tons GHG emissions in CO_2 equivalent. Consequently, the negative emotions from not doing anything to reduce farming-related GHG emissions is not only statistically significant, but also hold significance in further reducing farming-related GHG emissions.

Based on the results in Table 4.4, we fail to reject hypothesis 1 which is 'negative emotion from not taking any mitigation measures is negatively associated with farm-level environmental inefficiency score'. Due to the non-significance of the rest of the socio-psychological factors, we reject the remaining hypotheses. Among the non-significant factors, positive emotions, perceived behavioural control, age and long-term debt ratio have the expected sign in association with farm-level environmental inefficiency score.

Table 4.5 presents the results for the relation between socio-psychological & socio-economic factors and technical inefficiency. Caution is needed here for interpretations as the relations between these socio-psychological factors and technical inefficiency are exploratory in nature. The only statistically significant coefficients are from perceived social norm and short-term debt ratios. One unit increase of perceived social norm is associated with 0.158 increase in technical inefficiency. Consequently, a one unit increase of perceived social norm is associated with an increase of the average technical inefficiency from 0.05 to 0.208. This result suggests that farmers who feel greater pressure to conform to prevailing social norms in reducing GHG emissions use less efficient farming practices.

Short term debt ratio has a positive and statistically significant association with technical inefficiency. 0.01 unit increase in short term debt ratio will lead the average technical inefficiency to increase from 0.05 to 0.094. This implies that higher levels of short-term debt in relation to total assets are strongly correlated with a significant decrease in production efficiency. It suggests that farms with higher short-term debt burdens may face financial pressures or constraints that hinder their ability to operate efficiently.

Table 4.4: Bootstrapped coefficients results and marginal effects of all explanatory variables on the environmental inefficiency (calculated R^2: 0.39).

	Bootstrapped coefficients	Marginal effects	Variance Inflation Factor (VIF)
Intercept	0.194	-	-
Negative emotion	-0.063**	-0.005**	2.840
Personal norm	0.039	0.034	2.051
Perceived social norm	0.014	0.007	2.452
Positive emotion	-0.034	-0.004	2.159
Perceived goal feasibility	0.004	0.002	1.861
Attitude	0.033	0.027	1.833
Perceived behavioural control	-0.032	-0.005	1.716
Age	-0.004	-0.001	1.382
Short term debt ratio	0.001	0.0003	1.318
Long term debt ratio	-0.090	-0.027	1.357
Total subsides per hectare	0.024	0.019	1.241

Note: ***p < 0.01; **p < 0.05; *p < 0.10

4

Table 4.5: Bootstrapped coefficients results and marginal effects of all explanatory variables on the technical inefficiency (calculated R^2 0.33).

	Bootstrapped coefficients	Marginal effects	Variance Inflation Factor (VIF)
Intercept	0.063	-	-
Negative emotion	-0.088	-0.011	3.522
Personal norm	0.026	0.013	1.846
Perceived social norm	0.160**	0.158**	2.345
Positive emotion	-0.008	-0.008	2.002
Perceived goal feasibility	0.043	0.025	2.834
Attitude	-0.028	-0.007	2.337
Perceived behavioural control	-0.064	-0.010	2.438
Age	0.013	0.006	2.208
Short term debt ratio	8.531**	4.388**	1.525
Long term debt ratio	-0.684	-0.122	1.766
Total subsides per hectare	0.037	0.024	1.584

Note: ***p < 0.01; **p < 0.05; *p < 0.10

4.7 Discussion and Conclusion

This study explores the associations between a set of socio-psychological factors and socio-economic factors and the farm environmental and technical inefficiency for Dutch dairy farmers. Our empirical results show that among the seven socio-psychological factors, only negative emotion stemming from not taking climate measures has a statistically significant ($p < 0.05$) and negative coefficient with environmental inefficiency. Negative emotions have been identified as having a positive correlation with pro-environmental behaviour (N Harth et al., 2013; Mallett, 2012). Rees et al. (2015) demonstrated empirically that negative moral emotions (e.g. guilt and shame related to human-caused environmental damages) strongly predict actual pro-environmental behaviour with an experimental approach. Positive emotion, perceived behavioural control, age and long-term debt ratio had negative, yet statistically insignificant associations with farm environmental inefficiency scores.

Positive emotion (feeling good when succeeding in reducing GHGs emissions) has an insignificant negative association with farm environmental inefficiency. We cannot derive implications from this insignificant association between positive emotion and farm-level environmental inefficiency. Given the clear difference between positive and negative emotion in this study, it is advisable for future research to consider a distinct treatment of these emotions rather than employing a valence-based approach, which portrays positive and negative emotions as opposing ends of a single continuum (Lerner & Keltner, 2000; Onwezen et al., 2013).

Our results on the technical inefficiency imply that when the perceived social norm is higher, farms tend to be less efficient in their production. This finding is in contrary to the conclusion drawn by Hüttel et al. (2022), who found that social norms drive the adoption of precision farming, a practice known for cost saving and environmental preservation. Additionally, our finding on the positive and statistically significant association of short term debt ratio with technical inefficiency confirms with the adjustment theory of Paul et al. (2000). There is a clear difference between the short term debt ratio and long term debt ratio on the technical inefficiency. Due to the explorative nature of our analysis on technical inefficiency, future research is needed to explore the specific mechanisms through which social norms and short term debt ratio influence farm efficiency.

On average, our results point out that Dutch dairy farms could reduce GHG emissions by 10.19 % in the year of 2021, which is 175.98 tons of CO_2 equivalent, *ceteris paribus*. Farmers can close this environmental inefficiency gap by catching up with the mitigation practices of the best peers. In addition, our results show that the stronger the negative emotion from doing nothing to mitigate GHG emissions, the lower the farm-level GHG emissions. A one unit increase in negative emotion from not taking actions to mitigate GHG emission is associated with a 8.64 tons' additional reduction of GHG emissions in CO2 equivalent. Communication campaigns could highlight farmers' negative emotions associated with not taking climate mitigation measures. For example, presenting farmers with the adverse environmental impacts resulting from their farming practices may trigger negative moral emotions, such as feelings of guilt or shame (Rees et al., 2015). Furthermore, smart framing plays an important role in this light, considering Dutch farmers long for a more positive framing in the media (Gomes & Reidsma, 2021).

This study is the first one in the efficiency literature to explore the role of socio-psychological factors in explaining the environmental inefficiency as measured in reducing farming related GHG emissions. Although we only identified one salient factor being negative emotion, our study points out the importance of studying the role of farmers' socio-psychological factors in explaining better farm performance. It is crucial to exercise caution when extrapolating our findings, primarily due to the limited sample size of 74 observations and the study's specific focus on Dutch dairy farms.

To be more cautious, negative emotions from not taking actions to mitigate GHG emissions can also be seen as a reflection of farmers' intrinsic motivation in reducing GHG emissions. In other words, those who are interested in reducing GHG emissions will feel bad if they do not take any action to mitigate emissions. Our results could be an artefact of self-selection bias in our data collection through the online survey. Due to limited survey questions, we could not separate the respondents based on their level of intrinsic motivation as to reduce GHG emissions. All our respondents have indicated that they have taken some climate mitigation measures in the past three years prior to the year of 2021 (Wang, Höhler, et al., 2023). This can be explained by the fact that many farmers have participated in the 'on the way to climate neutral dairy' programme (FrieslandCampina, 2023). Nonetheless, further validation is needed to collect data from farmers who are not intrinsically motivated to take on climate mitigation measures.

We recommend future studies to continue study the role of socio-psychological factors in explaining lower environmental inefficiencies with larger and representative samples. Furthermore, there is a need for developing an integrated conceptual framework that incorporates socio-psychological factors, farmer characteristics, and farm economic factors as the determinants of environmental inefficiency. Incorporating longitudinal study designs and experimental approaches could be valuable in revealing the causal roles of these drivers.

5

Assessing reduction potential and shadow prices for greenhouse gas emissions and nitrogen surplus on Dutch dairy farms

5.1 Abstract

The environmental challenges of the dairy sector, lead to the need for evaluating both the environmental performance and the shadow prices of greenhouse gas emissions and nitrogen surplus. Applying parametric Deterministic Frontier Analysis to the by-production framework, our study quantifies both the technical and environmental efficiency of dairy farms. Furthermore, we assess the shadow prices associated with greenhouse gas emissions and nitrogen surplus. The empirical application focuses on a representative sample of 285 Dutch specialized dairy farms over the period of 2010 to 2019. Our results suggest that on average, the yearly reduction potential for GHG emission and nitrogen surplus are about 721 tons and 559 tons respectively. For the total on-farm revenue from livestock and crop production, the improvement potential is 174,813 euro on average. The estimated average shadow prices for GHG emissions and nitrogen surplus are 12.09 euro/kg and 22.31 euro/kg respectively using the DFA models. The estimated average shadow prices for GHG emissions and nitrogen surplus are 77.03 euro/ton and 6.08 euro/kg respectively using the quadratic functional form estimated using ordinary least squares regression models.

Key words

Dairy farms, deterministic frontier analysis, by-production framework, shadow prices, GHG emissions, nitrogen surplus.

5.2 Introduction

The Dutch dairy sector is among the largest dairy exporters in the world. It is characterised by high levels of input use, animal density and productivity (Kwakman, 2021; Vellinga et al., 2011). At the same time, undesirable nitrogen (N) surplus and greenhouse gas emissions generated from the production of dairy products pose intertwined environmental and related societal challenges (Jongeneel & Gonzalez-Martinez, 2021), such as soil acidification, biodiversity loss, ecosystem damages, air and water pollution, public health damages as well as climate change. In 73% of 162 Dutch nature reserves, nitrogen deposits have already exceeded ecological risk thresholds by 50% on average (Stokstad, 2019). Dutch farmers have to comply with many national directives related to nitrogen use, for instance the Nitrate Directive, the Water Framework Directive, the Birds and Habitats Directives, as well as the international treaty 'the Paris Agreement' (Wageningen University & Research, n.d.). In terms of reducing the GHG emissions, Dutch dairy farmers are currently taking voluntary mitigation measures to contribute to the national climate agreement (Rijksoverheid, 2022).

The increasing emissions of pollutants to the environment can be partly explained by the fact that the cost prices of negative externalities from dairy farming are not commonly accounted for in market prices and farmers' production decisions (Adenuga et al., 2019). The price associated with reducing an additional unit of undesirable outputs is typically referred to as the shadow price of these outputs (Zhou et al., 2014). Evaluating the environmental performance of dairy farms could help guide future policy measures (OECD, 2023), as it could show the potential for reducing emissions. In addition, estimating the economic costs of negative externalities has become an important area of research with the availability of more environmental data (Dakpo et al., 2016). Hence, the objective of this study is to quantify the reduction potential as well as the shadow prices of GHG emissions and N surplus for individual dairy farms. The reduction potential is evaluated through environmental efficiency analysis. 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).

To correctly model negative externalities from dairy farms, we need to understand their sources. The generation of nitrogen also brings along some greenhouse gases (GHGs). GHGs from dairy production mainly consist of methane (CH_4) and nitrous oxide (N_2O) from rumen fermentation, manure management and fertilization. Carbon dioxide (CO_2) is generated when using energy and tilling the soil. Nitrogen losses are in the form of nitrogen oxides (NO_x) and ammonia (NH_3). Nitrogen oxides (NO_X) are emitted by transportation, energy use and production of feed & fertilisers. Ammonia (NH_3) stems mostly from the excessive use of artificial fertiliser, and animal manure. The computation of N surplus at the farm level is based on the nutrient flows that enter and leave the farm and on the changes in inventories. The calculated farm N surplus provides an estimate of the amount of nutrients consumed in a farm within a given year but not converted into marketable products. The calculated N surplus includes Nitrogen that is transported from the farm through manure, and it excludes deposition supply, airborne nitrogen fixation by leguminous plants, soil organic nitrogen release (mineralization), and air emissions. Nitrogen surplus in this study includes nitrogen losses and N content in manure. Figure 5.1 provides an overview of where GHGs and N losses are generated from a dairy farm. Processes are marked by boxes. N losses are marked by clouds (NH_3 + NOx).

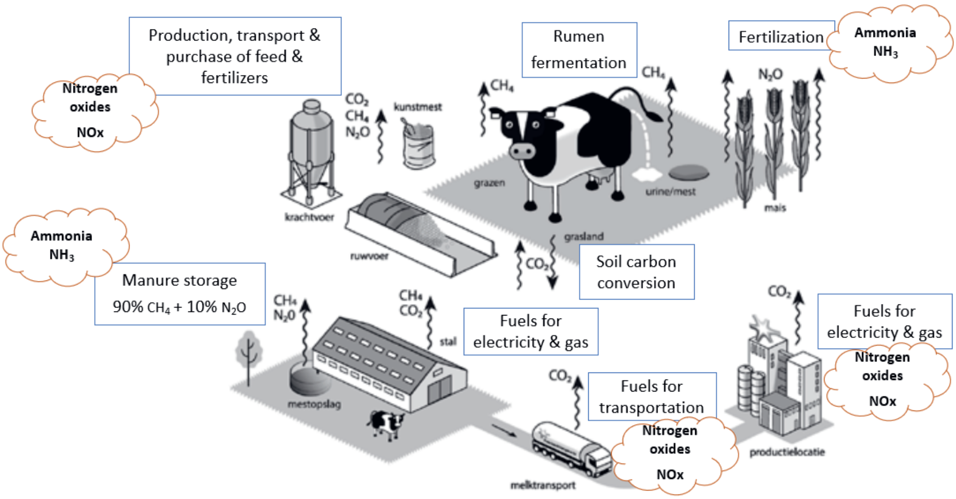

Figure 5.1: Greenhouse gas emissions and nitrogen losses from a dairy farm, adapted from (DuurzameZuivelketen, 2018).

The estimation of shadow prices through a production model could be done through parametric Deterministic Frontier Analysis, parametric Stochastic Frontier Analysis as well as non-parametric Data Envelopment Analysis. Various studies have quantified the shadow prices of undesirable outputs from the dairy sector: Wettemann and Latacz-Lohmann (2017) used an input-oriented DEA model and treated GHG emissions as undesirable outputs within the conventional technology; Njuki and Bravo-Ureta (2015) and Adenuga *et al.* (2019) used an output-oriented SFA model and treated pollutants as inputs; Huhtala and Marklund (2008) used an output-oriented DFA and treated phosphorous surpluses as weakly disposable inputs. Being a linear programming approach that can be straightforwardly implemented, DEA models are widely applied for evaluating the environmental efficiencies of decision making units. However, they lead to ambiguous shadow prices of efficient observations due to the presence of kinks in the frontier (Puggioni & Stefanou, 2019). Having a smooth frontier because of parametric specification, SFA models do not suffer from this problem. However, unlike DEA, the monotonicity properties of the estimated distance functions in SFA models are often violated in practice, which complicates the economic interpretation of the resulting shadow prices.

Parametric DFA models combine the convenience of being a linear programming approach complying with the monotonicity conditions as in DEA, with the property of yielding continuous frontiers as in SFA. To do so, previous studies have adapted the procedure of Aigner and Chu (1968) to the context of efficiency analysis by modelling pollutants as a strongly disposable input (for example Hailu & Veeman, 2001) or weakly disposable output (for example Färe et al., 2005). However, both approaches do not accurately model the by-production of pollution associated with intended production, and violate the materials balance principle (Coelli et al., 2007). The production of intended outputs inevitably generates by-products. Explicitly modelling this process, the by-production approach developed by Førsund (2009) and Murty et al. (2012) complies with the materials balance principle, and has been demonstrated to be valuable in empirical applications (for example Ang et al., 2022; Dakpo et al., 2016). The reason is that the by-production approach provides separate frontier estimations for the polluting and the desirable output technology in a production system following the material balance principle (MBP). Yet, to the best of our knowledge, the by-production approach has not been empirically implemented using parametric DFA.

The current paper addresses this research gap by combining the deterministic frontier analysis and the by-production approach to the efficiency assessment and shadow prices estimation of GHG emissions and N surplus on Dutch dairy farms. We operationalize parametric DFA using quadratic directional distance functions.

The contributions of this paper are threefold. First, our study offers insights into the environmental and technical efficiency of Dutch dairy farms, along with assessments of shadow prices for GHG emissions and N surplus. Our findings highlight significant reduction potential for both GHG emissions and N surplus on Dutch dairy farms, with a wide spectrum of shadow prices calculated across different farms. Second, our approach offers empirical flexibility while still being grounded in economic theory. The effect of polluting inputs on environmental efficiency is not straightforward. On the one hand, using more polluting inputs is costly, and thus decreases efficiency in the intended production technology, *ceteris paribus*. On the other hand, a higher level of polluting inputs under a certain pollution level indicates an improvement in efficiency in the pollution-generating technology. Our theoretical model accordingly shows that the shadow price of pollution can be both positive and negative. While negative shadow prices occur, our empirical analysis shows that shadow prices of GHG emissions and N surplus are predominantly positive. This suggests that reduction of both pollutants is costly. Third, these results could inform policy makers about the overall reduction potential of GHG emissions and N surplus on dairy farms and the farm-specific costs to reduce these negative externalities.

The remainder of this paper describes the method and data in section 5.3 and 5.4, respectively. The results section provides detailed model results, including inefficiency evaluation and shadow price estimation. The paper concludes with discussion and conclusion.

5.3 Method

In this section, we firstly describe the directional distance functions and the by-production approach which allow us to estimate the technical and environmental efficiency of Dutch dairy farms. Secondly, we provide several properties the distance functions have to satisfy. Lastly, we present the model formulation and the shadow price formula. Figure 5.2 shows a simplified concept of a dairy farm. We distinguish two types of production inputs: the polluting inputs (X^p) and the non-polluting inputs (X^{np}). Two types of outputs are produced: total desirable outputs (Y) and bad outputs which include the GHG emissions (b^{ghg}) and the N surplus (b^n).

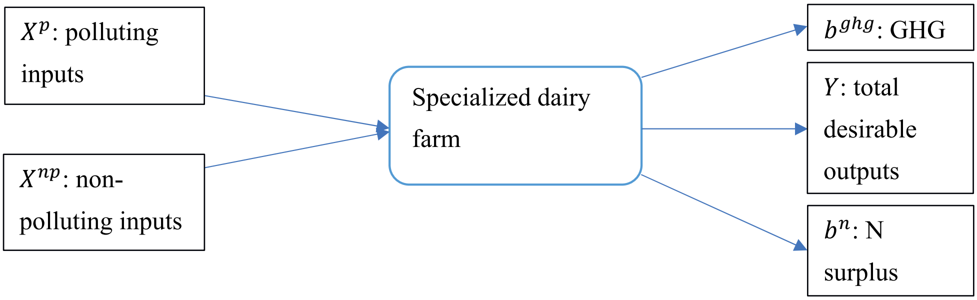

Figure 5.2: Simplified model structure of dairy farms.

The overall production possibility set is

$$P(x) = \{(Y, b) : X^p, X^{np} \; can\; produce\; (Y, b),\; b = \{b^{ghg},\; b^n\}\} \tag{1}$$

The directional output-oriented distance function per technology is characterized as below:

Conventional technology:

$$T_1 = \vec{D}_c(X^p,\, X^{np}, Y;\, \theta) = \max\left\{\theta : \left(Y + \theta g_y\right) \in P(x)\right\} \tag{2}$$

Polluting technology for GHG emissions:

$$T_2 = \vec{D}_{pe}(X^{pe},\, b^{ghg};\, v) = \max\left\{v : \left(b^{ghg} - v g_{ghg}\right) \in P(x)\right\} \tag{3}$$

Polluting technology for N surplus:

$$T_3 = \vec{D}_{pn}(X^{pn},\, b^n;\, \delta) = \max\{\delta : (b^n - \delta g_n) \in P(x)\} \tag{4}$$

The solution $\theta^*, v^*\; and\; \delta^*$ corresponds to the maximum expansion of the good output and contraction of and bad outputs respectively. The directional vectors g_y, g_{ghg}, and $g_n$specify in which direction the good outputs and bad outputs are scaled respectively, so as to obtain the projection on the frontier. We have selected the mean value of Y, b^{ghg} and b^n as directional vectors, following Färe et al. (2005), so that the inefficiency score measures respectively the potential expansion and reduction of good and bad outputs in their respective mean value. All farms are thus evaluated by the same directional vector.

In this paper, we have modelled the conventional technology and the polluting technology separately. Our approach is consistent with Murty et al. (2012)'s formulation of a unified technology in which the by-production technology is defined as the intersection of the conventional technology and the emission-generating technology. In line with Murty et al. (2012), the empirical approach involves separate estimation with regard to the conventional and emission-generating technologies. This leads to feasible projections in a distance function framework when considering the intersection as explained by (Murty & Russell, 2020a).

We have modelled GHG emissions and N surplus in two separate polluting technologies, T_2 and T_3. The reasons are that the polluting inputs for GHG emissions and N surplus are not the same, and the functional relationship between the polluting inputs and the bad outputs are different.

Following Färe and Primont (1995), the directional output-oriented distance function for the conventional technology T_1 has several properties listed below:

- $\vec{D}_c(X^p, X^{np}, Y;\ \theta) \geq 0$ *iff* $(X^p, X^{np}, Y) \in P(x)$ (5a)
- $\vec{D}_c(X^p, X^{np}, Y';\ \theta) \geq \vec{D}_c(X^p, X^{np}, Y;\ \theta)\ for\ Y' \leq\ Y \in P(x)$ (5b)
- $\vec{D}_c(X^{p\prime}, X^{np}, Y;\ \theta) \geq \vec{D}_c(X^p, X^{np}, Y;\ \theta)$ for $X^{p\prime} \geq\ X^p\ \in P(x)$ (5c)
- $\vec{D}_c(X^p, X^{np\prime},\ Y;\ \theta) \geq \vec{D}_c(X^p, X^{np},\ Y;\ \theta)$ for $X^{np\prime} \geq\ X^p\ \in P(x)$ (5d)
- $\vec{D}_c\left(X^p, X^{np}, Y + \rho g_y\ ; g_y\right) = \vec{D}_c\left(X_k, Y; g_y\right) -\ \rho, \rho \in \mathbb{R}$ (5e)

Property (5a) indicates that $\vec{D}_c(X^p, X^{np}, Y;\ \theta)$ is non-negative for all feasible production possibilities. When the generating unit is efficient, the distance function takes the value of zero. When the generating unit is operating below the efficient frontier, the distance function takes positive values. Property (5b) indicates, for a given level of inputs, that the distance to the frontier decrease when good output increases. Hence, the distance is non-increasing in the good outputs . Properties (5c) and (5d) posit for all the inputs for the conventional technology T_1, the distances are non-decreasing in the inputs. Property (5e) imposes the translation property. It indicates that the inefficiency can decrease by an amount of ρ if the good output is expanded by ρg_y.

Properties for the directional distance function for the polluting technology T_2 and T_3 have to be adjusted as we have modelled the negative externalities following the by-production approach (Førsund, 2009; Murty *et al.*, 2012). The by-production approach argues that the pollution is generated as by-product when producing good outputs. If everything else is held constant (pollution and production of good outputs), the more polluting inputs one firm uses, the more environmentally efficient that firm is. In terms of pollution, if everything else is held constant, the more pollution a firm generates, the less efficient that firm is.

The directional output-oriented distance functions for the polluting technology T_2 and T_3 have the properties listed below :

- $\vec{D}_p(X^p,\ b;\ \delta/v) \geq 0$ *iff* $(X^p,\ b) \in P(x)$ (6a)
- $\vec{D}_p(X^p,\ b';\ \delta/v) \geq \vec{D}_p(X^p,\ b;\ \delta/v)\ for\ b' \geq\ b \in P(x)$ (6b)
- $\vec{D}_p(X^{p\prime},\ b;\ \delta/v) \geq \vec{D}_p(X^p,\ b;\ \delta/v)\ for\ X^{p\prime} \leq\ X^p\ \in P(x)$ (6c)
- $\vec{D}_p(X^p,\ b\ - \rho g_b\ ; g_b\ ) =\ \vec{D}_p(X^p,\ b;\ \delta/v) -\ \rho, \rho \in \mathbb{R}$ (6d)

For simplicity reasons, we have used $\vec{D}_p$ to represent both $\vec{D}_{pe}$ and $\vec{D}_{pn}$; X^p to represent X^{pe} and X^{pn}; b to represent b^{ghg} and b^n. Property (6a) indicates that $\vec{D}_p(X^p,\ b;\ \delta/v)$ is non-negative for all feasible production possibilities. Property (6b) indicates for a given level of inputs, when bad outputs increase, the distance to the frontier will increase. Property (6c) posits for a given amount of bad outputs, that the distance to the frontier decreases when the polluting inputs increase. Property (6d) imposes the translation property. It means that the inefficiency can decrease by an amount of ρ if bad outputs are contracted by ρg_b.

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5.3.1 Model specification

We specify our directional output-oriented distance function with a quadratic form as below. Each dairy farm is denoted by subscript *k* and the total sample consist of *K* farms. We have also included a time-shifter η following the approach by Ang and Kerstens (2020). In this way, time directly influences the frontier through the time shifter (frontier can only shift without the changing of its shape) and all the other coefficients are time-invariant. The base year for this study is 2010 (t_b). Formulas for the conventional technology are presented first, followed by the ones for the two polluting technologies. We estimated the directional output-oriented distance function in the quadratic form following the deterministic linear programming procedure of Aigner and Chu (1968). Following Ang and Kerstens (2023) and Lamkowsky et al. (2023), we adapt the R code of Ang and Kerstens (2020) to the current context of shadow pricing.

Model for the conventional technology T_1

$$\vec{D}_c(X_k, Y_k\,; g_y) = \alpha + \sum_{e=1}^{E} \alpha^e X_k^e + \sum_{f=1}^{F} \beta^f Y_k^f + \frac{1}{2}\sum_{e=1}^{E}\sum_{e'=1}^{E} \alpha^{ee'} X_k^e X_k^{e'} + \frac{1}{2}\sum_{f=1}^{F}\sum_{f'=1}^{F} \beta^{ff'} Y_k^f Y_k^{f'} + \sum_{e=1}^{E}\sum_{f=1}^{F} \gamma^{ef} X_k^e Y_k^f + \eta(t - t_b) \tag{7}$$

In order to estimate the directional output distance function, we minimize the sum of the deviations of the estimated distance function from the efficient value of zero, subject to the constraints below:

$$\min \sum_{k=1}^{K} (\vec{D}_c(X_k, Y_k\,; g_y) - 0) \tag{8a}$$

s.t.

$$\vec{D}_c(X_k, Y_k\,; g_y) \geq 0, \forall\, k \tag{8b}$$

$$\frac{\partial \vec{D}_c(X_k, Y_k\,; g)}{\partial y} = \beta^f + \beta^{ff} Y_k^f + \frac{1}{2}\sum_{f \neq f'} (\beta^{ff'} + \beta^{f'f}) Y_k^{f'} + \sum_{e=1}^{E} \gamma^{ef} X_k^e \leq 0, \forall\, k \tag{8c}$$

$$\frac{\partial \vec{D}_c(X_k, Y_k\,; g)}{\partial x} = \alpha^e + \alpha^{ee} X_k^e + \frac{1}{2}\sum_{e' \neq e} (\alpha^{ee'} + \alpha^{e'e}) X_k^{e'} + \sum_{f=1}^{F} \gamma^{ef} Y_k^f \geq 0\,, \forall\, k \tag{8d}$$

$$\alpha^{ee'} = \alpha^{e'e}\ with\ e, e' = 1, \dots, E\ and\ e \neq e' \tag{8e}$$

$$\beta^{ff'} = \beta^{f'f}\ with\ f, f' = 1, \dots, F\ and\ f \neq f' \tag{8f}$$

$$\sum_{e=1}^{E} \alpha^e g_e^i - \sum_{f=1}^{F} \beta^f g_f^o = 1 \tag{8g}$$

$$\sum_{e'=1}^{E} \alpha^{ee'} * g_{e'}^i - \sum_{f=1}^{F} \gamma^{ef} * g_f^o = 0\,,\ \forall\, e \tag{8h}$$

$$\sum_{e=1}^{E} \gamma^{ef} * g_e^i - \sum_{f'=1}^{F} \beta^{ff'} * g_{f'}^o = 0, \forall\, f \tag{8i}$$

Constraints (8e) – (8i) satisfy the translation property of the directional distance function for the conventional technology T_1.

Model for the polluting technology T_2 and T_3

For simplicity reasons, we have used $\vec{D}_p$ to represent both $\vec{D}_{pe}$ and $\vec{D}_{pn}$; X_k to represent both X_k^{pe} and X_k^{pn}; b_k to represent b_k^{ghg} and b_k^n; g_b represent g_e and g_n.

$$\vec{D}_p(X_k, b_k\,; g_b) = \alpha_p + \sum_{m=1}^{M} \alpha^m X_k^m + \sum_{n=1}^{2} \beta^n b_k^n + \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M} \alpha^{mm'} X_k^m X_k^{m'} + \frac{1}{2}\sum_{n=1}^{2}\sum_{n'=1}^{2} \beta^{nn'} b_k^n b_k^{n'} + \sum_{n=1}^{2}\sum_{m=1}^{M} \gamma^{nm} b_k^n X_k^m + \eta_p (t - t_b) \tag{9}$$

In order to estimate the directional output distance function, we minimize the sum of the deviations of the estimated distance function from the efficient value of zero, subject to the constraints as below:

$$\min \sum_{k=1}^{K} (\overrightarrow{D_p}(X_k, b_k; g_b) - 0) \tag{10a}$$

s.t.

$$\overrightarrow{D_p}(X_k, b_k; g_b) \geq 0, \forall k \tag{10b}$$

$$\frac{\partial \overrightarrow{D_p}(X_k, b_k; g)}{\partial \mathrm{b}} = \beta^n + \beta^{nn} b_k^n + \frac{1}{2} \sum_{n \neq n'} (\beta^{nn'} + \beta^{n'n}) b_k^{n'} + \sum_{m=1}^{M} \gamma^{nm} X_k^m \geq 0, \forall k \tag{10c}$$

$$\frac{\partial \overrightarrow{D_p}(X_k, b_k; g)}{\partial x} = \alpha^m + \alpha^{mm} X_k^m + \frac{1}{2} \sum_{m' \neq m} (\alpha^{mm'} + \alpha^{m'm}) X_k^{m'} + \sum_{n=1}^{2} \gamma^{nm} b_k^n \leq 0, \forall k \tag{10d}$$

$$\alpha^{mm'} = \alpha^{m'm} \; with \; m, m' = 1, \dots, M \; and \; m \neq m' \tag{10e}$$

$$\beta^{nn'} = \beta^{n'n} \; with \; n, n' = 1, \dots, N \; and \; n \neq n' \tag{10f}$$

$$\sum_{m=1}^{M} \alpha^m g_m^i - \sum_{n=1}^{2} \beta^n g_n^o = 1 \tag{10g}$$

$$\sum_{m'=1}^{M} \alpha^{mm'} * g_{m'}^i - \sum_{n=1}^{2} \gamma^{nm} * g_n^o = 0, \; \forall m \tag{10h}$$

$$\sum_{m=1}^{M} \gamma^{nm} * g_m^i - \sum_{n'=1}^{2} \beta^{nn'} * g_{n'}^o = 0, \forall n \tag{10i}$$

Constraints (10e) – (10i) satisfy the translation property of the directional distance function for the polluting technology T_2 and T_3.

5.3.2 Shadow price estimation

The shadow price can be obtained from the duality relationship between the technology and economic value function (Färe et al., 1993). In this study, we have used the profit function. Shadow prices of negative externalities like GHG emissions and N surplus refer to the estimated economic price of these undesirable outputs. We have calculated the shadow price for GHG emissions and N surplus separately using two different revenue functions.

Shadow price formula for GHG emissions

We measured this shadow price using a profit function:

$$P(X_k^p, X_k^{np}, Y_k, b_k^{ghg}) = Max \{ py_k - q_{ghg} b_k^{ghg} - rx_k^{pv} - sx_k^{np} - ux_k^a - vx_k^m \} \tag{11a}$$

s.t.

$$\overrightarrow{D_c}\left(X_k, Y_k ; 0, g_y\right) \geq 0 \tag{11b}$$

$$\vec{D}_{pe}\left(X_k^{pe}, b_k^{ghg}; 0, g_e\right) \geq 0 \tag{11c}$$

The Lagrange function is formulated as:

$$L = R\left(X_k^p, X_k^{np}, Y_k, b_k\right) - \mu * \overrightarrow{D_c}\left(X_k, Y_k ; 0, g_y\right) - \lambda * \vec{D}_{pe}\left(X_k^{pe}, b_k^{ghg}; 0, g_e\right) \tag{12a}$$

We take partial derivatives of the Lagrange function with respect to X^{pv}, b^{ghg}, and y; and set them equal to zero: $\frac{\partial L}{\partial X^{pv}} = 0$; $\frac{\partial L}{\partial b^{ghg}} = 0$; $\frac{\partial L}{\partial y} = 0$. This yields:

$$-r - \mu \nabla_{X^{pv}} \vec{D}_c - \lambda \nabla_{X^{pv}} \vec{D}_{pe} = 0 \tag{12b}$$

$$-q_{ghg} - \lambda \nabla_{b^{ghg}} \vec{D}_{pe} = 0 \tag{12c}$$

$$p - \mu \nabla_y \vec{D}_c = 0 \tag{12d}$$

We can compute the shadow prices of GHG emissions as: $\boldsymbol{q_{ghg}} = -\boldsymbol{\lambda \nabla_{b^{ghg}} \vec{D}_{pe}}$. λ can be computed from first estimating μ from $p - \mu \nabla_y \vec{D}_c = 0$ (12d); then λ can be estimated using $-r - \mu \nabla_{X^{pv}} \vec{D}_c - \lambda \nabla_{X^{pv}} \vec{D}_{pe} = 0$ (12b).

Shadow prices of GHG emissions can be positive or negative. $\nabla_{b^{ghg}} \vec{D}_{pe}$ is non-negative. λ can be positive or negative. The sign of λ depends on the sign of $(-r - \mu \nabla_{X^{pv}} \vec{D}_c)$ and $\nabla_{X^{pv}} \vec{D}_{pe}$. According to the (10d), $\nabla_{X^{pv}} \vec{D}_{pe}$ is non-positive. The sign of $(-r - \mu \nabla_{X^{pv}} \vec{D}_c)$ can be either positive or negative depending on the value of r and $\mu \nabla_{X^{pv}} \vec{D}_c$. r is positive and $\mu \nabla_{X^{pv}} \vec{D}_c$ is non-negative. μ is negative as p is positive and $\nabla_y \vec{D}_c$ is non-positive, and $\nabla_{X^{pv}} \vec{D}_c$ is non-negative. Observe that shadow prices can also be negative if pollution were modelled as a weakly disposable output, which violates the materials balance principle. However, importantly, this violation is *not* the cause of the potentially negative sign. Equations (12a) - (12d) show that negative shadow prices would occur if the effect of the pollution-generating technology exceeded that of the conventional technology. The potentially negative shadow prices are derived from the by-production approach, and not an artefact of lower theoretical accuracy (Fare & et al., 1989).

Shadow price formula for N surplus

We measured this shadow price using a profit function:

$$P\left(X_k^p, X_k^{np}, Y_k, b_k^n\right) = Max\left\{py_k - q_n b_k^n - rx_k^{pv} - sx_k^{np} - ux_k^a\right\} \tag{13a}$$

s.t.

$$\overrightarrow{D_c}(X_k, Y_k; 0, g_y) \geq 0 \tag{13b}$$

$$\vec{D}_{pn}(X_k^{pn}, b_k^n;\ 0, g_n) \geq 0 \tag{13c}$$

The Lagrange function is formulated as:

$$L = R(X_k^p, X_k^{np}, Y_k, b_k^n) - \mu_2 * \overrightarrow{D_c}(X_k, Y_k; 0, g_y) - \lambda_2 * \vec{D}_{pn}(X_k^{pn}, b_k^n;\ 0, g_n) \tag{14a}$$

Take partial derivatives of the Lagrange function with respect to X^{pv}, b^n, and y; and set them equal to zero: $\frac{\partial L}{\partial X^{pv}} = 0$; $\frac{\partial L}{\partial b^n} = 0$; $\frac{\partial L}{\partial y} = 0$. This will give us :

$$-r - \mu_2 \nabla_{X^{pv}} \vec{D}_c - \lambda_2 \nabla_{X^{pv}} \vec{D}_{pn} = 0 \tag{14b}$$

$$-q_n - \lambda_2 \nabla_{b^n} \vec{D}_{pn} = 0 \tag{14c}$$

$$p - \mu_2 \nabla_y \vec{D}_c = 0 \tag{14d}$$

We can compute the shadow prices of the N surplus as: $\boldsymbol{q_n} = -\boldsymbol{\lambda_2 \nabla_{b^n} \vec{D}_{pn}}$. λ_2 can be computed from first estimating μ_2 from $p - \mu_2 \nabla_y \vec{D}_c = 0$ (14d); then λ_2 can be estimated using $-r - \mu_2 \nabla_{X^{pv}} \vec{D}_c - \lambda_2 \nabla_{X^{pv}} \vec{D}_{pn} = 0$ (14b).

Shadow prices of N surplus can be positive or negative. $\nabla_{b^n} \vec{D}_{pn}$ is non-negative**.** λ_2 can be positive or negative following the same reasoning as previously explained for λ.

5

5.4 Data description

Our study focuses on a sample of Dutch dairy farms over the period of 2010 to 2019. We obtained data from the Dutch Farm Accountancy Data Network (FADN), supplemented with GHG emissions and N surplus data from Wageningen Economic Research. Farmers participate in the FADN voluntarily. In the FADN, specialised 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 yet stratified panel data as farms stay in the sample for a period of 4 to 7 years. This approach ensures that the dataset accurately reflects the national context (van der Meer, 2019). On average, there are 285 dairy farms each year in our sample.

We distinguish technology-specific inputs and outputs. For the conventional technology, both polluting inputs X^{p} and non-polluting inputs X^{np} are used to generate total desirable outputs Y. For the polluting technology T_2, only the polluting inputs X^{pe} are used to generate the undesirable outputs, i.e. GHG emissions. X^{pe} include animal units, aggregated polluting inputs, and manure. For the polluting technology T_3, only the polluting inputs X^{pn} are used to generate the undesirable outputs, i.e. N surplus. X^{pn} include animal units, and aggregated polluting inputs.

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 (API). 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 from Eurostat (2022). We have used X^{pv} for X^{pe}, therefore r is the aggregated Törnqvist price index for variable polluting inputs. p is the aggregated Törnqvist price index for total on-farm desirable outputs.

We have listed the model input and output variables used for each technology consecutively below. The descriptive statistics can be found in Table 5.1. An average dairy farm in our sample has 151 animals in cow equivalent, 65.97 hectare of land, 0.4 million euro of outputs, 12 tons of N surplus (including ammonia, nitrogen oxides, and N content in the manure) and 1,535 tons of GHG emissions in CO_2 equivalent. In this study, we calculate the N content in the manure based on the same calculation as in Lamkowsky et al. (2021) with 4kg N per ton of manure based on statistics of the Netherlands Enterprise Agency (2019). In order to estimate the directional distance functions properly, we have scaled some of the model variables. Rescaling model variables can mitigate the dominant influence of model variables with large values on the results, and ensure the variables are on a comparable scale. We have divided all the monetary variables by 10,000 (X^{pv}, X^{npv}, X^{npf} and Y); total GHG emissions (E) by 10,000; total farm-level nitrogen surplus (N) by 10,000; manure [X^{m}] by 10,000; and labour (X^{labor}) by 100.

Input use for conventional technology T_1:

X^{np} Non-polluting inputs:

- Aggregated variable input [X^{npv}] in 10,000 euro, including animal health costs and animal water use (implicit quantity).
- Aggregated fixed input [X^{npf}] in 10,000 euro, including buildings, machinery & equipment (implicit quantity).
- Fixed input: labour [X^{labor}] in 100 hours, and total land use [X^{land}] in hectare.

X^{p} Polluting inputs:

- Fixed input: animal units [X^{a}] in cow equivalents.
- Variable inputs: aggregated polluting inputs [X^{pv}] in 10,000 euro, including purchased animal feed, crop protection products, purchased fertilisers, seeds, energy use (implicit quantity).

Outputs for conventional technology T_1:

Y Total desirable outputs:

- Aggregated total on-farm livestock and crop outputs [Y] in 10,000 euro (implicit quantity), including revenues from milk and milk products, cattle, and other livestock, as well as crop output revenues from wheat, barley, potatoes, and other arable crops.

Inputs use for polluting technology T_2 (GHG emissions):

X^{pe} Polluting inputs:

- Fixed input: animal unit [X^{a}] in cow equivalent.
- Variable inputs: aggregated polluting inputs [X^{pv}] in 10,000 euro, including purchased animal feed, crop protection products, purchased fertilisers, seeds, energy use (implicit quantity); Manure [X^{m}] in 10,000kg.

Outputs for polluting technology T_2:

b^{ghg} Undesirable outputs:

- Total GHG emissions [E] in carbon dioxide equivalent from crop and livestock production processes in 10,000 kg.

Inputs use for polluting technology T_3 (N surplus):

X^{pn} Polluting inputs:

- Fixed input: animal unit [X^a] in cow equivalent.
- Variable inputs: aggregated polluting inputs [X^{pv}] in 10,000 euro, including purchased animal feed, crop protection products, purchased fertilisers, seeds, energy use (implicit quantity).

Outputs for polluting technology T_3:

b^n Undesirable outputs:

- Total farm-level nitrogen surplus [N][1] including ammonia, nitrogen oxides, and N content in the manure in 10,000 kg.

Table 5.1: Descriptive statistics.

	Animal unit [X^a]	Aggregated polluting variable inputs [X^{pv}]	Aggregated non-polluting variable inputs [X^{npv}]	Aggregated non-polluting fixed inputs [X^{npf}]	Labour [X^{labor}]	Total land use [X^{land}]	Total GHG emissions in CO_2 equivalent [E]	Manure [X^m]	Total nitrogen surplus [N]	Aggregated total livestock and crop outputs [Y]
Unit	Cow equivalents	10,000 Euro	10,000 Euro	10,000 Euro	100 Hour	Hectare	10,000 Kg	10,000 Kg	10,000 Kg	10,000 Euro
Mean	151.06	11.73	1.94	50.34	47.40	65.97	153.46	54.33	1.20	40.65
Stand dev	98.38	9.45	1.41	42.44	27.88	39.95	112.80	92.76	1.08	32.85
Median	125.37	9.26	1.60	37.18	40.56	55.36	125.05	18.87	0.96	32.69
Minimum	14.73	0.26	0.08	1.95	13.50	8.45	3.35	0	-1.43	2.47
Maximum	828.52	94.21	19.44	412.43	374.51	360.20	958.20	1,259.60	10.16	522.22
1st Quartile	82.69	5.41	1.05	18.68	31.73	36.96	76.88	0.00	0.51	19.98
3rd Quartile	191.11	14.74	2.43	71.32	55.50	83.91	188.11	72.11	1.57	51.00

[1] There are 127 negative values for the N variable. Negative values of nitrogen surplus indicate a deficit of nitrogen on the farm. Farms with negative nitrogen surplus are treated the same way as farms with positive nitrogen surplus in our model.

5.5 Results

We estimated the directional output-oriented distance function in the quadratic form following the linear programming procedure of Aigner and Chu (1968). We implemented the R replication code based on Ang and Kerstens (2023) and adapted it to our case with the additional estimation of the two polluting technologies modelled via the by-production approach. In the conventional technology, there are three monotonicity violations regarding animal unit, one monotonicity violation regarding aggregated polluting variable inputs and one monotonicity violation regarding the labour use. In the polluting technology T_2 for the GHG emissions, there are two monotonicity violations regarding animal unit, two monotonicity violations regarding aggregated polluting variable inputs, and one monotonicity violations regarding the total manure. In the polluting technology T_3 for the N surplus, there is one monotonicity violation regarding the aggregated polluting variable inputs. All these monotonicity violations are very small values close to zeros. Therefore, we conclude that these violations are the results of optimization errors. We treat these small values as zeros.

The tolerance level is set at 1e-8 for the monotonicity constraints. The parameter estimates for quadratic DFA models regarding the conventional technology $\boldsymbol{T_1}$, the polluting technology $\boldsymbol{T_2}$ and $\boldsymbol{T_3}$ can be found in Appendix 5A, 5B & 5C.

We present the inefficiency scores in section 5.5.1, followed by shadow prices estimation results in section 5.5.2. To check the robustness of the shadow price estimates, we estimated a quadratic functional form using Ordinary Least Squares (OLS) regression models. The model formulations and results are in Appendix 5D.

5.5.1 Inefficiency scores

The summary statistics of the inefficiency estimates can be seen in Table 5.2. For the conventional technology, the mean inefficiency score is estimated as 0.43. This means that on average, *ceteris paribus*, the value of the total desirable outputs could be increased by a value that is 0.43 times the mean value of good outputs, which is 174,813 euro (0.43*406,542.10). For the least efficient farm in our sample, it turns out that the value of its total livestock and crop outputs could be increased by 1,752,197 euro (4.31*406,542.10).

For the polluting technology for GHG emissions, the mean inefficiency score is estimated as 0.47 using the mean value of GHG emissions as directional vector. This means that, on average the GHG emissions could be reduced by 721 tons of CO_2 equivalents (0.47*1,534.6 tons) on Dutch dairy farms, *ceteris paribus*. For the polluting technology for N surplus, the mean inefficiency score is estimated as 1.85 using the mean value of N surplus as directional vector.

This means that, on average, the N surplus could be reduced by 22.2 tons (1.85*12 tons), *ceteris paribus*. For the least efficient farm in terms of GHG emissions in our sample, *ceteris paribus*, its GHG emissions could be reduced by 4,128 tons. This maximum reduction of the least efficient farms in terms of N surplus is 104.88 tons. This reduction potential is more than the maximum of N surplus in the sample since some farms have a negative N surplus.

Table 5.2: Summary of inefficiency estimates by deterministic frontier analysis.

	Min	1st quartile	Median	Mean	3rd quartile	Max
Conventional technology	0	0.20	0.31	0.43	0.51	4.31
Polluting technology GHG emissions	0	0.34	0.43	0.47	0.53	2.69
Polluting technology N surplus	0	1.27	1.73	1.85	2.26	8.74

The histogram of inefficiency estimates for the conventional technology and the two polluting technologies can be seen in Figures 5.3, 5.4 and 5.5.

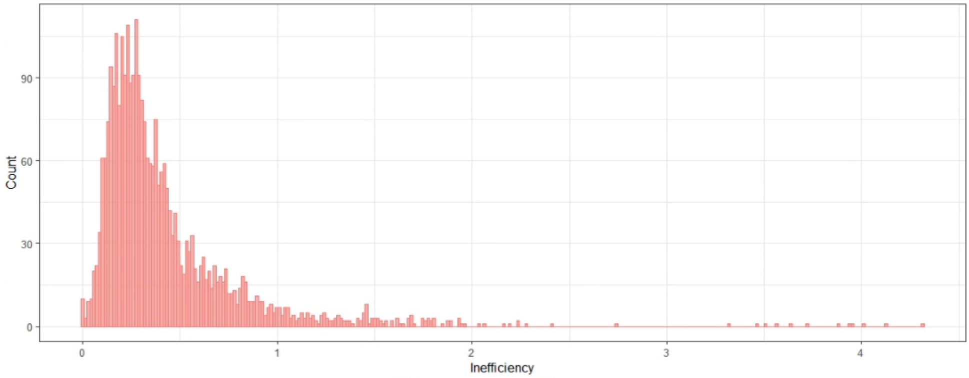

Figure 5.3: Histogram of inefficiencies for the conventional technology.

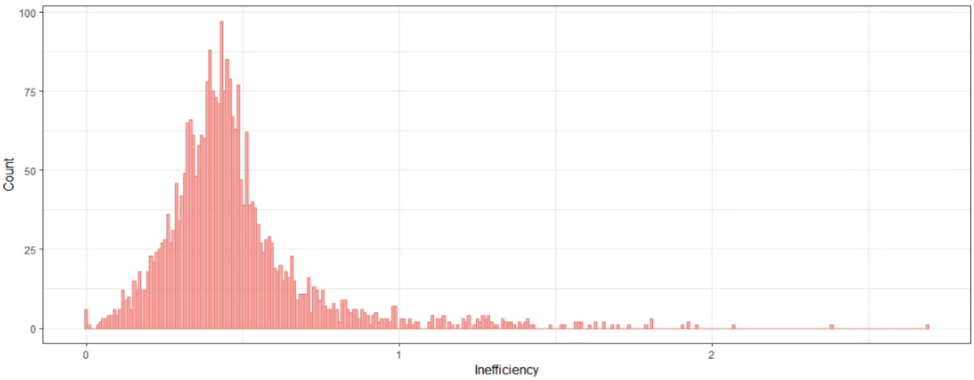

Figure 5.4: Histogram of inefficiencies for the polluting technology T_2 of GHG emissions.

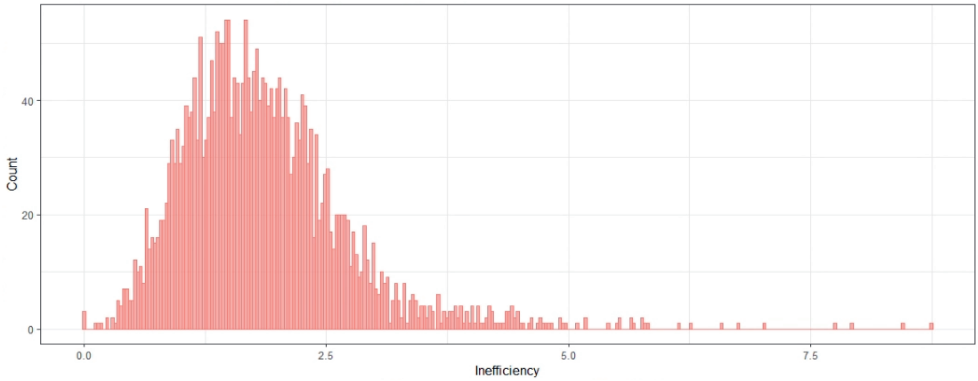

Figure 5.5: Histogram of inefficiencies for the polluting technology T_3 of N Surplus.

5.5.2 Shadow price estimation using the deterministic frontier analysis

The summary statistics of the shadow prices using the deterministic frontier analysis are presented in Table 5.3. Table 5.3 shows the estimation results after dropping the smallest shadow price for N surplus (-1.03e+14) and the two smallest shadow prices for GHG emissions (-6.34e+13, -5.25e+13). These very small estimates are caused by optimization errors. The mean shadow price for GHG emissions is estimated to be 12.09 euro/kg, i.e., the cost for Dutch dairy farmers to mitigate one kg of GHG emissions is 12.09 euro on average. The mean shadow price for N surplus is estimated to be 22.31 euro/kg. This informs us that the average cost for Dutch dairy farmers to mitigate one kg of N surplus is 22.31 euro on average. To visualize the distribution of the shadow price estimates, two kernel density plots are used to display the probability density function of each shadow price estimate (Figure 5.6 & Figure 5.7). Both distributions (Figure 5.6 & Figure 5.7) are left-skewed with one very large value on the right side.

The maximum shadow price for GHG emissions is 623.32 euro/kg and the minimum shadow price is -3.06 euro/kg. The maximum shadow price for N surplus is 458.62 euro/kg and the minimum shadow price is -41.09 euro/kg. This means for some farms it is extremely costly to reduce GHG emissions/N surplus and for other farms it is economically beneficial to reduce emissions/N surplus. The price of emission allowance traded on the European Union's Emission Trading System (ETS) is around 77 euro/ton of carbon dioxide (Statista, 2022). The median shadow price for GHG emissions is 3.66 euro/kg which is 3,660 euro/ton. The median GHG shadow price estimation is much higher than the market price of emission allowance traded on the ETS. Hence, it is very costly for Dutch dairy farms to reduce the farming-related GHG emissions.

To check the robustness of the shadow price estimation, we have deployed a quadratic functional form estimated using Ordinary Least Squares. Appendix 5D presents the model formulations in detail. Table D1 in Appendix 5D summarizes these shadow prices estimates for GHG emissions and N surplus using OLS. Using OLS, the mean shadow price for GHG emissions is estimated to be 77.03 euro/ton or 0.08 euro/kg; and the mean shadow price for N surplus is estimated to be 6.08 euro/kg.

Table 5.3: Summary of shadow prices (euro/kg) of GHG emissions and N surplus using the deterministic frontier analysis (after removing the extremely small estimations caused by optimization errors).

	Min	1st quartile	Median	Mean	3rd quartile	Max
Shadow price GHG emissions	-3.06	1.20	3.66	12.09	15.14	623.32
Shadow price N surplus	-41.09	15.71	20.24	22.31	25.07	458.62

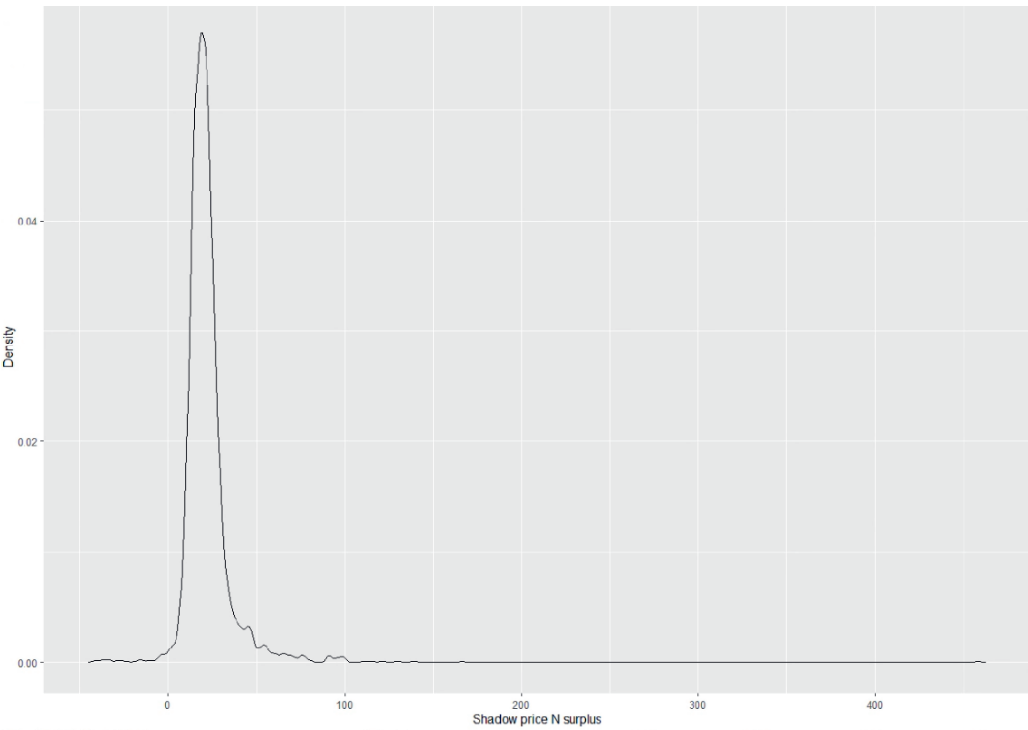

Figure 5.6: Kernel density plot of the N surplus shadow price.

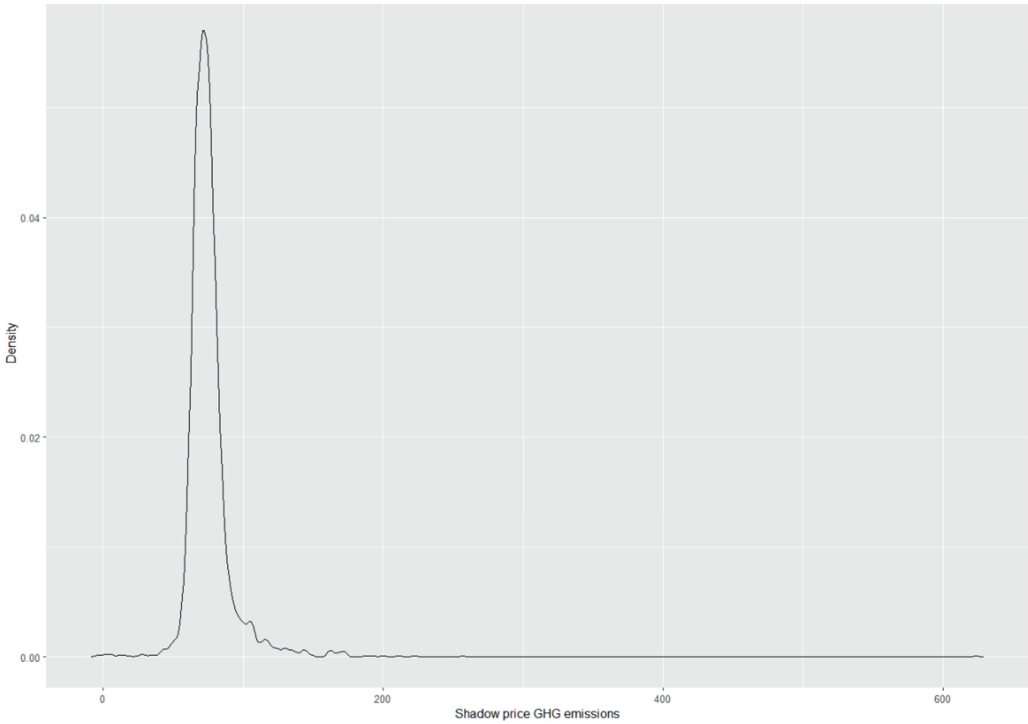

Figure 5.7: Kernel density plot of the GHG emission shadow price.

5

5.6 Discussion and Conclusion

In this study, we analysed the environmental efficiency of Dutch dairy farms and assessed the shadow prices of total GHG emissions and N surplus using a quadratic directional output-oriented distance function. We have demonstrated how to combine the deterministic frontier analysis with the by-production approach in modelling dairy production with negative externalities. Our results point to a potential average increase of 174,813 euro for revenues from total on-farm livestock and crop production. Furthermore, our model suggests that on average, GHG emissions in CO_2 equivalents can be reduced by 721 tons, and N surplus can be reduced by 22.2 tons.

Our findings indicate a substantial 43% potential increase in total production (in deflated revenue) for Dutch dairy farms on average. A result that exhibits a notable resemblance of 34% profit increase for Dutch dairy farms that was reported by Lamkowsky et al. (2021). Our results point out a 47% potential for reducing GHG emissions on Dutch dairy farms. 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 French suckler cow farms, Dakpo and Oude Lansink (2019) found an average inefficiency score of 26.5% for GHG emissions for the years of 2006-2014. Baležentis et al. (2022) found a 20% to 25% reduction potential of GHG emissions for Lithuanian dairy farms for the years 2015, 2017 and 2019. The estimated reduction potential of GHG emissions in this study is lower than Swedish dairy farms and higher than Lithuanian dairy farms and French suckler cow farms.

Furthermore, our study identifies an average of 22.2 tons reduction potential in terms of N surplus compared to an average of 6.56 tons reduction by Lamkowsky et al. (2021). However, it is important to note that we estimated the inefficiency scores per technology using DFA models whereas the estimations from Lamkowsky et al. (2021) were done as a subsequent maximization of profit and minimization of N surplus for the profit-maximizing levels of polluting inputs using DEA. In addition, the N surplus data used in Lamkowsky et al. (2021) differs from this paper in that they also included the biological and atmospheric fixations in nitrogen inflows. The average N surplus is 12.79 tons in Lamkowsky et al. (2021) whereas the average N surplus is 12 tons in this study.

Moreover, DEA models are in principle more conservative than DFA models in estimating inefficiencies. The reason is that DFA models are sensitive to extreme data points as DFA models involve specifying a functional production form which envelops all observations, also observations with large values in terms of outputs over inputs. Any deviation from the estimated frontier is considered inefficiency. We have checked the inefficiency estimates by deterministic frontier analysis after dropping the efficient observations per technology (see Appendix 5E). The results show that by removing the efficient observations per technology, the inefficiency estimates become smaller in general with only the maximum inefficiency score of conventional technology becoming larger. Hence, DFA does give relatively smaller estimations for inefficiency scores when the observations on the frontiers are removed.

Shadow prices indicate the loss of marketable outputs in euro from one unit reduction of undesirable outputs, in our case, the GHG emissions and N surplus. The estimated median GHG shadow price is 3.66 euro per kg of CO_2 equivalent for Dutch dairy farms using the DFA models, whereas the estimated GHG shadow price is 58.05 euro/ton of CO_2 equivalent using the OLS models. Baležentis et al. (2022) found the shadow price in the range of 41.54 to 55.89 euro per ton CO_2 equivalent for Lithuanian dairy farms. Wettemann and Latacz-Lohmann (2017) found an average shadow price of 165 euro/ton CO_2 equivalent for northern German dairy farms. Cecchini et al. (2018) found an average shadow price of 243.08 euro per ton of CO_2 equivalent for Italian cattle farms. Our OLS model results are more comparable to the shadow prices estimations of CO_2 equivalent in other studies, yet our DFA results are a lot larger than other studies.

Our estimated median shadow price for N surplus (N losses and N content in manure) is 20.24 euro/kg using the DFA model and 4.07 euro/kg using the OLS models. The average disposing cost of cattle manure over the year 2010-2019 was 8.41 euro/ton based on Wageningen Economic Research (2022), which is equivalent to 2.1 euros/kg of N content in the manure (as there are 4kg N per ton of manure based on statistic of the Netherlands Enterprise Agency (2019)). Our OLS model results are more comparable to the disposable costs of 2.1 euro per kg of N in the manure. Adenuga et al. (2019) found the mean shadow price of N surplus was 4.02 euro/kg for the Republic of Ireland, and 6.2 euro/kg for the Northern Ireland. N surplus is estimated based on the total N inputs minus the total N outputs, including the biological fixation and atmospheric deposition and excluding the manure in the study of Adenuga et al. (2019). Our OLS model results are more comparable to the shadow prices estimations of N surplus in other studies, yet our DFA results are larger than other studies.

Overall, we conclude that our estimations based on the OLS models are more in line with the results of earlier studies than the results from the DFA models. The reason why our shadow price estimations for GHG emissions and N surplus based on DFA models are so big could be due to the steep slope of the frontier in each polluting technology, in addition to the differences in modelling approaches and study areas/time from other studies. Considering the wide span of the shadow price estimations based on both models as well as the significant estimation differences, we suggest as future research to further estimate the shadow prices of these negative externalities using other modelling approaches. A meta-frontier model could be valuable in comparing different shadow price estimations from different group frontiers based on their economies of scale (Shen et al., 2021).

Appendix 5A: Parameter estimates of the quadratic directional output distance function for the conventional technology.

Coefficients	Variable	Value
a_0	Intercept	-0.0220
ah_1	x^1	0.0019
ah_2	x^2	0.0457
ah_3	x^3	0
ah_4	x^4	0
ah_5	x^5	-0.0006
ah_6	x^6	0.0052
alfa_1_1	x^1x^1	-1.522e-07
alfa_1_2	x^1x^2	-8.918e-05
alfa_1_3	x^1x^3	0
alfa_1_4	x^1x^4	0
alfa_1_5	x^1x^5	6.268e-05
alfa_1_6	x^1x^6	-8.811e-06
alfa_2_2	x^2x^2	0.0013
alfa_2_3	x^2x^3	0
alfa_2_4	x^2x^4	0
alfa_2_5	x^2x^5	-0.0001
alfa_2_6	x^2x^6	1.512e-05
alfa_3_3	x^3x^3	0
alfa_3_4	x^3x^4	0
alfa_3_5	x^3x^5	0
alfa_3_6	x^3x^6	0
alfa_4_4	x^4x^4	0
alfa_4_5	x^4x^5	0
alfa_4_6	x^4x^6	0
alfa_5_5	x^5x^5	-1.629e-05
alfa_5_6	x^5x^6	4.724e-06
alfa_6_6	x^6x^6	-2.637e-06
gamma_1_1	x^1y	0
gamma_2_1	x^2y	0
gamma_3_1	x^3y	0
gamma_4_1	x^4y	0
gamma_5_1	x^5y	0
gamma_6_1	x^6y	0
bh_1	y	-0.0246
beta_1_1	yy	0
dh_1	μ	0.0113

Note: X^1 = animal unit, X^2 = aggregated polluting variable inputs, X^3 = aggregated non-polluting variable inputs, X^4 = aggregated non-polluting fixed inputs, X^5 = labour, X^6 = land use, y = aggregated total livestock and crop outputs, μ = time shifter.

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Appendix 5B: Parameter estimates of the quadratic directional output distance function for the polluting technology T_2.

	Variable	Value
a_0	Constant	0.5358
ah_1	b^1	0.0065
alfa_1_1	$b^1 b^1$	0
gamma_1_1	$b^1 x^1$	0
gamma_1_2	$b^1 x^2$	0
gamma_1_3	$b^1 x^3$	0
bh_1	x^1	-0.0066
bh_2	x^2	1.940e-05
bh_3	x^3	3.824e-05
beta_1_1	$x^1 x^1$	1.007e-05
beta_1_2	$x^1 x^2$	-3.533e-06
beta_1_3	$x^1 x^3$	-1.243e-06
beta_2_2	$x^2 x^2$	2.143e-05
beta_2_3	$x^2 x^3$	-4.086e-05
beta_3_3	$x^3 x^3$	2.336e-06
dh_1	μ	-0.0363

Note: b^1 = total GHG emissions in CO_2 equivalent, X^1 = animal unit, X^2 = aggregated polluting variable inputs, X^3 = manure, μ = time shifter.

Appendix 5C: Parameter estimates of the quadratic directional output distance function for the polluting technology T_3.

	Variable	Value
a_0	Constant	0.4739
ah_1	b^1	0.8332
alfa_1_1	b^1b^1	0
gamma_1_1	b^1x^1	0
gamma_1_2	b^1x^2	0
bh_1	x^1	-5.309e-12
bh_2	x^2	-0.0275
beta_1_1	x^1x^1	-5.661e-14
beta_1_2	x^1x^2	0
beta_2_2	x^2x^2	0.0003
dh_1	μ	0.1453

Note: b^1 = total nitrogen surplus, X^1 = animal unit, X^2 = aggregated polluting variable inputs, μ = time shifter.

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Appendix 5D: Robustness check of the shadow price estimation via the quadratic function estimated using ordinary least squares regression models.

To check the robustness of the shadow price estimation, we used quadratic OLS regression models. SFA and DEA are both possible approaches to check the robustness with their own advantages and disadvantages in this case. The deterministic parametric method cannot incorporate random errors which the SFA addresses. However, the SFA method does not fully satisfy the monotonicity property when using distance functions (Rezek & Campbell, 2007). Nonparametric methods can also be used to estimate shadow prices for both the Shephard and directional distance function via DEA. However, the shadow prices are not limited to one unique value at the kinks as DEA lacks smoothness at the extreme efficient firms resulting from the convex hulls of observed data points (Puggioni & Stefanou, 2019).

For a simple check, we have adjusted the deterministic frontier analysis model with quadratic OLS regression models. The only difference is that there are no inefficiency estimates when using OLS models. Shadow prices for undesirable outputs are estimated using the duality theory and the LaGrange multiplier. OLS models have been used to calculate shadow prices. Zhang et al. (2021) have found that shadow price estimations using OLS and SFA are very similar for CO_2 emissions in Chinese coal-fired power plants. Below, we provide the formulas and results using both the OLS models.

Shadow price estimates for GHG using quadratic OLS models

The quadratic production function of GHG (E):

$$e = \beta_0 + \beta_1 x_a + \beta_2 x_{pv} + \beta_3 x_a^2 + \beta_4 x_{pv}^2 + \beta_5 x_a x_{pv} + \beta_6 x_m + \beta_7 x_m^2 + \beta_8 x_a x_m + \beta_{59} x_m x_{pv} + \varepsilon + \eta_{pe}(t - t_b) \quad (1)$$

The quadratic production function of total on-farm production:

$$y = \alpha_0 + \alpha_1 x_a + \alpha_2 x_{pv} + \alpha_3 x_{npv} + \alpha_4 x_{npf} + \alpha_5 x_{labor} + \alpha_6 x_{land} + \alpha_7 x_a^2 + \alpha_8 x_{pv}^2 + \alpha_9 x_{npv}^2 + \alpha_{10} x_{npf}^2 + \alpha_{11} x_{labor}^2 + \alpha_{12} x_{land}^2 + \alpha_{13} x_a x_{pv} + \alpha_{14} x_a x_{npv} + \alpha_{15} x_a x_{npf} + \alpha_{16} x_a x_{labor} + \alpha_{17} x_a x_{land} + \alpha_{18} x_{pv} x_{npv} + \alpha_{19} x_{pv} x_{npf} + \alpha_{20} x_{pv} x_{labor} + \alpha_{21} x_{pv} x_{land} + \alpha_{22} x_{npv} x_{npf} + \alpha_{23} x_{npv} x_{labor} + \alpha_{24} x_{npv} x_{land} + \alpha_{25} x_{npf} x_{labor} + \alpha_{26} x_{npf} x_{land} + \alpha_{27} x_{labor} x_{land} + \epsilon + \eta(t - t_b) \quad (2)$$

The profit maximization function of a dairy farm:

$$profit = \max_c (py - w_a x_a - w_{pv} x_{pv} - w_m x_m - w_{npv} x_{npv} - w_{npf} x_{npf} - w_{labor} x_{labor} - w_{land} x_{land} - s * e) \quad (3)$$

Using the LaGrange multipliers:

$$L = (py - w_a x_a - w_{pv}x_{pv} - w_m x_m - w_{npv}x_{npv} - w_{npf}x_{npf} - w_{labor}x_{labor} - w_{land}x_{land} - s * e) - \lambda\,[e - (\beta_0 + \beta_1 x_a + \beta_2 x_{pv} + \beta_3 x_a^2 + \beta_4 x_{pv}^2 + \beta_5 x_a x_{pv} + \beta_6 x_m + \beta_7 x_m^2 + \beta_8 x_a x_m + \beta_{59} x_m x_{pv} + \varepsilon + \eta_{pe}(t - t_b))] - \theta\,[y - (\alpha_0 + \alpha_1 x_a + \alpha_2 x_{pv} + \alpha_3 x_{npv} + \alpha_4 x_{npf} + \alpha_5 x_{labor} + \alpha_6 x_{land} + \alpha_7 x_a^2 + \alpha_8 x_{pv}^2 + \alpha_9 x_{npv}^2 + \alpha_{10} x_{npf}^2 + \alpha_{11} x_{labor}^2 + \alpha_{12} x_{land}^2 + \alpha_{13} x_a x_{pv} + \alpha_{14} x_a x_{npv} + \alpha_{15} x_a x_{npf} + \alpha_{16} x_a x_{labor} + \alpha_{17} x_a x_{land} + \alpha_{18} x_{pv} x_{npv} + \alpha_{19} x_{pv} x_{npf} + \alpha_{20} x_{pv} x_{labor} + \alpha_{21} x_{pv} x_{land} + \alpha_{22} x_{npv} x_{npf} + \alpha_{23} x_{npv} x_{labor} + \alpha_{24} x_{npv} x_{land} + \alpha_{25} x_{npf} x_{labor} + \alpha_{26} x_{npf} x_{land} + \alpha_{27} x_{labor} x_{land} + \epsilon + \eta(t - t_b))] \quad (4)$$

Take 1[st] order derivatives with respect to y, e, x_{npv}, x_{npf}, and x_{pv}:

$$\frac{dL}{dy} = p - \theta = 0 \quad (5)$$

$$\frac{dL}{de} = -s - \lambda = 0\,;\, s = -\lambda \quad (6)$$

$$\frac{dL}{dxpv} = -w_{pv} - \lambda(-\beta_2 - 2\beta_4 x_{pv} - \beta_5 x_a) - \theta\,(-\alpha_2 - 2\alpha_8 x_{pv} - \alpha_{13} x_a - \alpha_{18} x_{npv} - \alpha_{19} x_{npf} - \alpha_{20} x_{labor} - \alpha_{21} x_{land}) = 0 \quad (7)$$

It is possible to get the shadow price estimates for S in (6) through (5) and (7).

Shadow price estimates for N using quadratic OLS models

The quadratic production function of N surplus (N):

$$n = \beta_0 + \beta_1 x_a + \beta_2 x_{pv} + \beta_3 x_a^2 + \beta_4 x_{pv}^2 + \beta_5 x_a x_{pv} + \varepsilon + \eta_{pn}(t - t_b) \quad (1)$$

The quadratic production function of total on-farm production:

$$y = \alpha_0 + \alpha_1 x_a + \alpha_2 x_{pv} + \alpha_3 x_{npv} + \alpha_4 x_{npf} + \alpha_5 x_{labor} + \alpha_6 x_{land} + \alpha_7 x_a^2 + \alpha_8 x_{pv}^2 + \alpha_9 x_{npv}^2 + \alpha_{10} x_{npf}^2 + \alpha_{11} x_{labor}^2 + \alpha_{12} x_{land}^2 + \alpha_{13} x_a x_{pv} + \alpha_{14} x_a x_{npv} + \alpha_{15} x_a x_{npf} + \alpha_{16} x_a x_{labor} + \alpha_{17} x_a x_{land} + \alpha_{18} x_{pv} x_{npv} + \alpha_{19} x_{pv} x_{npf} + \alpha_{20} x_{pv} x_{labor} + \alpha_{21} x_{pv} x_{land} + \alpha_{22} x_{npv} x_{npf} + \alpha_{23} x_{npv} x_{labor} + \alpha_{24} x_{npv} x_{land} + \alpha_{25} x_{npf} x_{labor} + \alpha_{26} x_{npf} x_{land} + \alpha_{27} x_{labor} x_{land} + \epsilon + \eta(t - t_b) \quad (2)$$

The profit maximization function of a dairy farm:

$$profit = \max_c (py - w_a x_a - w_{pv}x_{pv} - w_{npv}x_{npv} - w_{npf}x_{npf} - w_{labor}x_{labor} - w_{land}x_{land} - c * n) \quad (3)$$

Using the LaGrange multipliers:

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$$L = \left(py - w_a x_a - w_{pv} x_{pv} - w_{npv} x_{npv} - w_{npf} x_{npf} - w_{labor} x_{labor} - w_{land} x_{land} - c * n\right) - \mu\,[n - (\beta_0 + \beta_1 x_a + \beta_2 x_{pv} + \beta_3 x_a^2 + \beta_4 x_{pv}^2 + \beta_5 x_a x_{pv} + \varepsilon + \eta_{pn}(t - t_b))] - \gamma\,[y - (\alpha_0 + \alpha_1 x_a + \alpha_2 x_{pv} + \alpha_3 x_{npv} + \alpha_4 x_{npf} + \alpha_5 x_{labor} + \alpha_6 x_{land} + \alpha_7 x_a^2 + \alpha_8 x_{pv}^2 + \alpha_9 x_{npv}^2 + \alpha_{10} x_{npf}^2 + \alpha_{11} x_{labor}^2 + \alpha_{12} x_{land}^2 + \alpha_{13} x_a x_{pv} + \alpha_{14} x_a x_{npv} + \alpha_{15} x_a x_{npf} + \alpha_{16} x_a x_{labor} + \alpha_{17} x_a x_{land} + \alpha_{18} x_{pv} x_{npv} + \alpha_{19} x_{pv} x_{npf} + \alpha_{20} x_{pv} x_{labor} + \alpha_{21} x_{pv} x_{land} + \alpha_{22} x_{npv} x_{npf} + \alpha_{23} x_{npv} x_{labor} + \alpha_{24} x_{npv} x_{land} + \alpha_{25} x_{npf} x_{labor} + \alpha_{26} x_{npf} x_{land} + \alpha_{27} x_{labor} x_{land} + \epsilon + \eta(t - t_b))] \quad (4)$$

Take 1st order derivatives with respect to y, nm, x_{npv}, x_{npf}, and x_{pv}:

$$\frac{dL}{dy} = p - \gamma = 0 \quad (5)$$

$$\frac{dL}{dn} = -c - \mu = 0\,;\, C = -\mu \quad (6)$$

$$\frac{dL}{dxpv} = w_{pv} - \mu(-\beta_2 - 2\beta_4 x_{pv} - \beta_5 x_a) - \gamma\left(-\alpha_2 - 2\alpha_8 x_{pv} - \alpha_{13} x_a - \alpha_{18} x_{npv} - \alpha_{19} x_{npf} - \alpha_{20} x_{labor} - \alpha_{21} x_{land}\right) = 0 \quad (7)$$

It is possible to get the shadow price estimates *C* in (6) through (5) and (7).

Table D1 summarizes these shadow prices estimates in for GHG emissions and N surplus using OLS models. Using OLS models, the mean shadow price for GHG emissions is estimated to be 77.03 euro/ton; and the mean shadow price for N surplus is estimated to be 6.08 euro/kg. The parameter estimates of the quadratic OLS models for each technology can be seen in the following pages.

Table D1: Summary of shadow prices of GHG emissions and nitrogen surplus using the quadratic OLS models.

	Min	1st quartile	Median	Mean	3rd quartile	Max
Shadow price GHG emissions (euro/ton)	-1456.52	19.61	58.05	77.03	102.85	7532.75
Shadow price N surplus (euro/kg)	-1513.76	1.27	4.07	6.08	7.39	2872.72

Parameter estimates of the quadratic OLS model for the conventional technology.

Variable	Coefficient
Intercept	-2.054e+00
x^1	6.724e-02
x^2	1.622e+00
x^3	-5.352e-01
x^4	-1.649e-02
x^5	-8.322e-02
x^6	1.812e-01
x^1x^1	-5.462e-04
x^1x^2	1.208e-04
x^1x^3	2.859e-02
x^1x^4	9.682e-04
x^1x^5	2.736e-03
x^1x^6	- 4.976e-04
x^2x^2	3.351e-02
x^2x^3	-1.997e-01
x^2x^4	-5.394e-03
x^2x^5	-1.693e-02
x^2x^6	6.580e-03
x^3x^3	-3.228e-01
x^3x^4	8.822e-03
x^3x^5	6.124e-02
x^3x^6	-3.237e-02
x^4x^4	-6.900e-04
x^4x^5	-3.098e-04
x^4x^6	5.299e-04
x^5x^5	-2.213e-04
x^5x^6	-2.190e-03
x^6x^6	1.183e-04
η	6.725e-01

Note: X^1 = animal unit, X^2 = aggregated polluting variable inputs, X^3 = aggregated non-polluting variable inputs, X^4 = aggregated non-polluting fixed inputs, X^5 = labour, X^6 = land use, y = aggregated total livestock and crop outputs, η = time shifter.

Parameter estimates of the quadratic OLS model for the polluting technology T_2: total GHG emissions.

Variable	Coefficient
Constant	-1.436e+01
x^1	7.522e-01
x^2	3.134e+00
x^3	8.391e-02
x^1x^1	-1.291e-03
x^1x^2	3.096e-02
x^1x^3	-7.834e-04
x^2x^2	-1.500e-01
x^2x^3	6.354e-03
x^3x^3	-8.058e-05
η_{pe}	2.535e+00

Note: X^1 = animal unit, X^2 = aggregated polluting variable inputs, X^3 = manure, η_{pe} = time shifter.

Parameter estimates of the quadratic OLS model for the polluting technology T_3: total nitrogen surplus.

Variable	Coefficient
Constant	8.640e-02
x^1	2.491e-03
x^2	6.132e-02
x^1x^1	-7.288e-06
x^1x^2	2.986e-04
x^2x^2	-2.000e-03
η_{pn}	-1.577e-02

Note: X^1 = animal unit, X^2 = aggregated polluting variable inputs, η_{pn} = time shifter.

Appendix 5E: Summary of inefficiency scores with full sample and after dropping the efficient observations via DFA models.

Table E1: Summary of inefficiency scores for the conventional technology.

	Min	1st quartile	Median	Mean	3rd quartile	Max
Conventional technology (full sample: 2854 observations)	0	0.20	0.31	**0.43**	0.51	**4.31**
Conventional technology (drop the efficient observations: 2846 observations)	0	**0.16**	**0.25**	**0.37**	**0.43**	**5.26**

Table E2: Summary of inefficiency scores for the GHG technology.

	Min	1st quartile	Median	Mean	3rd quartile	Max
GHG technology (full sample: 2854 observations)	0	0.34	0.43	0.47	0.53	**2.69**
GHG technology emissions (drop the efficient observations: 2849 observations)	0	**0.24**	**0.35**	**0.40**	**0.50**	**2.34**

Table E3: Summary of inefficiency scores for the N surplus technology.

	Min	1st quartile	Median	Mean	3rd quartile	Max
N surplus technology (full sample: 2854 observations)	0	1.27	1.73	1.85	2.26	**8.74**
N surplus technology (drop the efficient observations: 2851 observations)	0	**1.07**	**1.51**	**1.61**	**2.01**	**7.21**

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6

General discussion

In response to the imperative of meeting national reduction targets, the current policies for the Dutch dairy sector emphasize the voluntary adoption of climate mitigation measures by farmers and the integration of circular agriculture principles. The overall objective of this thesis was to assess the potential for, and costs of reducing GHG emissions with a special reference towards the role of farmers' behavioural factors in the adoption of mitigation measures and farm environmental performance.

Farmers’ decision making takes place in a dynamic environment, characterised by economic, political, social and ecological changes. The decisions we studied in this thesis centre on farmers’ voluntary adoption of climate mitigation measures in different stages (Chapter 2), and the role of land optimization in delivering better farm performance (Chapter 3). Farm performance is assessed by quantifying the environmental inefficiency in generating GHG emissions, and technical inefficiency in producing marketable outputs (Chapter 3). Socio-psychological and socio-economic determinants of environmental and technical inefficiency in Dutch dairy farming are identified in Chapter 4. The reduction potential and shadow prices for GHG emissions and nitrogen surplus are quantified in Chapter 5.

The remainder of this chapter is structured as follows. Section 6.1 synthesizes results across the four research chapters and compares these results to the existing literature, followed by implications for policy and business separately in section 6.2. Section 6.3 reflects on methods and data employed in this thesis and section 6.4 suggests directions for future research. Section 6.5 concludes with a list of main conclusions across chapters.

6.1 Synthesis of results

In this synthesis, we first discuss the role of socio-psychological factors in farmers’ decision making. Subsequently, we discuss the role of socio-demographical and socio-economic factors in farmers’ decision making. We then go into the reduction potential and economic costs of reducing GHG emissions and nitrogen surplus on Dutch dairy farms. Lastly, we comment on behavioural measures and financial incentives in farmers’ adoption decisions.

6.1.1 Socio-psychological factors in farmers’ decision making

The associations of eleven socio-psychological factors with different adoption intentions have been studied in Chapter 2 based on the SSBC model. A subset of socio-psychological factors based on the SSBC model has been used to check their associations with farm environmental and technical inefficiency in Chapter 4. This reduced set of explanatory variables results from the independence criteria for selecting explanatory factors in the second stage regression. This set comprises seven socio-psychological factors from the pre-decisional and pre-actional stages.

First, we found that negative emotion, personal norm, perceived goal feasibility, action planning, and coping planning have varying effects across four adoption stages. These stage-dependent linear relations are contrary to the linear relations of explanatory variables and the adoption intentions as postulated by the TPB model (Ajzen, 1991). Compared to the TBP model, the SSBC model allows assessing the intensity of a more comprehensive set of social-psychological factors across four stages. The ANOVA analysis in Chapter 2 revealed significant differences among the means of these five mentioned socio-psychological factors across stages, but not for positive emotion, perceived social norm, attitude, perceived behavioural control, maintenance self-efficacy, and recovery self-efficacy. Yet, previous studies using the SSBC model have found that the 'entire set of differently chosen' socio-psychological factors exhibited different effects across stages (Bamberg, 2013b; Ohnmacht et al., 2018; Weibel et al., 2019). Differences in significant factors may stem from variations in sample characteristics, variable choices, model specifications, social and cultural contexts, and random behavioural fluctuations.

Second, the SSBC model provides a novel theoretical lens in identifying and contrasting the stage-specific influencing factors on farmers' adoption intentions. Personal norm is positively associated with our sample farmers' goal intention in reducing on-farm GHG emissions within the coming three years (Chapter 2), but it is not associated with the environmental inefficiency in generating on-farm GHG emission (Chapter 4). Attitude and goal intention are positively associated with our sample farmers' behavioural intention in adopting their preferred mitigation measures in the coming three years (Chapter 2), but they are not associated with the environmental inefficiency (Chapter 4). It becomes apparent that different socio-psychological factors are at play depending on whether it is for future adoption or current farm performance in terms of reducing GHG emissions. In Chapter 4, negative emotion arising from not taking mitigation measures was found to be negatively and significantly associated with environmental inefficiency, while perceived social norm showed a positive and statistically significant association with technical inefficiency.

Personal norm as a positive and significant factor for goal intention is the felt obligation that acting in a certain way is right or wrong. A positive association between personal norm and goal intention to reduce beef consumption has been found by Klöckner (2017). Positive associations between personal norm and pro-environmental behaviour have also been found in dietary choices by de Groot et al. (2021), in pro-environmental land management by Price and Leviston (2014), as well as in a meta-analysis by Bamberg and Möser (2007). **Attitude as a positive and significant factor for behavioural intention** is measured by whether adopting a preferred mitigation option is advantageous and important for sample farmers in Chapter 2. As also shown by Pannell et al. (2006), farmers need to be convinced of the comparative advantages of an innovation before changing from old practices. Yet, there are mixed results in the TPB literature when it comes to the role of attitude for intentions (Kollmuss & Agyeman, 2002; Sheeran, 2002). In the SSBC studies, attitude is found to be the main factor of choosing alternative behaviours when it comes to reducing beef consumption in Norway (Klöckner, 2017). However, there is a limited influence of attitude on behavioural intention in the context of moving into energy-efficient homes (Schaffner et al., 2017).

Negative emotions can be understood as goal-incongruent emotions such as guilt or shame related to human-caused environmental damages in this thesis. Among the sampled Dutch dairy farmers in 2021, stronger negative emotions are associated with lower environmental inefficiency (Chapter 4). A larger score for negative emotions may drive farmers to adopt more environmentally friendly technologies and practices, leading to efficiency improvement and hence reduced emissions. A one unit increase in negative emotions is associated with a decrease in the overall inefficiency by 0.5% to 9.69%. This corresponds to a total reduction of 167.35 tons of GHG emissions in CO_2 equivalent, equivalent to an additional reduction of 8.63 tons of GHG emissions in CO_2 equivalent. In the literature, both positive and negative emotions have been found to determine pro-environmental behaviour, although the influence of negative emotions like fear or guilt prevails (Böhm, 2003; Elgaaied, 2012; N. Harth et al., 2013; Mallett, 2012; Schaffner et al., 2015). A causal relationship between negative moral emotions and actual pro-environmental behaviour was found in an experimental study by Rees et al. (2015). The potential causal relation between negative emotion from inaction and the environmental efficiency needs to be further validated in the context of Dutch dairy farming.

Perceived social norm refers to individual's perception or belief about commonly accepted behaviour within a social group regarding reducing GHG emissions in this thesis. A one unit increase of perceived social norm is associated with an increase of the average technical inefficiency from 0.05 to 0.208 (Chapter 4). This result suggests that farmers who feel greater pressure to conform to prevailing social norms tend to use less efficient farming practices. One possible explanation is that farmers conforming to social norms on reducing GHG emissions might invest efforts in emission reduction, leading to a temporary reduction in technical efficiency. However, the insignificant positive association between perceived social norm and the goal intention to reduce emissions in Chapter 2 does not strongly support this explanation. This results may arise from farmers' resistance to change, even when changes could enhance technical efficiency. On the contrary, social norm has been found as a driver for adopting precision farming which saves costs and preserves the environment (Hüttel et al., 2022), for determining the goal intention to reduce beef consumption in Norway (Klöckner, 2017) and for residences in the city of Lucerne to move into energy-efficient homes (Schaffner et al., 2017).

6.1.2 Socio-demographical and socio-economic factors in farmers' decision making

In Chapter 2, we examined farmers' socio-demographic factors, including age and education level, along with annual farm income and livestock density. We treated these four factors as control variables for adoption stages. In Chapter 4, socio-economic factors such as age, short-term debt ratio, long-term debt ratio, and total subsidies per hectare were employed as control variables in the analysis of farm technical and environmental inefficiency. The different choices for control variables in Chapter 2 and 4 are influenced by the common choices in adoption literature and efficiency literature respectively. In the adoption literature, control variables usually consist of farmer demographic characteristics and farm financial and structural features (Knowler & Bradshaw, 2007; Kreft et al., 2021; Mozzato et al., 2018; Serebrennikov et al., 2020). In Chapter 4, we shifted the focus of control variables more towards financial structure as reflected by debt ratios and government support as in subsides/hectare following (Gadanakis et al., 2020; Minviel & Latruffe, 2017; Zhu et al., 2023; Zhu & Oude Lansink, 2010).

In Chapter 2, we found age exhibits an inverted U relationship with adoption stages which is consistent with the finding by Chatzimichael et al. (2014). However, in Chapter 4, we did not elicit any statistically significant relations between age and farm technical/environmental inefficiency scores. We conclude that younger farmers in our sample are *ceteris paribus* more likely in later adoption stages than older farmers for climate mitigation measures. Farmers aged 31 are mostly likely in the post-actional stage, while farmers aged 45 are typically in the actional stage and farmers aged 64 are commonly in the pre-actional stage.

Farmers holding bachelor's or master's degrees in agriculture are more likely to be in later adoption stages compared to those with only practical farming experience among the surveyed farmers. Conversely, those with full-time professional education or agricultural courses/internships are less likely to be in the actional stage but more likely to be in the stages of selecting measures or post-actional stages than those with only practical experience. In summary, higher education levels generally correlate with later adoption stages, except for farmers with professional education who tend to skip the actional stage. Our finding is consistent with Niles et al. (2016) who concluded that education is a positive predictor for the likelihood of mitigation measures. Yet, no clear relationship was found between education and climate mitigation behaviour among Dutch farmers by Moerkerken et al. (2020), even a negative relation was observed with energy saving measures.

We found that higher livestock density correlates with farmers being more likely to be in later adoption stages. Similarly, livestock density positively associates with the adoption of manure treatment technologies (Case et al., 2017; Gebrezgabher et al., 2015). Annual farm income is not a statistically significant factor in adoption stages. Among the four socio-economic factors on farm performance, only the short-term debt ratio is found to be positively associated with technical inefficiency. This finding confirms with the adjustment theory of Paul et al. (2000) that farmers with a lower short-term debt ratio can more easily adjust to changes and hence increase their technical efficiency.

6.1.3 Reduction potential and economic costs

In Chapter 3, the largest annual average GHG reduction potential was found to be 214.58 tons CO_2 equivalents, while in Chapter 5, it was estimated to be 721 tons CO_2 equivalents, both *ceteris paribus*. In other words, in Chapter 3, the environmental inefficiency was estimated at 11.8% as of farms' respective GHG emissions using DEA models. In contrast, the environmental inefficiency was estimated to be 47% as of the average level of all farms' GHG emissions in Chapter 5 using DFA models. This discrepancy is primarily attributed to variations in estimation models, with minimal influence stemming from slight variations in sample compositions. The quadratic functional form in DFA models needs to fit all observations (Chapter 5), whereas non-parametric DEA models (Chapter 3), utilizing a convex combination of observed decision-making units, are more flexible in reflecting the frontier. Additionally, the average inefficiency estimates based on DFA models became smaller when efficient observations were removed (Chapter 5). Overall, DEA models are more conservative in estimating the inefficiency than DFA models. In terms of sample compositions, in Chapter 3, only specialized dairy farms utilizing unsold crops as animal feed and using animal manure as fertilisers were modelled. Notably, there are fewer farms in Chapter 3 (190 farms) compared to Chapter 5 (285 farms), but both samples consist of specialized Dutch dairy farms in the period from 2010 to 2019.

Several other studies have looked into environmental inefficiency on dairy farms using the DEA models. For French suckler cow farms, Dakpo and Oude Lansink (2019) found an average environmental inefficiency of GHG emissions of 28.4%. 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 Lithuanian dairy farms, Baležentis et al. (2022) found a 20% to 25% reduction potential of GHG emissions for the years 2015, 2017 and 2019. The environmental inefficiency of GHG emissions on Dutch dairy farms, as assessed by the DEA model in Chapter 3, is lower than that of French suckler cow farms, as well as Swedish and Lithuanian dairy farms.

In Chapter 5, we also looked into nitrogen surplus in addition to GHG emissions. Our study identified an average of 22.2 tons reduction potential in terms of nitrogen surplus compared to an average of 6.56 tons reduction by Lamkowsky et al. (2021). However, it is important to note that we estimated the inefficiency scores for the nitrogen surplus using DFA models whereas Lamkowsky et al. (2021) estimated a subsequent maximization of profit and minimization of nitrogen surplus for the profit-maximizing levels of polluting inputs using DEA. In addition, the nitrogen surplus data used in Lamkowsky et al. (2021) differs from Chapter 5 in that they also included the biological and atmospheric fixations in nitrogen inflows. The average nitrogen surplus is 12.79 tons in Lamkowsky et al. (2021) whereas the average nitrogen surplus is 12 tons in Chapter 5. In other years, for nitrogen surplus on Dutch dairy farms, the absolute reduction potential was estimated to be 8.16 tons between 1991 and 1994 (Reinhard et al., 1999), and 3.99 tons between 2015 to 2018 (Zhu et al., 2023). The variations in nitrogen surplus reduction potential observed for Dutch dairy farms between Chapter 5 and other studies may stem from differences in estimation methods, sample periods, and, to a lesser extent, variations in nitrogen surplus accounting methods.

Our results in Chapter 3 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. Specifically, on average 25.3% of the total farm size should be allocated to cropland. This represents an increase of 6.7% compared to the current land allocation. Our finding on efficiency gains from land optimization is lower than the estimate by Ang and Kerstens (2016) for English and Welsh farms. This difference could be explained by noting that our study focuses exclusively on dairy farms whereas Ang and Kerstens (2016) have included mixed farms and specialized crop farms. Additionally, different production environments may contribute to the differences in efficiency gains between studies. Land optimization brings efficiency gains when conventional outputs are to be expanded, and it does not bring efficiency gains when only reducing GHG emissions. This can be explained by the modelling choice as we have excluded land use in the residual GHG emission technology, due to the current Dutch soil carbon balance in cultivated land (DuurzameZuivelketen, 2018).

We estimated the shadow prices using both DFA models and OLS regression models (Chapter 5). The system of three DFA models yielded average shadow prices of 12.09 euro/kg for GHG emissions and 22.31 euro/kg for nitrogen surplus. In contrast, the quadratic functional form estimated through OLS regression models resulted in average shadow prices of 77.03 euro/ton for GHG emissions and 6.08 euro/kg for nitrogen surplus. The substantial size of our shadow price estimations for GHG emissions and nitrogen surplus using DFA models compared to OLS models may be attributed to the steep slope of the frontier in each polluting technology, coupled with differences in modelling approaches, study areas and time, compared to other studies.

The results from our OLS models align more closely with estimations from other studies. Previously, Baležentis et al. (2022) found a shadow price for CO_2 in the range of 41.54 to 55.89 euro per ton CO_2 equivalent for Lithuanian dairy farms. Wettemann and Latacz-Lohmann (2017) found an average shadow price of 165 euro/ton CO_2 equivalent for northern German dairy farms. Cecchini et al. (2018) found an average shadow price of 243.08 euro per ton of CO_2 equivalent for Italian cattle farms. The GHG shadow price for Dutch dairy farms estimated by OLS models, is thus higher than Lithuanian dairy farms and lower than German dairy and Italian cattle farms.

In terms of nitrogen surplus, Adenuga et al. (2019) found the mean shadow price of 4.02 euro/kg for the Republic of Ireland, and 6.2 euro/kg for the Northern Ireland. Adenuga et al. (2019) included biological fixation and excluded the manure for counting nitrogen surplus which is different than the nitrogen surplus data we used in Chapter 5. The shadow price we derived for nitrogen surplus on Dutch dairy farms using OLS is higher than those estimated on Irish farms.

6.1.4 Behavioural measures and financial incentives in adoption decisions

Farmers' decision making models often assume that farmers are maximizing profit or utility, without taking into account farmers' emotion, norm, attitude and the influence from their social networks. At the same time, most policy problems are both economic and behavioural problems necessitating a hybrid approach that combines behavioural insights and traditional economic policy tools (Shukla et al., 2023).

We found that negative emotion is negatively associated with environmental inefficiency, whereas perceived social norm and short term debt ratio are positively associated with technical inefficiency (Chapter 4). Furthermore, our shadow price estimations (Chapter 5) indicate that the private costs of reducing GHG emissions and nitrogen surplus are not neglectable for farmers. However, our sample farmers have already adopted some climate mitigation measures in the past voluntarily (Chapter 2). In part, this observation could be explained by the fact that most measures the sample farmers have taken in the past were cost-effective or cost-saving (Zijlstra et al., 2019). Meanwhile, many Dutch dairy farmers have already taken steps to mitigate climate impact through the "On the Way to Climate Neutral Dairy" program led by the largest dairy cooperative in the Netherlands (FrieslandCampina, 2023). Moreover, farmers may have been willing to contribute to the environment voluntarily to some extent. Barreiro-Hurle et al. (2023) found that farmers were willing to contribute 10.8% to 28.1% from their income to the environment, even though they were not fully compensated. This finding (Barreiro-Hurle et al., 2023) is contrary to the widespread view that farmers will not adopt sustainable practices unless the costs are offset (Piñeiro et al., 2020).

Furthermore, for the sample Dutch dairy farmers (survey in Chapter 2), participants have given their opinions on seven possible incentives for reducing GHG emissions. The two most favoured incentives are ‘receiving financial compensation’ and ‘getting a price premium’, followed by ‘law enforcement’, ‘emission trading scheme for agriculture sector’, and ‘free practical advice’. The two least preferred incentives are societal wishes, and monitoring farm GHG emissions via a smart app. Hence, Dutch dairy farmers tend to favour financial incentives and are less motivated by broader societal expectations when it comes to reducing GHG emissions. Similarly, perceived social norm is associated with lower technical efficiency in conventional farm production as found in Chapter 4. Moreover, results from a national choice experiment among Dutch dairy and crop farmers have shown the importance of combined public and private financial incentives in facilitating the transition to nature-inclusive farming (Koetse & Bouma, 2022), with price premium as a significant factor in explaining the shift from mainstream farming to nature-inclusive farming (Koetse & Bouma, 2023).

In short, financial compensation is the stated most preferred incentive and negative emotion stemming from not taking mitigation measures is the revealed behavioural facilitator in reducing GHG emissions. Personal norm and attitude exhibit positive associations with adoption intentions of mitigation measures. In conclusion, aligning financial incentives, eliciting negative emotions from inaction positively, and fostering positive personal norm and attitude could enhance the adoption of GHG mitigation measures among Dutch dairy farmers.

6.2 Implications for policy and business

This thesis holds implications for policy makers and Dutch dairy businesses seeking to reduce GHG emissions. The following sections provide recommendations for both.

6.2.1 Policy recommendations

The following policy recommendations are based on the insights from both behavioural measures and economic instruments in Chapters 2-5. The economic instruments discussed comprise a uniform GHG emission tax, tradable permits, and abatement payments.

Within the realm of behavioural measures, policy makers should tailor behavioural factors based on farmers' specific adoption stages. Specifically, in the pre-actional stage, facilitating farmers to evaluate the pros and cons of specific climate mitigation measures has the potential to enhance their receptiveness and hence their positive *attitude* (Chapter 2). This could be accomplished through learning from peers (Lamkowsky et al., 2021), utilizing farm extension services (Farstad et al., 2022) and smart applications in calculating the mitigation potential and trade-offs with other farming objectives (FrieslandCampina, 2020). Attitude regarding GHG reduction could also be positively influenced by strengthening personal norms as suggested by de Groot et al. (2021). We found targeting *personal norm* would strengthen goal intention in the pre-decisional stage (Chapter 2). Personal norms could be enhanced via raising awareness about the impacts of global warming and about how farming activities contribute to the carbon footprint. Besides, highlighting social norms through examples of fellow farmers actively abating GHG emissions could also help in enhancing person norms (Jansson & Dorrepaal, 2015).

In the pre-actional stage, farmers' *goal intention* in mitigating emissions should also be strengthened (Chapter 2). To enhance farmers' goal intention, the Dutch government should highlight the long-term benefits of reducing GHG emissions and address short-term costs by providing compensation (OECD, 2017). This can be facilitated through established sector partnerships, such as the Sustainable Dairy Chain. Farstad et al. (2022) also suggest that a combination of a structural approach (like subsidy schemes) and behavioural approach is important to promote more adoption of climate mitigation measures for Norwegian agriculture.

In addition to the identified behavioural factors outlined in Chapter 2, farmers under 45 with bachelor's or master's degrees in agriculture and those operating farms with high livestock density are more likely to have already adopted mitigation measures (Chapter 2). Policy makers may find it beneficial to specifically target this demographic for the promotion of additional mitigation measures. Conversely, farmers over 45 with practical farming experience and farms with low livestock density may be better suited for initiatives aimed at encouraging the initial uptake of climate mitigation measures.

It is also important to take into account farmers' preferences when promoting climate mitigation measures. It became evident that our sample farmers exhibit varying preferences. Among a list of mostly cost-effective GHG mitigation measures (survey in Chapter 2), the five most preferred options are 1) increase feed efficiency (less losses, more frequent feeding), 2) increase of legumes in grass, 3) renewable energy production, 4) decrease artificial N-fertiliser, and 5) decrease concentration share in ration. Conversely, the least favoured climate mitigation options include reducing the number of young livestock and increasing the maize share within the ration. The most preferred measure is related to efficiency improvement, which is consistent with the findings from Beldman, Pishgar-Komleh, et al. (2021). Our sample farmers also prefer measures which reduce nitrogen surplus, reflecting a highlighted urgency to tackle the nitrogen crisis in the Netherlands. The lack of popularity for emission-reduction floor suggests that the private costs associated with mitigating GHG emissions may pose a barrier to the adoption of more expensive measures.

From an economic perspective, implementing a uniform GHG emissions tax across farms could be optimal for achieving the GHG reduction target (Tarruella et al., 2023). However, setting the correct GHG tax would involve rigorous and extensive knowledge of marginal social abatement costs, a challenging task (Oates, 1996; Pretty et al., 2000), especially in the agricultural sector (Bullock, 2012; Ollikainen et al., 2020) with high heterogeneity across farming systems. For practical implementation, if the tax levels are lower than the private abatement costs, farmers may choose to pay the tax instead of investing in mitigation measures. In contrast, if the tax levels are set too high, some farmers may leave the business due to tax burden (Tarruella et al., 2023). To understand farmers behaviour towards such a GHG emission tax, it is necessary to estimate the private abatement costs. We have used both DFA and OLS models to estimate the shadow prices of GHG emissions and nitrogen surplus as farmers' private abatement costs. Results show a very large difference between these two models, but the OLS model results are more in line with earlier studies. The average shadow prices for GHG emissions and nitrogen surplus are estimated at 77.03 euro/ton and 6.08 euro/kg, respectively, using OLS models (Chapter 5).

Additionally, the polluter pays principle may face strong political opposition from powerful farmer organizations (Rontard & Hernandez, 2022). Tradable permits for carbon markets is an attractive solution for heterogenous sectors like agriculture, as there is no need to calculate the abatement costs (Grosjean et al., 2018). Yet, there are only very few cases in which such tradable permits have been applied in the agricultural sector at government levels (OECD, 2017), considering the measurement and monitoring costs for GHG emissions.

Abatement payments will likely increase the acceptability of emission reductions by farmers as our sample farmers' most preferred incentive is financial compensation (Chapter 2). Payment approaches should be dependent upon the implementation of the associated measure (Sattler et al., 2023) and that will require clear targets at farm or regional level. A recent study by Tarruella et al. (2023) has demonstrated that regional targets are more cost-efficient than farm-level ones in reducing GHG emissions. This implies that the government would set regional targets and compensate farmers collectively for achieving these targets. This mirrors the cooperative approach used for biodiversity conservation in the Netherlands (Barghusen et al., 2021; Jongeneel & Gonzalez - Martinez, 2023; Sattler et al., 2023). This approach enables farms with lower abatement costs to make a more significant contribution, mitigates trade-offs with production goals, and avoids resistance to polluter-pays instruments such as taxes or tradable permits (Sterner et al., 2019; Tarruella et al., 2023).

When it comes to program design, communication campaigns could strategically tap into negative emotions associated with inaction among farmers (Chapter 4). This can be especially relevant once the causal effect is identified - a task acknowledged as a major challenge (Landmann, 2020). One effective approach involves presenting farmers with the adverse environmental and agricultural consequences of their farming practices, thereby triggering moral emotions such as guilt or shame (as suggested by Rees et al. (2015)). It is worth noting that framing these messages in a positive manner is crucial, especially since Dutch farmers prefer a more positive media portrayal, as highlighted by Gomes and Reidsma (2021).

Lastly, thinking at a higher level, effective climate policy measures could entail a bundle of good technical and informatics solutions (Chai et al., 2023) with tailored targets to enhance positive personal norm and attitude, embedded within a broader package of abatement payments at regional level (Inman et al., 2018; Tarruella et al., 2023), and coupled with communication campaigns designed (Stuart et al., 2014) to positively evoke negative emotions from inaction (Gomes & Reidsma, 2021; Rees et al., 2015). Future research is needed to investigate the cost-effectiveness of this proposed policy bundle in the context of Dutch dairy or regions with similar agricultural practices.

6.2.2 Business recommendation

The following business recommendations aim to provide farm managers with actionable strategies in terms of improving farm efficiencies and the adoption of climate mitigation measure.

Better management practices play an important role in improving farm environmental inefficiency. Achieving a simultaneous 5.1% expansion in production and reduction in GHG emissions is feasible, with land optimization contributing 0.6% to this combined improvement. This involves allocating an additional 6.7% of the total farm size to cropland and closing inefficiency gaps. The largest GHG emission reduction potential, at 11.8%, could be achieved by adopting the farming practices of top-performing peers, without altering input and output levels (Chapter 3). Possible best efficiency-related management practices consist of optimizing feed rations, reducing losses, improving grazing management, reducing herd replacement rate by increased longevity, optimizing young stock management, using energy efficiently, applying more grazing, no-tillage on the grassland and reducing the renewal rate of grassland (Wageningen University & Research, 2019). The first two management practices, optimizing feed rations and reducing losses, align with the preferred measures by our sample farmers as indicated in the survey in Chapter 2.

Furthermore, farms with high short-term debt ratios are less efficient in terms of total farm production. Farm businesses with high short-term debt ratios could strategically manage debt, considering options like reduction, restructuring, or refinancing. Seeking professional advice tailored to the farm's specific circumstances from the financial sector is recommended, e.g. Dutch banks may provide an interest-only period for those who face short-term high debt following investments made on the farms (Koetse & Bouma, 2022). To reduce GHG emissions, farm managers with strong personal norms and a positive attitude towards adopting climate measures (Wang, Höhler, et al., 2023) could enhance their efforts by engaging in more knowledge exchange and social learning within farming communities, as highlighted by Kreft et al. (2023), as this social learning is instrumental in effectively achieving reduction targets.

6.3 Reflections on methods and data

This thesis, comprising a collection of articles, has made several contributions to the literature by (i) investigating the influencing behavioural factors per adoption stage based on the SSBC model, (ii) exploring reduction pathways across farms incorporating circularity principles with and without land optimization, (iii) proposing an integrated multi-production efficiency framework addressing the reduction of negative externalities, (iv) exploring shadow prices using two different modelling methods.

Yet, the research has several limitations, which need to be taken into account when interpreting the results. Below, I discuss the limitations for the methods and data used in this thesis.

Method

Correlation vs. causal relations. Correlation does not imply a causal relation; in our case, observational data limits the options for causal inference, even though the research questions in Chapter 2 and 4 involve causality. While randomized experiments are considered the ‘gold standard’ for causal inference, field experiments studying the causal effects of interventions on technology adoption by farmers are predominantly conducted in low-middle-income countries (Ashraf et al., 2009; Balew et al., 2023; Barrett et al., 2022; Bulte et al., 2014; de Brauw et al., 2018; Herberich et al., 2009; Hossain et al., 2019; Murphy et al., 2020; Omotilewa et al., 2019; Oyinbo et al., 2022; Shikuku et al., 2019). In contrast, studies in high-income countries typically employ agricultural students for lab experiments (Grüner et al., 2022; Lefebvre et al., 2020). Experimental study design choices between low-middle-income countries and high-income countries are influenced by resource availability, ethical considerations, and the demand for real-world applicability. Utilizing instrumental variables, regression discontinuity designs, and quasi-experimental approaches aids in drawing causal inferences from observational data. However, challenges like identification bias and estimation bias arise, particularly in our case with many explanatory variables, complicating the actual application when identifying exogeneous variations (Felton & Stewart, 2023; Rohlfing & Zuber, 2019; Varian, 2016).

Conducting quality experimental research is always demanding and costly, involving issues such as recruitment challenges, ethical concerns and detecting heterogenous treatment effects through carefully designed experiments (Palm-Forster & Messer, 2021). The behavioural and experimental literature examining producer behaviour in environmental decision making is growing but small compared to the extensive research focused on consumer behaviour (Palm-Forster & Messer, 2021). Statistical regression tests conducted in this thesis provide a good starting point in understanding the strength and direction of various socio-psychological factors. In Chapter 2, we employed multiple linear regression tests and multinomial logistic regression to examine statistical relationships based on the SSBC theory (Bamberg, 2013b). In Chapter 4, we utilized a bootstrap truncated regression model (Simar & Wilson, 2007) to pinpoint the explanatory factors influencing both farm environmental and technical inefficiency. Results from research with FADN farmers are more applicable in real-life situations as there is no need to extrapolate the findings from commonly conducted lab experiments with agricultural students (Lefebvre et al., 2020).

Our statistical regression tests open up avenues for further research, and if possible, determine causation experimentally and investigate the underlying mechanisms of such causation. The design of experiments informing agri-environmental programs and policies usually follows four stages as recommended by Palm-Forster and Messer (2021): (i) laboratory experiments with students, (ii) artefactual and framed field experiments with the target population, (iii) field experiments, and (iv) randomized controlled trials (RCTs).

DEA vs. DFA vs. SFA vs. StoNED method. Nowadays, the most commonly applied efficiency models are nonparametric Data Envelopment Analysis and parametric Stochastic Frontier Analysis, both introduced in the late 1970s. The main advantage of DEA is its flexibility, due to its nonparametric nature. Yet, the main disadvantage of the method is that it does not separate statistical noise from inefficiency (Andor & Hesse, 2014). Aigner et al. (1977) and Meeusen and van Den Broeck (1977) developed a stochastic parametric model, called SFA. Its main advantage is its ability to consider the statistical noise while simultaneously measuring efficiency. In Chapter 3 and 4, we have developed a network DEA model to assess the performance of dairy farms. The advantage of such a network DEA model is that intermediate products generated and consumed within the production system can be modelled explicitly, which makes the approach suitable for modelling the circularity principle (Rebolledo-Leiva et al., 2021). Our network DEA model can also be applied to dairy farms in other countries with similar circular principles. The limitations of the network DEA model are alike to those of the single-process DEA model, namely, sensitivity to outliers. However, the network structure introduces additional complexities in its implementation within SFA models.

In Chapter 5, the main aim was to estimate the shadow prices of GHG emissions and nitrogen surplus. DEA models, commonly applied for assessing the environmental efficiencies of decision making units, tend to generate ambiguous shadow prices of efficient observations owing to kinks in the frontier (Puggioni & Stefanou, 2019). SFA models, with a smooth frontier from parametric specification, avoid the issue of ambiguous shadow prices. Nonetheless, unlike DEA, violations of monotonicity properties in SFA models can complicate the economic interpretation of resulting shadow prices in practice. Parametric Deterministic Frontier Analysis models combine the convenience of being a linear programming approach complying with the monotonicity conditions as in DEA, with the property of yielding continuous frontiers as in SFA. However, DFA models yielded estimated shadow prices for GHG emissions nearly 157 times higher than those derived from Ordinary Least Squares regression models. The OLS model estimates aligned more closely with findings from comparable studies. The substantial disparity may be attributed to the limitations of DFA models. DFA models are less flexible as all observations have to be fitted under a pre-specified functional form. Besides, DFA models lack the capacity to incorporate random noise and exhibit sensitivity to extreme values. All these limitations can result in a pronounced and potentially unrealistic slope of the frontier.

There have been ongoing attempts to develop methods that combine the strengths of DEA and SFA models (among others, Fan et al. (1996); Kneip and Simar (1996); Kumbhakar et al. (2007); (Zhou et al., 2020)). The Stochastic non-smooth envelopment of data (StoNED) method, introduced by Kuosmanen and Kortelainen (2012), is a promising candidate (Andor & Hesse, 2014). StoNED is a stochastic and semi-parametric method, requiring no prior explicit assumptions about the functional form of the production function and allowing the estimation of noise (Kuosmanen & Kortelainen, 2012). Andor and Hesse (2014) have shown that in noisy scenarios, the nonparametric StoNED pseudolikelihood estimator constitutes a promising alternative to the SFA maximum likelihood estimator.

Modelling circular agriculture. In the network DEA model, we have addressed circularity aspects within one integrated multi-production technology framework that accounts for GHG emissions (Chapter 3 and 4). However, circular agriculture could happen at different scales, other than on the farm level. In the network DEA model, there are no interactions between farms, and the analysis does not account for waste streams from non-farm entities, such as urban and industrial waste. Furthermore, we found that a trade-off between reducing GHG emissions and expanding production does exist. Balanced climate policies considering the interplay between environmental objectives and economic gains are necessary. In the current thesis, the trade-off is not explicitly modelled. Roughly speaking, an additional 6.7% reduction of GHG emissions will mean a 'loss' of 5.1% increase in total production.

Beyond the primary emphasis on mitigating GHG emissions in this thesis, the transition to circular agriculture encompasses a broader spectrum of environmental and social objectives. These include but are not limited to biodiversity conservation, promotion of social health, enhancement of water quality, assurance of food security, and prioritizing the health and well-being of both farmers and consumers. This thesis acknowledges the broader spectrum of environmental and social objectives, it does not explicitly consider how these objectives could be integrated into the network DEA model or other types of mathematical programming models.

Moreover, it is equally important to quantify the positive value of eco-system services as well as estimating the shadow prices of negative externalities. This thesis however does not provide specific methodologies or results in this regard.

Data

Behavioural data. The collection of behavioural data via the national farm accountancy data network brings research opportunities in better understanding farmers adoption behaviour. The survey in Chapter 2 was intentionally kept brief to avoid overburdening FADN farmers. In this chapter, it was decided to measure latent constructs with only one item in most cases. Consequently, utilizing structural equation modelling to test the SSBC model became unfeasible. Although the non-proportional odds model would be suitable for examining the varying effects of socio-psychological factors across different stages, its application was not practical in this study due to the small sample size (Wang, Höhler, et al., 2023). Our FADN-based online survey for collecting behavioural data is easily adaptable to countries using the same system. Employing standardized procedures and offering financial incentives across participating FADN countries could increase response rates, enabling large sample sizes for cross-country comparisons. It's important to note that the results obtained from Dutch dairy farmers have limitations in terms of broader generalization due to the specific contextual factors unique to the Netherlands.

GHG emission data. GHG emission data was only available for Dutch specialized dairy farms collected by Wageningen Economic Research. Additional emission data from mixed farms, crop farms should be collected to further validate the potential of land optimization in delivering better farm performance using the network DEA model developed in Chapter 3 (Wang, Ang, et al., 2023).

The GHG emission data for period 2010-2019 in Chapter 3 is derived from the Duurzame Zuivelketen project (Doornewaard et al., 2020) by considering the emission factors and following the calculation rules outlined by the International Dairy Federation and the Emission Registration ("EmissieRegistratie" in Dutch). While the emission data for the year of 2021 in Chapter 4 is based on the latest KringloopWijzer tool in which GHG emissions are calculated based on the nutrients cycles on each farm (Dijk et al., 2020). The KringloopWijzer utilizes farmer-specific data, incorporating defaults for upstream emissions in concentrate production. There are plans to enhance precision by integrating company-specific data from most compound feed companies into the Kringloopwijzer. Additional background data and emission factors are primarily sourced from literature, Feedprint, and IPCC (Beldman, Lesschen, et al., 2021).

Furthermore, we studied the GHG emissions in CO_2 equivalent throughout the thesis. Detailed data as in methane, nitrous oxide and carbon dioxide separately could have provided additional insights into the environmental inefficiency and shadow price per emission source as different migration measures target on different GHG gases in practice.

Sample size. The dairy farm data across the four chapters was sourced from the Dutch FADN. The survey data used in Chapter 2 and 4 was collected through a panel of Dutch dairy farmers registered with FADN. After data cleaning and merging, Chapter 2 contained 93 complete observations, and Chapter 4 had 74 farm observations.

To the best of our knowledge, the additional data collection in Chapters 2 and 4 represents the first attempt to match behavioural data to accountancy data among FADN farms. They are representative of the Dutch dairy farm population in terms of livestock density. However, the small sample size poses limitations. Notably, the FADN farmers in our sample had higher incomes than the average Dutch dairy farmers, which can influence the generalizability of our findings. The small sample size in Chapter 2 limits our ability to detect small effect sizes. Similarly, in Chapter 4, while we obtained interesting correlation results, caution is required in drawing general conclusions for the entire population of Dutch dairy farmers from this small sample.

Conversely, in Chapter 3 and 5, the data used is representative of the Dutch dairy sector over the same time span of 2010-2019. On average, there were 285 dairy farms each year in Chapter 5 and 190 dairy farms each year in Chapter 3. The variation in sample size is a result of restricting our analysis in Chapter 2 to dairy farms that reuse crop residues for livestock production and reuse manure for crop fertilization.

6.4 Future research

The findings and methodology presented in this thesis pave the way for several promising directions in future research. Firstly, we suggest future studies to further explore the causal role of personal norm, attitude, and goal intention on Dutch dairy farmers' adoption of climate mitigation measures. A longitudinal intervention study with target farmers would be the ideal approach to systematically evaluate the causal role of identified behavioural factors in Chapter 2 based on the SSBC model (Bamberg, 2013a), especially among farmers in the pre-decisional and pre-actional stages. An objective way of assigning farmers to matching adoption stages would be via revealed investments or farm management practices on reducing GHG emissions. Given the challenges in conducting behavioural experiments with farmers mentioned earlier, lab experiments with agricultural students could be a cost-efficient logical next step for eliciting potential causal relations (Palm-Forster & Messer, 2021).

Secondly, it would be interesting to further validate the potential of land optimization in delivering better farm performance using the network DEA model developed in Chapter 3. This validation can happen when additional GHG emission data becomes available for other farm types, which would enhance the validity of this analysis in Chapter 3. The assessment of circular agriculture beyond the farm level, at local or regional levels, would also be a valuable research by itself.

Furthermore, the existing efficiency literature lacks an integrated conceptual framework to explain inefficiency, underscoring the necessity for a thorough examination of explanatory variables. A worthwhile approach could be to conduct a literature review on the selection of explanatory variables for environmental inefficiency and assess the additional insights obtained by incorporating behavioural variables. To accomplish this, the collection of behavioural data linked to pro-environmental farming practices becomes indispensable.

Lastly, the modelling exercises on quantifying the shadow prices of GHG emissions and nitrogen surplus using the DFA model open up opportunities for further exploration. We recommend future research to explore shadow prices of these negative externalities using alternative efficiency models: DEA, SFA and StoNED method. A meta-frontier model, as suggested by Shen et al. (2021), could offer valuable insights by comparing shadow price estimations from different group frontiers based on their scale.

6.5 Main conclusions

- Personal norm, attitude, and goal intention explain future adoption in reducing GHG emissions but do not explain past performance in generating GHG (Chapter 2-4).
- Negative emotion, personal norm, perceived goal feasibility, action planning, and coping planning have varying effects across four adoption stages of the SSBC model (Chapter 2).
- Farmers younger than 45 years old, with full agricultural education, and high livestock density are more likely to have taken steps in adopting mitigation measures (Chapter 2).
- Negative emotion stemming from inaction is the most important revealed behavioural facilitator in reducing GHG emissions (Chapter 2-4).
- A lower short-term debt ratio is associated with lower technical inefficiency, while a higher perceived social norm is linked to higher technical inefficiency (Chapter 2-4).
- While optimizing land can reduce GHG emissions and boost farm production simultaneously, its contribution is modest, comprising just 0.6% to this combined improvement (Chapter 3).
- GHG emissions per farm could be reduced by 11.8% on average if the total farm production, input use and land use were kept constant. However, the GHG emissions per farm could be reduced by only 4.5% on average if crop and livestock production were simultaneously expanded by 4.5% with constant input and land use (Chapter 3)
- The average annual GHG reduction potential, determined by DEA models, is 214.58 tons CO_2 equivalents, while DFA models estimate it at 721 tons CO_2 equivalents, both *ceteris paribus* (Chapter 3 and 5).
- The average annual nitrogen surplus reduction potential is 22.2 tons using DFA models (Chapter 5).
- Shadow prices for GHG emissions and nitrogen surplus, estimated using DFA models, are 12.09 euro/kg and 22.31 euro/kg, respectively. In comparison, OLS regression models yield shadow prices of 77.03 euro/ton for GHG emissions and 6.08 euro/kg for nitrogen surplus (Chapter 5).

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Summary

The increasing global demand for milk, driven by the expanding world population and increasing wealth, is contributing to land use changes such as native grassland and forests that are converted into agricultural land for grazing and animal feed production. This transformation is resulting in greenhouse gas emissions and biodiversity loss. Additionally, the production of dairy products generates greenhouse gas emissions, mainly in the form of methane and nitrous oxide. Concurrently, the dairy production is susceptible to the detrimental effects of climate change. The Dutch agriculture sector contributes to 15% of the country's total GHG emissions, with dairy cattle alone responsible for the largest share at 34%. The Dutch agriculture sector faces a challenge to further reduce its GHG emissions with 1Mt by 2030 in order to meet the national target. Current policy focuses on farmers' voluntary adoption of climate mitigation measures and the integration of circular agricultural principles. Farmers are confronted with strict environmental regulations on nitrogen and phosphates, and a majority of the Dutch dairy farmers rejects the Dutch government's recent buy-out scheme aimed at reducing ammonia and nitrous oxide by 50% by 2030.

Policies addressing agri-environmental issues often neglect behavioural factors, hindering a comprehensive economic analysis of farmers' decision-making and potentially impeding realistic and effective outcomes in achieving policy targets. Adoption of mitigation measures, efficient production and resource optimization are essential components in meeting emission targets. Existing literature has not explored the impact of Dutch dairy farmers' socio-psychological and socio-demographic factors on their adoption behaviour of climate mitigation measures over time. Additionally, the potential of land optimization for improved farm performance and the economic costs of mitigating negative externalities remains unaddressed. The overarching objective of this thesis was to assess the potential for, and costs of reducing GHG emissions with a special reference towards the role of farmers' behavioural factors in the adoption of mitigation measures and farm environmental performance on Dutch dairy farms. Four research chapters addressed this overarching objective using data from specialised Dutch dairy farmers registered within the Farm Accountancy Data Network.

Chapter 2 investigated Dutch dairy farmers' adoption behaviour of climate mitigation measures using a self-regulated stage model of behavioural change. We tested the statistical relationship of stage-specific socio-psychological factors with individual farmer's intentions of planning or adopting on-farm climate mitigation measures. In addition, we tested the statistical relationship of farmers' socio-demographical factors with adoption stages. Our findings suggest that negative emotion, personal norm, perceived goal feasibility, action planning, and coping planning vary significantly by stage. Furthermore, personal norm, attitude, goal intention, behavioural intention, and implementation intention are found to be statistically significant and positive influencing factors on adopting climate mitigation measures. Lastly, farmers younger than 45 years old with full agricultural education and farms with high livestock density are more likely to have taken steps in adopting mitigation measures.

Chapter 3 assessed 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 with the by-production approach. 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.

Chapter 4 explored the influence of socio-psychological and socio-economic factors on environmental inefficiency of farming related GHG emissions, as well as the associations of these factors with farm technical inefficiency. We investigated this by utilizing a two-stage approach. First, the network Data Envelopment Analysis model developed in Chapter 3 was used to assess the environmental and technical inefficiency scores of Dutch dairy farms. Second, a bootstrap truncated regression model was used to identify the statistical associations between the explanatory factors and environmental and technical inefficiencies. Perceived social norm and short term debt ratio have statistically positive associations with technical inefficiency. Negative emotions from not taking climate mitigation measures are negatively associated with farm environmental inefficiency. When promoting GHG mitigation measures, communication campaigns could consider taking into account farmers' negative emotions related to not taking climate mitigation measures.

Chapter 5 assessed the reduction potential and shadow prices for GHG emissions and nitrogen surplus on Dutch dairy farms. We operationalized a parametric deterministic frontier analysis model using quadratic directional distance functions. As a robustness check, we employed Ordinary Least Squares regression models. Our results suggest that on average, the yearly reduction potential for GHG emission and nitrogen surplus are about 721 tons and 559 tons respectively. For the total on-farm revenue from livestock and crop production, the improvement potential is 174,813 euro on average. The estimated average shadow prices for GHG emissions and nitrogen surplus are 12.09 euro/kg and 22.31 euro/kg, respectively, with DFA models. Ordinary least squares regression models produce estimates closer to other studies, with values of 77.03 euro/ton for GHG emissions and 6.08 euro/kg for nitrogen surplus.

The general discussion in Chapter 6 synthesizes results from the four research chapters, exploring congruities and divergences between chapters and relevant literature. Guided by four themes, the discussion covers the impact of socio-psychological factors on farmers' decision-making, the role of socio-demographic and socio-economic factors, the reduction potential and economic costs of mitigating GHG emissions and nitrogen surplus, and insights into behavioural measures and financial incentives in farmers' adoption decisions. Besides, implications for policy and business are provided separately based on the findings of this thesis. Reflections on the methods and data are followed by recommendations for future research.

This thesis makes scientific contributions through the development of the network DEA model to assess the potential of land optimization for farms with circularity principles, addressing the reduction of negative externalities. Additionally, it contributes through the application of the SSBC theory to study farmers' voluntary adoption behaviours of climate mitigation measures. Furthermore, our modelling exercises quantify shadow prices of GHG emissions and Nitrogen surplus using the DFA model and the OLS model.

Main conclusions

- Personal norm, attitude, and goal intention explain future adoption in reducing GHG emissions but do not explain past performance in generating GHG (Chapter 2-4).
- Negative emotion, personal norm, perceived goal feasibility, action planning, and coping planning have varying effects across four adoption stages of the SSBC model (Chapter 2).
- Farmers younger than 45 years old, with full agricultural education, and high livestock density are more likely to have taken steps in adopting mitigation measures (Chapter 2).
- Negative emotion stemming from inaction is the most important revealed behavioural facilitator in reducing GHG emissions (Chapter 2-4).
- A lower short-term debt ratio is associated with lower technical inefficiency, while a higher perceived social norm is linked to higher technical inefficiency (Chapter 2-4).
- While optimizing land can reduce GHG emissions and boost farm production simultaneously, its contribution is modest, comprising just 0.6% to this combined improvement (Chapter 3).
- GHG emissions per farm could be reduced by 11.8% on average if the total farm production, input use and land use were kept constant. However, the GHG emissions per farm could be reduced by only 4.5% on average if crop and livestock production were simultaneously expanded by 4.5% with constant input and land use (Chapter 3)

- The average annual GHG reduction potential, determined by DEA models, is 214.58 tons CO_2 equivalents, while DFA models estimate it at 721 tons CO_2 equivalents, both *ceteris paribus* (Chapter 3 and 5).
- The average annual nitrogen surplus reduction potential is 22.2 tons using DFA models (Chapter 5).
- Shadow prices for GHG emissions and nitrogen surplus, estimated using DFA models, are 12.09 euro/kg and 22.31 euro/kg, respectively. In comparison, OLS regression models yield shadow prices of 77.03 euro/ton for GHG emissions and 6.08 euro/kg for nitrogen surplus (Chapter 5).

Scarlett Wang

Wageningen School of Social Sciences (WASS)

Completed Training and Supervision Plan

Wageningen School of Social Sciences

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1 Managing a research project			
WASS Introduction Course	WASS	2020	1
Writing Research Proposal	WUR	2020	6
Basic statistics	PE&RC and WIMEK	2020	1.5
"Understanding social-psychological factors affecting farmers' climate actions"	95th Annual Conference of the Agricultural Economics Society, online	2021	1
"Including behavioural economic elements in farm models"	16th Congress of the European Association of Agricultural Economics, online	2021	1
"Dutch farmers' intention to adopt climate mitigation measures"	96th Annual Conference of the Agricultural Economics Society (AES), Leuven, Belgium	2022	1
"The potential of circularity to decouple greenhouse gas emissions from production: an application to the Dutch dairy sector"	XVII European workshop on efficiency and productivity analysis (EWEPA) Porto, Portugal	2022	1
"Assessing Reduction Potential and Shadow Prices for Greenhouse Gas Emissions and Nitrogen Surplus on Dutch Dairy Farms"	XVII EAAE congress, Rennes, France	2023	1
BEC PhD meetings	WUR	2020-2023	2
MINDSTEP meetings	MINDSTEP, The Hague	2019, 2022	2
A2 Integrating research in the corresponding discipline			
Behavioural & Experimental Economics UEC51306	WUR	2021	6
Summer school: Theory and Practice of Efficiency & Productivity Measurement	WASS	2022	4.5
B) General research related competences			
B1 Placing research in a broader scientific context			

Academic publication and presentation in the social sciences	WASS	2020	4
Introduction to R and R Studio	PE&RC and WIMEK	2021	0.9
Tidy data transformation and visualization with R	PE&RC	2021	1.2
Attending Economic Seminars	WUR	2018-2022	0.5
B2 Placing research in a societal context			
Make an impact: increasing the relevance of research through science-society	WGS	2021	1
C) Career related competences/personal development **C1 Employing transferable skills in different domains/careers**			
Brain training	WGS	2020	0.3
Searching and organising literature for PhD candidates	WUR Library	2020	0.6
Teaching assistant BEC22306 Corporate financial management ORL 32806 Sustainability analysis	WUR	2021, 2023	1.5
Career perspectives	WGS	2022	1.6
Total			**39.6**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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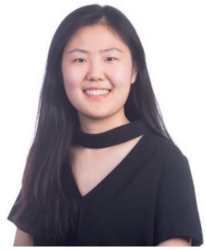
About the author



Scarlett Wang (汪思嘉) grew up in Xingtai City, the oldest city in North China, situated near the scenic Tai-hang mountain range. Fascinated by biology, mathematics, and English during her high school years, Scarlett opted for a double degree program in Horticulture and Agri-business for her bachelor studies. In the initial two years at Hebei Agricultural University in China, she focused on plant science studies. Later, she was introduced to the Dutch horticultural sector while studying Agri-business at Inholland University of Applied Sciences in Delft.

Scarlett continued her academic journey by pursuing a Master's degree in Management, Economics, and Consumer Studies at WUR, specializing in Operations Research and Logistics. Throughout her Master's program, Scarlett demonstrated excellent team collaboration skills in various interdisciplinary projects, student challenges, and internships. For her MSc thesis, Scarlett developed a mixed-integer linear optimization model for the commercial production planning of plant tissue culture for a software company Mprise.

Driven by the curiosity to conduct academic research, Scarlett started her PhD within the Business Economics Group at WUR. Her PhD was part of the Horizon 2020 'Modelling individual decisions to support the European policies related to agriculture' (MINDSTEP) project. Throughout her PhD, Scarlett not only acquired new skills in econometrics and mathematical programming but also delved into social-psychological theories. This interdisciplinary approach expanded her expertise and deepened her interest in the intersection of behavioural economics and data science.

In addition to her research, Scarlett actively took on the role of a PhD representative for the BEC group, collaborating with three other dedicated PhD fellows. Utilizing her communication skills and keen observations, she actively advocated for initiatives aimed at enhancing the well-being and success of her fellow PhD colleagues. In her free time, Scarlett finds joy and peace in Zumba dancing, working out in the gym, reading a variety of books, visiting art museums, spending time in nature, and sharing delightful moments with friends.

List of publications

Scientific articles

Wang, S., Ang, F., & Oude Lansink, A. (2023). Mitigating greenhouse gas emissions on Dutch dairy farms. An efficiency analysis incorporating the circularity principle. Agricultural Economics, 00, 1-19. https://doi.org/https://doi.org/10.1111/agec.12804

Wang, S., Höhler, J., Ang, F., & Oude Lansink, A. (2023). Dutch dairy farmers' adoption of climate mitigation measures – The role of socio-psychological and socio-demographical factors. Journal of Cleaner Production, 427, 139187. https://doi.org/https://doi.org/10.1016/j.jclepro.2023.139187

Project deliverables

Report on modelling greenhouse gas emission including adoption behaviour of farmers regarding mitigation strategies and interfaces to the MINDSTEP model toolbox. John Helming (WR), Pieter Willem Blokland (WR), Marc Müller (WR), Gerbert Roerink (WEnR), David Schäfer (UBO), Scarlett Wang (WU), Frederic Ang (WU) | 2023

Report on modelling crop management practices and interfaces to the MINDSTEP model toolbox. Fabienne Femenia (INRAE), Alain Carpentier (INRAE), Obafemi Philippe Koutchade (INRAE), Elodie Letort (INRAE), Scarlett Wang (WU), Frederic Ang (WU), Paolo Sckokai (UNICATT), Alessandro Varacca (UNICATT) | 2023

Report on the validation of the MINDSTEP model toolbox approach & proof of concept. Franziska Appel (IAMO), Frederic Ang (WU), Scarlett Wang (WU), Marc Müller (WR), John Helming (WR), Fabienne Femenia (INRAE), Obafemi-Philippe Koutchade (INRAE), Felicity Addo (IIASA), Paolo Schokai (UCSC), María Rosell (GEO), Katalin Balazs (GEO) | 2023

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