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Closing productivity gaps among Dutch dairy farms can boost profit and reduce nitrogen pollution

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Abstract

Agricultural productivity growth can simultaneously increase profit and reduce pollution. Yet, the impact of productivity growth on both has not been quantified. The objective of our study was to develop an approach to quantify the extent to which agricultural productivity growth can increase profit and reduce pollution. Focusing on nitrogen pollution, we applied the approach to a sample of 341 intensive Dutch dairy farms for the years 2006–2017. Using a Bennet–Lowe formulation, we measured economic and nitrogen productivities over time and across farms. We applied Data Envelopment Analysis to determine the potential for productivity growth from reducing economic and nitrogen inefficiencies and assessed the impact on profit and nitrogen pollution levels. Using a two-stage by-production model, we set profit maximisation as the overarching objective to account for the economic production behaviour of farmers. We found that if laggard farmers adopted the best practices of their best peers, they could on average increase annual gross profit by 34% and simultaneously reduce the N surplus by 50% during the time period, which is a win–win situation for farmers and the environment. The magnitude of these gains corroborates the suggestion that productivity growth could be a game-changer for agricultural sustainability.

1. Introduction

One of the greatest challenges of the 21st century is to ensure food security for all, including for today's and future generations (Foley *et al* 2011). Population growth will further raise food demand, while the global food supply is at risk if we do not become better stewards of the natural environments and resources needed to grow food (Godfray *et al* 2010, Springmann *et al* 2018, Willett *et al* 2019). Agriculture is a major driver of land degradation, depletion of groundwater aquifers, biodiversity loss and climate change, pushing the environment beyond the 'planetary boundaries of a safe operating space for humanity' (West *et al* 2014, Steffen *et al* 2015, Folberth *et al* 2020). An important factor affecting the viability of solutions to achieve food security is the need for farming families and businesses working in the agricultural sector to make a living (Graeub *et al* 2016). Food production depends on healthy natural ecosystems as well as on farmers. Sustainable food systems therefore must have a positive or neutral environmental impact, be economically profitable and bring societal benefits (FAO 2018).

Agricultural productivity growth can simultaneously increase profit and reduce environmental pollution. Productivity is a measure of the effectiveness of converting inputs to outputs, and productivity growth describes the ability to produce more outputs using less inputs. Productivity growth can increase profit, as it makes it possible to sell more outputs while purchasing less inputs[3]. Environmental pollution occurs when the production process does not only yield intended outputs but also unintended by-products (Førsund 2009, Murty *et al* 2012). For example, nitrogen fertiliser applied to crops may wash off the fields and pollute waterways. According to the principle of material balance, the mass of all inputs

[3] For an analytical treatment of the linkage between profit and productivity, we refer to Diewert (2005).

equals the mass of all outputs (intended outputs and unintended by-products), assuming no accumulation or recycling (James 1985). Improving the effectiveness of converting pollution-generating inputs to intended outputs leads to less production of unintended by-products per unit of input, thus decreasing environmental pollution.

Information on the potential to increase profit and reduce pollution through productivity growth is relevant for guiding agricultural policy. Although productivity growth is increasingly recognised as a game-changer for agricultural sustainability, so far any attempts to quantify the potential are limited (Lusk 2017, Coomes *et al* 2019). The objective of the current paper is to develop an approach to quantify the potential of agricultural productivity growth to increase profit and reduce pollution. Growth can be achieved by technological progress and efficiency increases (Färe *et al* 1994). Research and development can stimulate technological progress. Catching up with the best-practice technology through better farm management, enhancing scale economies and improving resource allocations contribute to efficiency gains. The current potential for productivity growth stems from these efficiency gains.

Several agronomic studies determine the potential to increase efficiency and profit and to reduce environmental pollution through implementing best practices (Chapman *et al* 2017, Corea *et al* 2017, Larson *et al* 2020, Correa-Luna *et al* 2021). These studies do not explicitly consider the production relationship between the inputs, outputs and unintended by-products. Production economic studies address this by explicitly modelling the conversion of all marketable inputs to outputs and have been extended to incorporate pollutants. Using a production frontier approach, farms are benchmarked to determine production inefficiencies in comparison to their best peers. Single-equation efficiency models have been used to estimate economic and environmental inefficiencies (see for example Reinhard *et al* 1999, Fernández *et al* 2002), but these models proved to have methodological deficiencies. Environmental pollution was either modelled as input or as output, which ignores the physical reality and leads to unacceptable implications for trade-offs (Coelli *et al* 2007, Murty *et al* 2012). The by-production efficiency model developed by Førsund (2009) and Murty *et al* (2012) overcomes the methodological problems of the single-equation model (Dakpo and Ang 2019).

The identification of inefficiencies allows for the assessment of productivity gaps. 'Transitive' productivity measures permit consistent comparison of productivity across farms and over time. However, so far only few productivity measures are known to be transitive. Procedures are available to make productivity indicators transitive, but these lead to the problem that unchanged levels of inputs and outputs can unintuitively result in productivity differences. The transitive Lowe and Färe–Primont productivity indices are expressed as ratios. Ratio-based measures can become undefined when one or more variables are close to or equal to zero and do not make the gains explicit in terms of profit. The Bennet–Lowe productivity indicator, which was recently developed by Ang (2019), has the difference-based and additively complete structure of the Bennet indicator (Chambers 2002, Walden *et al* 2017) and the transitivity property of the Lowe index. Being a difference-based indicator, it overcomes the problem of becoming undefined when one or more variables are close or equal to zero. Like profit, it can be expressed in monetary terms. So far, the indicator has not been applied to the context of pollution.

A last consideration is the production behaviour of farmers in determining the potential productivity growth. Past studies using the by-production approach have computed technical efficiency levels with regard to the technological limits (see for example Murty *et al* 2012, Serra *et al* 2014, Dakpo *et al* 2019b). Generally, farmers are willing to make structural changes to reduce pollution if these also increase profit and hesitate to do so if these reduce profit (Schulz *et al* 2014, Kuhfuss *et al* 2016). For a realistic outlook on the potential of productivity growth to increase profit and decrease pollution, it is therefore important to account for the economic production behaviour of farmers.

The contributions of our study are threefold. First, we extended the by-production efficiency approach to the productivity context using a Bennet–Lowe formulation. By doing so, we can make consistent comparisons over time and across farms and quantify the potential of productivity growth to increase profit and decrease environmental pollution. Second, we accounted for the economic production behaviour of farmers by using a two-stage approach. We assumed that farmers are foremost profit maximisers and within this space aim to minimise pollution. In line with these assumptions, we first determined the optimal quantities of pollution-generating inputs to maximise profit and in the second stage minimised pollution for the pre-determined quantities. Third, we applied our approach to a case study of nitrogen pollution on Dutch dairy farmers for 2006–2017 to show the added value of the analysis. While our approach is applicable to multiple farm types, regions and pollutants, we applied it to nitrogen (N) pollution from the Dutch dairy sector. N is an essential nutrient in agricultural production and N pollution decreases biodiversity and human health, and contributes to climate change (Galloway *et al* 2003, Sutton *et al* 2011, Kanter *et al* 2020).

2. Materials and methods

2.1. Model

We computed economic and N productivity indicators using a Bennet–Lowe formulation to conceptualise the effectiveness of converting agricultural inputs to outputs and ability to avoid on-farm accumulation of N surplus. Both indicators are computed for constant prices to remove the effect of price fluctuations.

Economic productivity is measured as revenues minus variable costs for constant prices:

$$\text{Economic productivity}_t = \boldsymbol{p}_0\boldsymbol{y}_t - \boldsymbol{w}_0\boldsymbol{x}_t \tag{1}$$

where $\boldsymbol{p}_0$ and $\boldsymbol{w}_0$ are respectively the vector of average output and input prices, and $\boldsymbol{y}_t$ and $\boldsymbol{x}_t$ the observed marketable output and input quantities at time t.

N productivity is defined as the difference between the economic value of N-containing inputs and the costs of disposing the N surplus for constant prices and describes the ability to convert all on-farm N sources and N inflows to marketable farm outputs, and to recycle and minimise N losses effectively:

$$\text{Nitrogen productivity}_t = \boldsymbol{w}_{0z}\boldsymbol{z}_t - \boldsymbol{s}_0\boldsymbol{b}_t \tag{2}$$

where $\boldsymbol{z}_t$ are the quantities of N-containing inputs, $\boldsymbol{b}_t$ is the observed N surplus, $\boldsymbol{w}_{0z}$ are the reference prices of these inputs, and $\boldsymbol{s}_0$ is the shadow price of the surplus and based on the costs of disposing manure.

Next, we computed the productivity change over time:

$$\Delta\,\text{Economic productivity} = \boldsymbol{p}_0\Delta\boldsymbol{y} - \boldsymbol{w}_0\Delta\boldsymbol{x} \tag{3}$$

$$\Delta\,N\,\text{productivity} = \boldsymbol{w}_{0z}\Delta\boldsymbol{z} - \boldsymbol{s}_0\Delta\boldsymbol{b} \tag{4}$$

where Δ describes the change from period t to $t+1$. We estimated the productivity gaps using data envelopment analysis (DEA), which is a linear programming method to estimate inefficiencies (Charnes *et al* 1978). We accounted for structural differences, by including land area, herd size, value of machinery and buildings, and labour costs as fixed inputs so as to only estimate the gap originating from differences in farm management. Additionally, we accounted for the economic production behaviour of farmers by assuming that farmers that are making production changes, would prioritise raising profit over reducing the N surplus. We therefore determined the optimal quantities of N-containing inputs to maximise economic productivity and estimated the maximum N productivity for these quantities. To account for technological progress and weather events that can have impact on the production frontier, we benchmarked farms per year. The maximum economic productivity for each year was estimated using the following linear programming problem for farm k belonging to the sample of $i = 1,\ldots, N$ farms:

$$\underset{\boldsymbol{\lambda}_{it},\boldsymbol{x}_{kt},\boldsymbol{y}_{kt}}{\textbf{Max}}\ \cdot\boldsymbol{p}_0\boldsymbol{y}_{kt} - \boldsymbol{w}_0\boldsymbol{x}_{kt} \tag{5}$$

s.t.:

$$\sum_{i=1}^{N}\boldsymbol{\lambda}_{it}\boldsymbol{y}_{it} \geq \boldsymbol{y}_{kt} \tag{5a}$$

$$\sum_{i=1}^{N}\boldsymbol{\lambda}_{it}\boldsymbol{x}_{it} \leq \boldsymbol{x}_{kt} \tag{5b}$$

$$\sum_{i=1}^{N}\boldsymbol{\lambda}_{it}\boldsymbol{l}_{it} \leq \boldsymbol{l}_{kt} \tag{5c}$$

$$\sum_{i=1}^{N}\boldsymbol{\lambda}_{it} = 1 \tag{5d}$$

$$\boldsymbol{\lambda}_{it} \geqslant 0 \tag{5e}$$

where $\boldsymbol{p}_0$ and $\mathbf{w}_0$ are the output and input prices, $\boldsymbol{x}_{kt}$ the variable inputs, $\boldsymbol{l}_{kt}$ the fixed inputs, $\boldsymbol{y}_{kt}$ the outputs, and $\boldsymbol{\lambda}_{it}$ the intensity weights of farm k and time t. The optimisation program finds the combination of $\boldsymbol{x}_{it}$ and $\boldsymbol{y}_{it}$ for each farm that yields the highest profit given the prices $\boldsymbol{p}_0$ and $\boldsymbol{w}_0$ and fixed inputs $\boldsymbol{l}_{kt}$. It does so by assessing the profit of all farms and assigning intensity weights to the farms with the highest profit subject to the constraints. If no other farm, subject to the constraints, has a higher economic productivity, the programme will weigh the farm considered as one and all others as zero.

We computed the minimum N surplus in the by-production technology for farm k and year i for the optimised levels of N-containing inputs from the main technology as follows:

$$\underset{\boldsymbol{\mu}_{it},\,\boldsymbol{b}_{kt}}{\textbf{Min}}\ \cdot\boldsymbol{s}_0\boldsymbol{b}_{kt} \tag{6}$$

s.t.:

$$\sum_{i=1}^{N}\boldsymbol{\mu}_{it}\boldsymbol{z}_{it} \geqslant \boldsymbol{z}^{*}_{kt} \tag{6a}$$

$$\sum_{i=1}^{N}\boldsymbol{\mu}_{it}\boldsymbol{b}_{it} \leq \boldsymbol{b}_{kt} \tag{6b}$$

$$\sum_{i=1}^{N}\boldsymbol{\mu}_{it} = 1 \tag{6c}$$

$$\boldsymbol{\mu}_{it} \geqslant 0 \tag{6d}$$

where $\boldsymbol{\mu}_{it}$ is the intensity weight of farm k and time t in the by-production technology. Here, $\boldsymbol{z}^{*}_{kt}$ is the optimal amount of N-containing inputs and a subset of $\boldsymbol{x}^{*}_{kt}$. The asterisk (*) is used to indicate that these

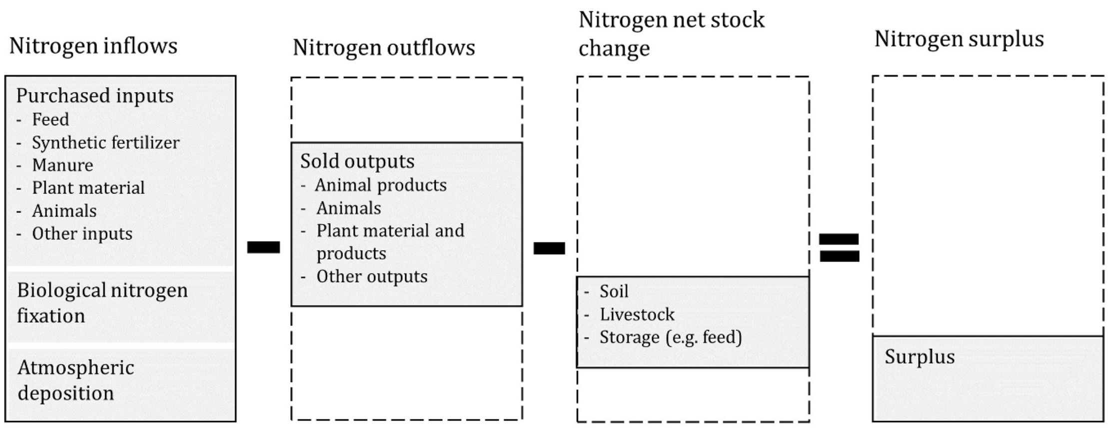

Figure 1. Overview of all subsections of the N surplus indicator.

are not the observed levels but the optimal input levels computed in the first optimisation step.

Combining equations (1) and (5), the economic productivity gap, which is the economic productivity inefficiency, was computed as the difference between maximum economic productivity minus the observed economic productivity:

$$\text{Economic productivity gap}_t = \boldsymbol{p}_0 \left(\boldsymbol{y}_t^* - \boldsymbol{y}_t\right) - \boldsymbol{w}_0 \left(\boldsymbol{x}_t^* - \boldsymbol{x}_t\right) \quad (7)$$

where $\boldsymbol{x}_t^*$ and $\boldsymbol{y}_t^*$ are the levels of the optimised inputs and optimised marketable outputs. The N productivity gap, which is the N productivity inefficiency, was computed as the difference between the observed N surplus and the minimum N surplus:

$$N\ \text{productivity gap}_t = \boldsymbol{b}_t - \boldsymbol{b}_t^* \quad (8)$$

where $\boldsymbol{b}_t^*$ is the level of the minimised N surplus.

2.2. Data selection

We used unbalanced yet stratified panel data of 341 dairy farms in the Netherlands over the time period 2006–2017, collected as part of the Farm Accountancy Data Network of the European Union. Only conventional dairy farms were included in the dataset. Weights were attached to the sample farms according to their representation of Dutch dairy farms from the Dutch Agricultural Census to make the dataset representative to the national context (van der Meer *et al* 2019). Prices and price indices for the years 2006–2017 were drawn from the Eurostat database and averaged over the whole period (Eurostat 2019). The price of N surplus was based on the private costs of disposing manure N off-farm assuming a N content of 4 kg N ton^{-1} of cattle slurry based on statistics of the Netherlands Enterprise Agency (2019) and an average disposing cost of 10.74 euro ton^{-1} of cattle slurry based on statistics of Wageningen Economic Research (2020). Implicit quantities of inputs and outputs were determined as ratio of the monetary value to prices. Inputs and outputs were aggregated using chained Törnqvist price indices (e.g. Ang and Oude Lansink 2018).

We distinguished four fixed inputs (land, labour, capital and animals), eight variable inputs (seeds and planting materials, purchased feed, pesticides, fertiliser, energy, veterinary costs, contract work and costs of renting machinery), two intended outputs (sales of dairy products and cattle, and sales of other agricultural outputs) and one unintended by-product, which is the N surplus. A summary of the data is provided in the supplementary materials, table S1 (available online at stacks.iop.org/ERL/16/124003/mmedia). Because of limited data disaggregation for other agricultural outputs, we could not distinguish between non-dairy livestock sale and dairy and non-dairy livestock herd growth.

2.3. Estimation of the N surplus indicator

The N surplus per farm was estimated as the difference between all farm N inflows and marketable N outflows not including manure and was corrected for N stock changes. The estimation is illustrated in figure 1. The N inflows considered are marketable inputs, the deposition of reactive N from the atmosphere and biological fixation by leguminous plants. The N outflows considered are all marketable outputs except manure. Thus, N surplus includes N losses and N in manure that is stored on farm, transported to other farms or to manure treatment companies. N stock changes refer to changes of the N stock in soil, livestock and storage of feed and other inputs on the farm. Dutch farmlands have a long history of intensive agricultural use and are generally 'saturated' with N. We therefore assumed that they have reached an equilibrium stage where the amount of N mineralised is equal to the amount of N immobilised, and hence no stock changes occur in the soil. One exception is peat soils, where on-going drainage causes high rates of net mineralisation that were added to the N surplus. All calculations are based on the computations

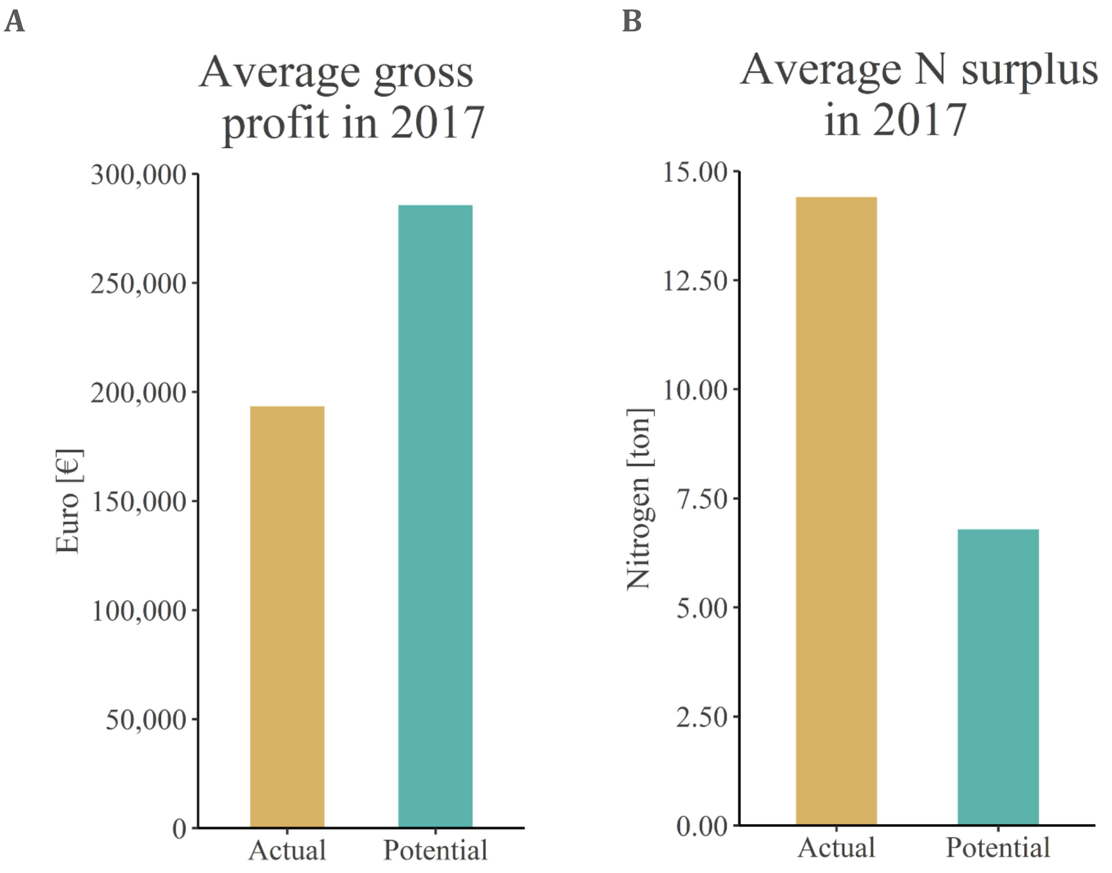

Figure 2. Actual and potential annual gross profit and N surplus of the average Dutch dairy farm in 2017 for average 2006–2017 prices.

of N surpluses by Wageningen Economic Research (Lukács *et al* 2018).

3. Results

3.1. Productivity gaps

Figure 2 shows the potential to raise annual farm profit and to reduce annual N surplus for the average Dutch dairy farm. We assume here that farmers would prioritise increasing farm gross profit and within this space seek to minimise N surplus. The structural determinants of the farm including the value of farm capital, labour input, herd size or land size remain unchanged. For the years 2006–2017, the average annual economic productivity gap between the average Dutch dairy farm and the best performing peers was 68 292 euro or 34% of annual gross profit. Revenues could be increased from 419 580 euro to 555 610 euro, equivalent to 32%. The side-by-side average annual N productivity gap was equivalent to 6 563 kg N surplus per farm, equal to 50% of the average farm N surplus during this time period. This amounts to an annual reduction of 113 kiloton of N for the entire Dutch dairy farming sector. A breakdown for different farm types is included in the supplementary materials (table S3). The simultaneous decrease in unintended by-products (N surplus) and increase in intended outputs (milk, livestock and crops) could have led to a reduction of 34.3 kg N surplus to 12.2 kg N surplus accrued per 1 000 euro worth of marketable outputs produced.

3.2. Synergies and trade-offs between the objectives to maximise gross profit and to reduce N surplus

The profit gain and N surplus reduction in figure 2 hold for the average Dutch dairy farm in our sample. We found that productivity growth (foremost driven by the objective to maximise profit) could have led to reductions in farm N surplus in 96% of the analysed cases between 2006 and 2017. On average 40% of farmers could have reduced the amount of fertiliser and 72% of farmers the amount of purchased feed while raising farm profit (figure 3), because improved utilisation of inputs, better allocation of resources and more internal recycling of nutrients would reduce the need for these costly inputs. Other farmers should have actually increased the amount of fertiliser and purchased feed to raise profit as they are currently undersupplied. Still, for only 2% of farms would this have led to an increase in the N surplus. Others could have compensated for the increase in N inflows through increased production, thus leading to more N outflows.

3.3. Productivity growth over time

We computed the economic and N productivity levels for all farms and years to identify trends over

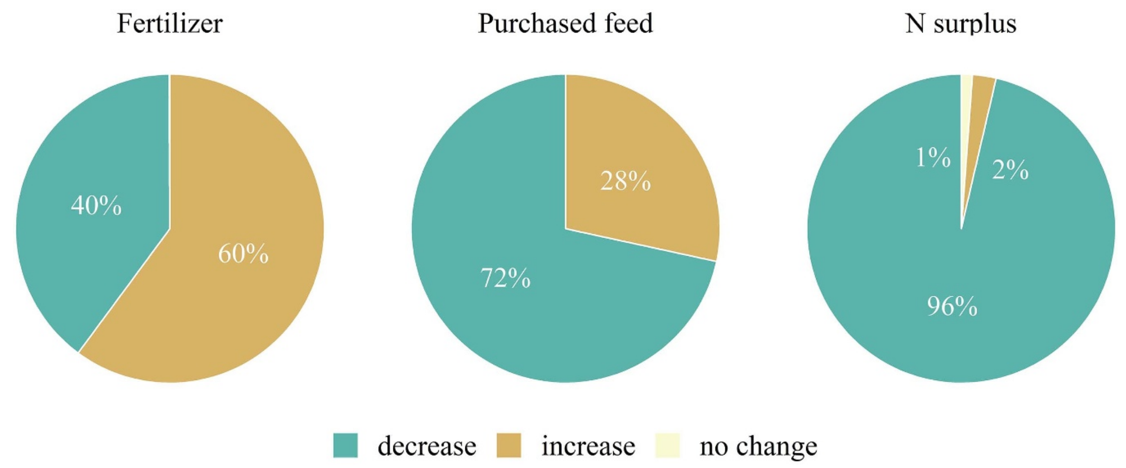

Figure 3. Changes in purchased feed and fertiliser and in N surplus after closing the productivity gaps, as percentage of farms that are increasing or decreasing the inputs and N surplus, 2006–2017.

time. Dutch dairy farms were overall becoming more productive but some more than others (figure 4). This indicates an increasing heterogeneity amongst farms over time. We also computed the average productivity gaps between Dutch dairy farmers and their best peers and found that, despite the large potential to increase farm profit and reduce N surplus, the gaps were not closing over time (see supplementary materials, figure S1).

We conducted several robustness checks. Soil type was not associated with productivity (see supplementary materials, table S5 and figure S2). Since the Netherlands is a small country, weather conditions are similar for the sample. We investigated the potential impact of outliers by removing the top 5% of farms in terms of economic and N productivity levels from the sample. This removal did not affect the efficiency estimates much (see supplementary materials). We also determined the nitrogen productivity gap with regard to N losses instead of N surplus, which in our case is a composite indicator containing N losses, manure N temporarily stored on farm and manure N exported off-farm (see supplementary materials, table S3). The results show the extent to which the N losses on farm can be reduced through efficiency gains and more export of manure off-farm. Yet, without resourceful end use, the regional relocation of manure does not reduce N losses. We also estimated the economic and N productivity gaps if farmers minimised costs instead of maximising profit. In that case, average profit could still be increased by 16% and average N surplus could be reduced by 56% (See supplementary materials, table S4). Lastly, we compared the productivity growth and gaps using the Bennet–Lowe indicator with estimates using Fisher and Lowe indices (see supplementary materials, tables S5 and S6). The results show that the estimates of potential N surplus reduction using the Bennet–Lowe indicator are more conservative than those using the Fisher and Lowe indices.

4. Discussion

By benchmarking farms with their best peers, we found an average economic productivity gap (profit inefficiency) of 34% between 2006 and 2017 amongst the Dutch dairy farms. Ang and Oude Lansink (2018) found an average dynamic profit inefficiency of 40% on Belgian dairy farms between 1996 and 2008. Others studied technical inefficiency, which is by definition smaller than profit inefficiency. For example, Skevas (2020) found an average technical inefficiency of 16% on Dutch dairy farms between 2009 and 2016, and Areal *et al* (2012) of 16% on UK dairy farms between 2000 and 2005. Our estimate relates to the cumulative impact of adopting the best practices of the best peers and excludes the impact of increasing economies of scale (e.g. farming more land or increasing the herd size). Increasing economics of scale is not realistic for all farms in our case study because of the physical limitations to land expansion, rigid land and labour markets and milk and phosphate quotas. For the estimation we used average prices for the time period to capture changes in quantities of inputs and outputs, not in prices. What we find is a large potential for economic gain for Dutch dairy farmers through catching up to the productivity levels of their best peers.

We also found an average N productivity gap of 50%, which is the difference between the average N surplus currently generated in the sample farms and the average minimum N surplus that could be generated while maximising profit. Two other studies have used a system approach to estimate the potential to reduce N surplus in dairy farms. Mu *et al* (2018) used an eco-efficiency approach and found that dairy farms in Western Europe could simultaneously

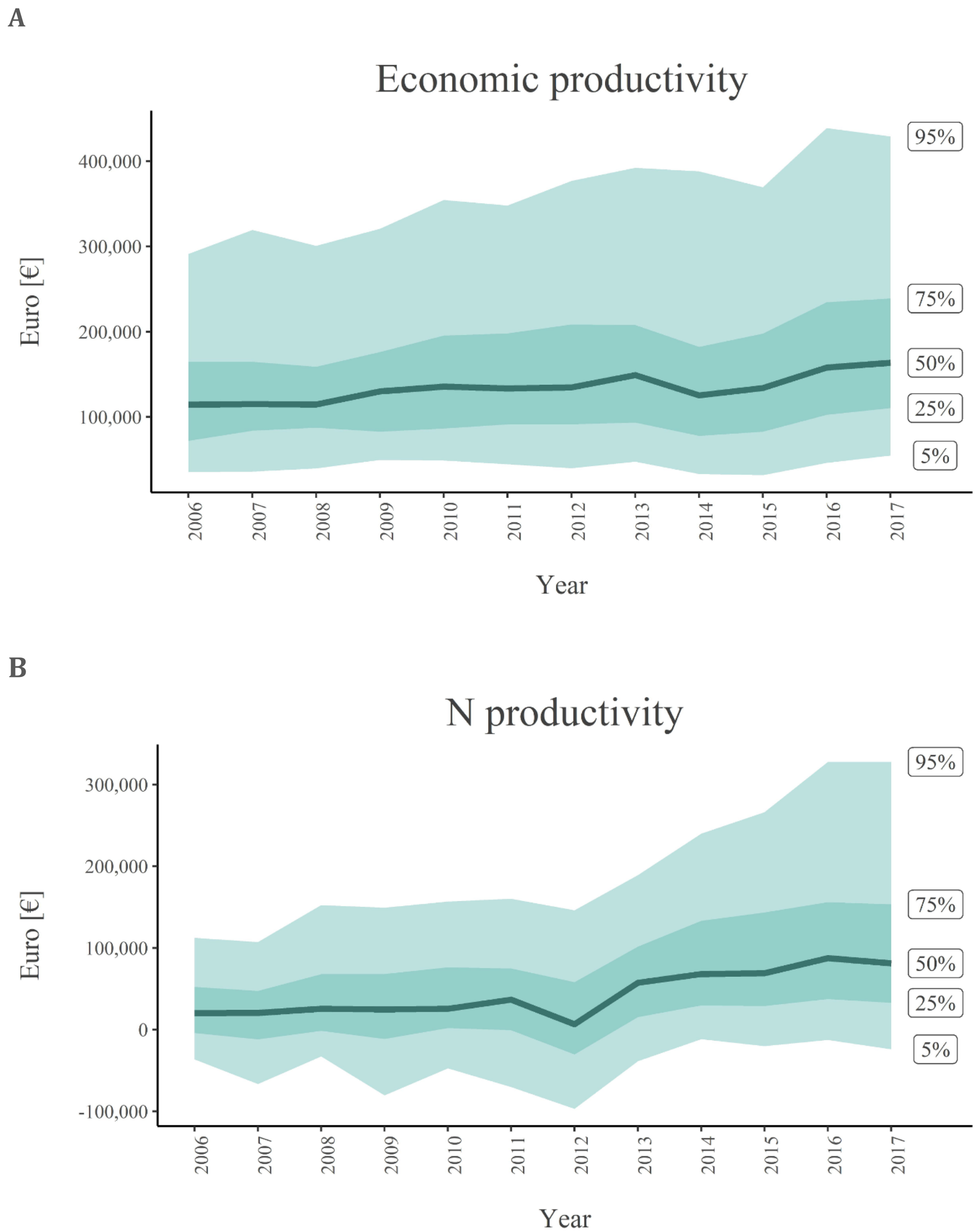

Figure 4. Development of (a) economic productivity and (b) nitrogen productivity at constant prices among Dutch dairy farms from 2006 to 2017. The percentiles on the right-hand side depict the share of observations among Dutch dairy farms that fall below the line. The dark line illustrates the median farm. The productivity indicators were determined using constant prices and are therefore quantity indicators, describing changes in the ability to convert inputs to outputs (not changes in prices).

reduce N surplus by ca. 35% and increase gross profit by ca. 3%. Iribarren *et al* (2011) used an eco-efficiency approach and found that Spanish dairy farms could reduce acidification and eutrophication caused by farm N pollution by 20% and increase profit by 40%. These estimates (3%–40% for profit and 20%–35% for N surplus/pollution) are somewhat lower than our estimates (34% for profit and 50% for N surplus), likely because the inefficiencies were estimated with regard to multiple environmental objectives and no economic objective. Still, our results are consistent with theirs in that productivity growth driven by efficiency gains can increase farm profit and reduce N pollution. Known practices for dairy farms include low-protein animal feeding, improved timing and splitting of animal slurry application to fields, improved timing of harvesting, better conservation of harvested and purchased feed, improved cow longevity and reduced replacement rate and enhanced soil quality conservation. While not all practices increase gross profit and reduce N surplus, in 96% of the studied cases adopting the sum of practices implemented by the best peers, would reduce the farm N surplus. Not all productivity growth reduces N surplus, but there is a large potential. What we find is that there is not only large potential for private but also for public gains if Dutch dairy farmers catch up to the productivity levels of their best peers.

Our results also indicate persistent economic and N productivity gaps throughout the studied period. Similarly, Keizer and Emvalomatis (2014) found that overall productivity was increasing in the Dutch dairy sector between 1995 and 2000 but that technical inefficiencies persisted over time. Skevas *et al* (2018) also found that technical inefficiencies on German dairy farms were persistent between 1999 and 2009 with an autocorrelation of 0.95 between the years. Contrary to our findings, Dakpo *et al* (2019a) found that technical inefficiencies decreased amongst French dairy farms between 2002 and 2015. One reason that the farmers in our sample were not catching up to the productivity levels of their best peers during the time period of our study might be that they are not aware of this room to improve their farm productivities. Not all farmers openly discuss their realised profit, manure and fertiliser application with other farmers. Two studies on dairy calf management showed that benchmarking can be a strong motivation for farmers to improve management (Atkinson *et al* 2017, Sumner *et al* 2018). Also, farmers might lack the knowledge to improve farm management (Baumgart-Getz *et al* 2012). The extension services in the Netherlands are privatised. There is some evidence that privatised extension services in the EU are disadvantaging smaller farms (Labarthe and Laurent 2013, Prager *et al* 2016, Knierim *et al* 2017). Laurent *et al* (2006) found that privatisation led to farmers being less willing to share the advice they received and paid for in order to keep a competitive advantage. Because the advice is demand-driven, less focus might be placed on farm sustainability or N management than would be desirable from a public perspective (Klerkx and Jansen 2010). Thus, while there is a large potential for private and public gains from increasing farm productivity on Dutch dairy farms, we find that it has not been tapped during the time period of our study.

Finally, we note that the size of the productivity gaps also depends on the modelling choices. The economic and N productivity gaps were computed with regard to the objective to maximise profit and in doing so to minimise N surplus. Dutch dairy farmers might have other economic objectives and non-economic objectives (e.g. animal welfare, see Hansson *et al* (2018)). Additionally, allocative inefficiency may arise due to market imperfections (e.g. subsidies). Lastly, one could consider statistical noise in a structured way by adapting Ang (2019)'s DEA framework to a stochastic frontier analysis framework. Hence, additional studies are needed to further analyse the productivity gaps.

5. Conclusions

We developed an approach for assessing increases in profit and decreases in pollution through agricultural productivity growth following the adoption of best practices of sector frontrunners. The approach was applied to N pollution from 341 conventional Dutch dairy farms over the time period 2006–2017. Bennet–Lowe productivity indicators were used to measure economic and N productivities over time and across farms. The productivity gaps across farms were quantified using DEA. Here, the economic and N efficiencies were estimated in two stages using a by-production model with the overarching economic objective to maximise profit.

We found that the dairy farms in our sample could have simultaneously increased the gross profit by on average 34% and could have reduced the N surplus by on average 50%, by adopting the best practices employed by their best peers. Our estimations are based on a sample of farms and larger productivity gaps might prevail across the entire Dutch dairy sector. While trade-offs exist, in 96% of the analysed cases, reaching the economic productivity levels of their best peers would also allow for reduction in N surplus. Despite the large potential gains, the productivity gaps have not decreased during the time period of our study.

The magnitude of the potential to reduce N surplus while increasing profit has considerable implications. There is a strong need to reduce N losses to the environment, to which the global dairy sector is an important contributor (Pelletier and Tyedmers 2010, Uwizeye *et al* 2020). Along these lines, the Dutch 'Governmental Advisory Body for Nitrogen' has recommended a major transition of livestock production in the Netherlands to reduce ammonia emissions of the agricultural sector by 50% within 10 years. Our findings show that stimulating lower performing Dutch dairy farms to catch up to the productivity levels of their best peers could be an effective strategy to reduce N pollution. In this light, policy interventions to facilitate wide-scale adoption of best practices employed by sector frontrunners are essential for creating a win-win situation for Dutch dairy farmers and the environment. Governments should create platforms, mechanisms and programmes to advocate for better farm management, and facilitate information exchange, training, advice and peer learning. These should then be carried further in collaboration with industry, farmers' organisations, environmental protection organisations and related stakeholders.

Our findings suggest that productivity growth could be a game-changer for agricultural sustainability. The general structure of our approach makes it possible to also study other sectors and other environmental pollutants. Applying the approach developed here to other contexts would show the extent to which closing productivity gaps can increase agricultural sustainability.

Data availability statement

No new data were created or analysed in this study. The code is available upon request. The data are confidential, but can be requested at Wageningen Economic Research.

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