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Abstract

Increasing dairy farm productivity while simultaneously mitigating greenhouse gases emissions is a common policy goal in many countries. In this paper, we assess trade-offs and synergies between these goals for pasture-based dairy farms in Brazil. We apply stochastic frontier analysis within a translog hyperbolic distance function specification, including methane emissions as an undesirable output and accounting for annual climatic types. Our results indicate that on average, farmers can improve their production by 9.4% while simultaneously reducing methane emissions by 8.7%. The adoption of more productive cows and improved pastures have a positive effect on the environmental efficiency of the farms. Farmers operating in warmer and dryer climate types tend to have lower environmental efficiency. Calculating shadow prices for methane emitted on farms indicates that the mean abatement costs of methane are US $2,254 per tonne. Overall, by reducing inefficiency, dairy farmers can significantly increase farm production while simultaneously reducing emissions and thus contribute to national commitments to eradicate hunger and mitigate methane emissions.

Keywords: shadow price, technical efficiency, eco-efficiency, GHG mitigation, Balde cheio, Köppen classification

1 Introduction

Dairy farming is fundamental to the economy of many countries, markedly low- and middle-income countries (LMICs), where it plays a pivotal role in employment generation, livelihoods and food security in rural areas (FAO, 2010; OECD-FAO, 2021). Estimates indicate that worldwide 133 million farm holdings keep dairy animals (FAO and GDP, 2018). In LMICs, smallholder famers also rely on milk production for a less risky and regular source of income and food, adding to the income of seasonal crop harvests. Moreover, dairy activities are traditionally conducted by women in many of these countries, contributing to their empowerment, income and household food security (FAO et al., 2020; Ravichandran et al., 2020), especially in households where men outmigrate seeking work in other regions (Ravichandran et al., 2020). In terms of nutrition, milk serves as a high-quality source of protein, vitamins and minerals for humans, playing an indispensable role for nutrition in LMICs, where the rate of undernourished children remains high. For instance, there is strong evidence that the consumption of cow's milk and products by undernourished children has positive effects on their growth (FAO, 2013; FAO et al., 2020; Weaver et al., 2013), while households owning dairy cattle also have children with higher growth and lower rates of undernourishment (FAO et al., 2020). Moreover, dairy is critically important for sustain local food security in rural areas during commercial food shortages, e.g., due to pandemics (OECD-FAO, 2021).

Concurrently, dairy farming contributes to greenhouse gas (GHG) emissions, which are major drivers of global warming. Globally, the dairy herd is responsible for emitting around 2.1 Gt of CO_2eq.[1], representing ~ 30% of all emissions in the livestock sector (Gerber et al., 2013; Herrero et al., 2016). These emissions comprise carbon dioxide, nitrous oxide and remarkably methane, which represents more than 50% of all emissions. GHG emissions from dairy farming considerably vary across countries and production systems, although a strong negative correlation between the carbon footprint of milk and animal productivity has been identified (FAO and GDP, 2018; Gerber et al., 2011; Vogel and Beber, 2022). Moreover, regions that present milk with a higher carbon footprint (or lower productivity) are also those with higher rates of undernourished children and people suffering from chronic food deprivation (FAO and GDP, 2018; Gerber et al., 2011). These

[1]Carbon dioxide equivalent (CO_2eq.) based on the Global Warming Potential 100 years-time horizon (GWP_{100}).

findings suggest that improving the productivity of dairy cows is an effective strategy to improve the environmental sustainability of dairy farms and increase food security in LMICs. Consequently, dairy farmers can be considered as key players for achieving the sustainable development goals (SDGs) linked to eradicating hunger and undertaking actions against climate change.

Globally, policy-makers face the challenge of designing strategies to mitigate GHG emissions to comply with international climate commitments and national laws while maintaining and improving socioeconomic and ecosystem services provided by dairy farms (Brazil, 2021a; Clay et al., 2020; Gerber et al., 2013; Ravichandran et al., 2020). However, the implementation of such strategies at farms is complex and context-specific, generating outcomes that are likely to produce synergies as much as trade-offs (Campbell et al., 2018; Clay et al., 2020; Novo et al., 2015). Unveiling these complexities and finding the most suited strategies is keen for the design of adapted policies to promote the dairy sector and contribute to development goals in LMICs.

In this study, we assess economic and environmental synergies and trade-offs of pasture-based dairy farms managed under the influence of sustainable development strategies. We analyse a sample of Brazilian dairy farmers participating in Embrapa's [2] *Balde Cheio* (Full Bucket-FB) programme in the state of Minas Gerais and investigate their ability to maximise desirable outputs while minimising methane emissions. We estimate a stochastic translog hyperbolic distance function, allowing for asymmetric treatment of desirable and undesirable outputs in the multi-output production frontier (Cuesta et al., 2009; Le et al., 2020; Mamardashvili et al., 2016; Skevas et al., 2018). Moreover, this approach enables identifying drivers of environmental inefficiency and calculating shadow prices for methane, the most concerning GHG emitted on dairy farms (Reisinger et al., 2021; UN-CCAC, 2021).

The Brazilian dairy farming is rapidly evolving and has become one of the main components of the national agri-food sector. According to the most recent agricultural census, in the 2006-2017 period the number of dairy farms in the country decreased from 1.35 M to 1.17 M farms (13%), while the number of milked animals declined by 9% from 12.7 M to 11.5 M cows, and conversely milk production increased by 70% in the same period. In 2020, national milk production reached 36.5 Mt, generating around US $12 billion in value for farmers and placing Brazil as the third-largest dairy milk producer in the world (Embrapa, 2021; Rocha et al., 2020).

[2] Brazilian Agricultural Research Corporation (https://www.embrapa.br/en/international).

Moreover, national dairy production contributes to local food security in rural areas. For instance, more than one-quarter of the milk produced in the country does not enter the dairy processing industry (IBGE, 2018), indicating that it is either consumed directly by the household or commercialised locally through short supply chains. On the environmental side, Brazilian dairy farms play an important role in the conservation of grassland and key biodiversity areas in the form of Legal Reserve and Permanent Preservation Areas, which are spared on farms (Embrapa Territorial, 2020). Nevertheless, by hosting one of the largest dairy herds in the world, the country substantially contributes to GHG emissions. In 2019, dairy farming in Brazil was responsible for emitting 53.8 Mt CO_2eq., representing 2.5% of the national and 9.3% of the agri-food sector CO_2eq. emissions (SEEG, 2020). Overall, the national dairy herd presents low productivity and high GHG intensity, with methane accounting for almost three-quarters of all emissions (SEEG, 2020).

A number of studies have analysed the environmental efficiency of dairy farms. Early approaches treated externalities as inputs in the production function, focusing on farmers' ability to minimise the surplus of nitrogen (N) and phosphorus (P) compounds in Dutch dairy farming (Reinhard et al., 2002, 2000, 1999). Mamardashvili et al. (2016) investigated the environmental efficiency and abatement costs of N surplus in Swiss dairy farms located in mountainous areas. The authors applied hyperbolic and enhanced hyperbolic distance functions to investigate the farmers' ability to expand the production of desirable outputs while reducing Nitrogen N pollution. Applying a similar approach, Skevas et al. (2018) revisited the Dutch case to investigate the effects of agri-environmental policies and production intensification on the environmental efficiency of dairy farms. Adenuga et al. (2019) compared the environmental efficiency and abatement costs of N surplus for dairy farms on the island of Ireland. In terms of P surplus, March et al. (2016) applied the non-parametric data envelopment analysis (DEA) to assess the environmental efficiency of dairy farms in Scotland, while Adenuga et al. (2020) compared farmers from Northern Ireland by applying the stochastic hyperbolic distance function. Studies evaluating the environmental efficiency of dairy farmers in terms of GHG emissions have also gained attention in the dairy sector. A pioneering study considering GHGs in the environmental efficiency of dairy farms was proposed by Njuki and Bravo-Ureta (2015), who employed a quadratic directional distance function with a CO_2eq. pollution index to investigate the impacts of GHG regulations in the US dairy sector. The same approach was applied by Njuki et al. (2016) to study the effects of dairy enterprise size on the environmental efficiency and abatment costs of CO_2eq. of dairy farms in the northeastern US. Wettemann and Latacz-Lohmann (2017) applied DEA techniques to derive ranges of efficiencies and abatement costs for specialised dairy farms in northern Germany. Le et al. (2020) employed the stochastic hyperbolic distance function to compare technical and environmental efficiency and calculate CO_2eq. abatement costs for dairy production in Alberta, Canada.

We expand the literature on environmental efficiency of dairy farms in multiple directions. First, most studies thus far have evaluated intensive high-productive systems in developed countries (e.g., Adenuga et al., 2019; Le et al., 2020; Njuki et al., 2016; Reinhard et al., 1999; Skevas et al., 2018; Wettemann and Latacz-Lohmann, 2017). By contrast, we analyse pasture-based dairy production in Brazil, where dairy farms on average present low yields, operate with limited access to technology and face different policy incentives. Second, instead of evaluating a CO_2eq. index, we focus exclusively on methane emissions as an undesirable output. Thus, we provide a better understating of the environmental efficiency of dairy farms in terms of the most important GHG emitted in the dairy sector. In this approach, we also calculate methane-specific shadow prices, providing an indication of the abatement costs of this GHG for dairy farms in Brazil. This might hold interest for national policy design, particularly given the recent commitments that the Brazilian government assumed to cut methane emissions as a signing party of the Global Methane Pledge.[3] Finally, we include the annual climate type concept in our production function to evaluate the effects of climatic regions on farms' environmental efficiency. This approach is based on the Köppen-Geiger climate classification and might be relevant since there is increasing evidence of the impact of climatic elements on the technical (Gori Maia et al., 2021; Perez-Mendez et al., 2019) and environmental efficiency (Le et al., 2020; Njuki et al., 2016; Njuki and Bravo-Ureta, 2015) of dairy farms.

2 Methods

2.1 Theoretical framework

The theoretical foundations for investigating production in a dynamic environment where a bundle of inputs is employed to produce multiple outputs were introduced by the seminal works

[3] Signatory countries committed to cutting global methane emissions by 30% from 2020 levels by 2030 (EU, 2021).

of Debreu (1951) and Shephard (1953, 1970). Ever since, distance functions (DF) have proved very useful in the empirical measurement of efficiency, notably by Farrell (1957) (Kumbhakar and Lovell, 2003). Under this framework, an input distance function seeks the maximum radial contraction of the input vector at a constant output. Conversely, the output distance function seeks the maximum radially expansion of output vectors at given inputs (Kumbhakar and Lovell, 2003). Despite being extensively applied to evaluate the production processes of marketable goods, the idea of radially expanding outputs altogether is limited when undesirable by-products are part of the decision-making unit outputs.

These limitations gave rise to further developments of the DF taking the form of directional distance functions (DDFs) (Chambers et al., 1996). One of the advantages of this approach is the possibility of applying the output DDF to evaluate the environmental efficiency of decision-making units by seeking a maximum increment in desirable outputs while simultaneously reducing undesirable outputs (Chambers et al., 1998; Chung et al., 1997). This mechanism is enabled by introducing a directional vector into the function in an additive form to scale desirable and undesirable outputs in opposite directions (Färe et al., 2005; Färe and Grosskopf, 2000). Several empirical studies evaluating environmental efficiency follow from these developments (e.g., Njuki et al., 2016; Njuki and Bravo-Ureta, 2015; Picazo-Tadeo et al., 2005; Riera and Brümmer, 2022). Limitations associated with the DDF include the fact that the results are subjective to the selection of the directional vectors, which are normally arbitrarily chosen (Atkinson and Tsionas, 2016; Holtkamp and Brümmer, 2018). Besides, it does not satisfy the property of commensurability, i.e., the results are sensitive to measurement units (Peyrache and Coelli, 2009; Skevas et al., 2018).

Another approach to estimate the environmental efficiency is the hyperbolic distance function (HDF) proposed by Färe et al. (1989), based on the work of Färe et al. (1985). Instead of projecting a straight line towards the frontier, the graph representation follows a hyperbolic path allowing inputs and outputs to be treated asymmetrically (Färe et al., 1985). Färe et al. (1989) developed their framework applying the non-parametric DEA approach. The parametric stochastic framework considering the HDF was proposed by Cuesta and Zofío (2005), while proper adjustments to accommodate undesirable outputs were amended by Cuesta et al. (2009). The HDF satisfies the commensurability property (Skevas et al., 2018) and overcomes the arbitrariness of selecting a directional vector. Moreover, the HDF also enables calculating shadow prices for non-marketable by-products. One limitation often associated with the HDF is that by relying on the weak disposability assumption, it may not comply with the mass balance principle, i.e., the first law of thermodynamics. A number of developments have been undertaken to address this limitation (e.g., Dakpo et al., 2016; Førsund, 2021; Murty et al., 2012; Murty and Nagpal, 2020). Nonetheless, these developments also have constraints that are not completely solved (see Ang and Dakpo, 2021; Dakpo et al., 2016; Murty and Russell, 2021). In addition, HDF has been used in a variety of case studies examining environmental performance and efficiency in dairy production systems, which thus enables comparability with similar work.

To characterise the technology set with undesirable by-products, an additional vector representing undesirable outputs is appended to the traditional representation. It is then represented by a feasible combination of vectors of inputs $x = (x_1, x_2, \dots, x_n)$, desirable outputs $y = (y_1, y_2, \dots, y_n)$ and undesirable by-products $b = (b_1, b_2, \dots, b_n)$. Following Cuesta et al. (2009), the technology can be represented by the graph set

$$T = \{(x, y, b): x \in R_+^K, \mathrm{y} \in R_+^M, \mathrm{b} \in R_+^R, x\ can\ produce\ (y, b)\}. \ (1)$$

The corresponding HDF can be defined as in eq. (2), where $D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b})$ represents the HDF and θ is a scalar. Given the available number of inputs, the HDF represents a maximum expansion of the desirable output vector and equiproportionate contraction of the undesirable output vector, placing producers at the boundary of the production technology T.

$$D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) = min\left\{\theta > 0: \left(\boldsymbol{x}, \frac{\mathrm{y}}{\theta}, \boldsymbol{b}\theta\right) \in T\right\} \ (2)$$

$D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b})$ ranges between 0 and 1. If a farm presents $D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) = 1$, it is located at the boundary of the production possibility set and is considered environmentally-adjusted technical efficient (Dalheimer, 2020). If the technology satisfies the traditional axioms, then our HDF satisfies the properties P1 to P4 below (Cuesta et al., 2009; Cuesta and Zofío, 2005; Färe et al., 1985).

P1. Almost homogeneity: $D_H(\boldsymbol{x}, \mu\boldsymbol{y}, \mu^{-1}\boldsymbol{b}) = \mu D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}); for\ \mu > 0$

P2. Non-decreasing in desirable outputs: $D_H(\boldsymbol{x}, \lambda\boldsymbol{y}, \boldsymbol{b}) \leq D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}); \lambda \in [0,1]$

P3. Non-increasing in undesirable outputs: $D_H(\boldsymbol{x}, \boldsymbol{y}, \lambda\boldsymbol{b}) \leq D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}); \lambda \geq 1$

P4. Non-increasing in inputs: $D_H(\lambda\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) \leq D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}); \lambda \geq 1$

Following the almost homogeneity condition and selecting a normalising output variable M, we can set $\theta = \frac{1}{y_M}$, and express $D_H(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b})$ as

$$D_H\left(\boldsymbol{x}_i, \frac{\mathbf{y}_i}{y_M}, \boldsymbol{b}_i y_M\right) = \frac{1}{y_M} D_H(\boldsymbol{x}_i, \mathbf{y}_i, \boldsymbol{b}_i). (3)$$

By taking logs of both sides of eq. (3), we reach

$$lnD_H(\boldsymbol{x}_i, \mathbf{y}_i, \boldsymbol{b}_i) = lnD_H\left(\boldsymbol{x}_i, \frac{\mathbf{y}_i}{y_M}, \boldsymbol{b}_i y_M\right) + lny_{Mi}. (4)$$

The hyperbolic efficiency is defined as $HE_i = D_H(\boldsymbol{x}_i, \mathbf{y}_i, \boldsymbol{b}_i)$. We substitute and rearrange the equation solving for lny_M, and finally append an error term v_i to capture statistical noise:

$$-\ln y_{Mi} = lnD_H\left(\boldsymbol{x}_i, \frac{\mathbf{y}_i}{y_M}, \boldsymbol{b}_i y_M\right) - lnHE_i + v_i. (5)$$

2.1.1 Shadow price

The shadow price can be interpreted as the production of desirable output that must be foregone to reduce one unit of the undesirable output under analysis (Färe et al., 2005; Zhou et al., 2014). Shadow prices are particularly relevant for studying production systems where by-products are not marketable. An ingenious approach to calculating shadow prices is based on the duality between the HDF and the profitability (Return to the dollar) function (Färe et al., 2002; Färe and Grosskopf, 1998).

Assuming that a producer seeks to maximise profit, she faces the problem described in eq.(6) (Cuesta et al., 2009; Färe et al., 2002).

$$\prod(x,\ p_y, p_b) = \max_{x,y}\left\{\frac{p_y y}{p_b b}:\ D_H(x, y, b)\ \leq 1\right\}\ \ (6)$$

where p_y is the price of desirable output and p_b is the unknown price of the undesirable output. The first-order conditions to the problem in eq. (6) are equal to eq. (7) and eq. (8), respectively.

$$\frac{p_y y}{p_b b} = \lambda \frac{\partial D_H}{\partial y} y = \lambda \left(\frac{\partial lnD_H}{\partial lny}\right) D_H\ \ \ (7)$$

$$\frac{p_y y}{p_b b} = -\lambda \frac{\partial D_H}{\partial y} b = -\lambda \left(\frac{\partial lnD_H}{\partial lnb} \right) D_H. (8)$$

The resulting price ratio equals eq. (9), which enables calculating the shadow price of the undesirable output b in terms of the main desirable output y_M.

$$- p_y \frac{\frac{\partial D_H}{\partial b}}{\frac{\partial D_H}{\partial y_M}} = p_y \frac{dy_M}{db} \,]_{D_H=1} \; (9)$$

It is noteworthy that the shadow price refers to the estimation at the frontier, assuming that the farmer is fully efficient, i.e., $D_H = 1$.

2.2 Methane emissions

Given that direct measurement of methane emissions is complex and expensive, we estimate the emissions following the Guidelines for National Greenhouse Gas Inventories (IPCC, 2019a). Methane originated from enteric fermentation and manure management are the two sources considered in the guidelines. Enteric fermentation emissions are derived based on the daily feed intake of the herd. We calculate the daily gross energy (GE) intake and apply the simplified tier 2 method to calculate the daily dry matter intake (DMI) for each animal category declared by the farmers (i.e., cows, calves, heifers, bulls) (IPCC, 2019b). Finally, we apply the equations for predicting enteric methane based on DMI described by Ribeiro et al. (2020). Forage and concentrate ration information are presented in Appendix A, Tables A1 and A2, respectively.

Methane originated from manure is derived from information on manure volatile solids (VS) content and manure management system. The VS excretion is calculated based on the daily GE intake of the animals and feed quality (IPCC, 2019a). Based on expert information, we assume that 80% of the manure from animals handled on a daily basis was deposited on pastures, while the remaining 20% was deposited onto barns, milking parlour or handling areas, and thus entered the storage system. The default value of 0.19 m^3 CH_4 (kg VS)$^{-1}$ is adopted as the maximum methane producing capacity of VS excreted (IPCC, 2019a).

2.3 Study area and data

We analyse a sample of 208 dairy farms distributed across the state of Minas Gerais (MG) in south-eastern Brazil (see Figure 1). MG has an area of ~586,522 km^2 and is covered by three out of six Brazilian biomes (IBGE, 2021). The state has a long tradition in milk production and is the largest milk producer in Brazil (IBGE, 2018). In 2021, MG produced a total of 9.4 Mt milk, representing 27% of the national production (Embrapa, 2021).

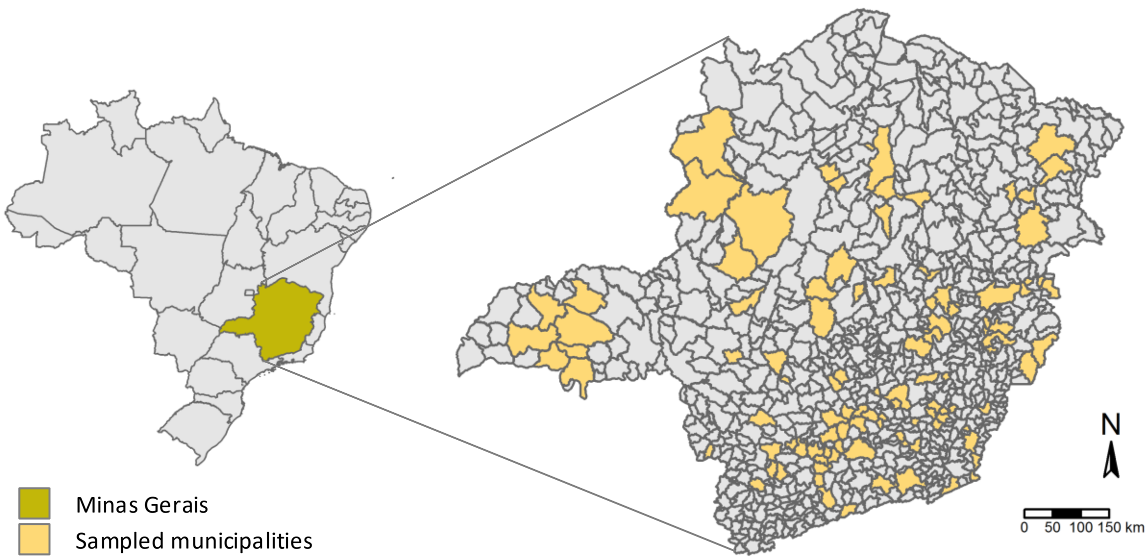

Figure 1. Location of the state of Minas Gerais and sampled municipalities

The cross-sectional dataset was collected in 2017 as part of Embrapa's *Balde Cheio* (Full Bucket-FB) programme.[4] The FB programme was created by the Embrapa's South-Eastern Livestock Research Centre in 1999 and aims at sustainable intensification of dairy farms in Brazil through technology transfer and participatory learning. The database includes a complete socioeconomic characterisation of the household and technical and economic information related to the dairy enterprise. The sample includes exclusively pasture-based producers, which is the most common dairy production system in Brazil. The descriptive statistics of selected farm variables are presented in Table 1.

[4] For a complete description of the programme and its modus operandi, see Novo et al. (2015), https://doi.org/10.1080/14735903.2014.945320 .

Table 1. Variables overview and summary statistics

Variable (N=208)	Mean	Std.Dev	Min	Max
Capital (1,000 US$[a])	2.53	2.3	0.21	12.24
Purchased feed (1,000 US$)	15.45	13.95	0.99	78.11
Other expenses (1,000 US$)	11.76	10.84	1.08	51.65
Land (ha)	40.9	35.41	1	217
Labour (working units)	1.73	0.77	1	4
Lactating cows (N)	23.74	14.57	5	82
Herd size (N)	62.1	38.4	9	213
Milk sold (t FPCM[b])	108.74	83.72	15.37	440.59
Animals sold (1,000 US$)	4.66	5.11	0	29.9
Methane CH_4 (t)	4.95	3.28	0.88	20.87
Buyer (N)	4.62	2.34	1	12
Daily milk yield (kg cow^{-1})	12.45	3.55	4.12	23.12
Experience (years)	20.73	13.62	2	60
Improved pasture (% of pastures)	0.15	0.18	0	1
Milk price (US$)	0.36	0.04	0.28	0.56
Cows in the herd (%)	0.75	0.09	0.41	0.91
Technical visits (N)	13.67	4.65	0	35
Bull in the herd (yes: 1; no: 0)	0.71			
Hired labour (yes: 1; no: 0)	0.82			
Rent land (yes: 1; no: 0)	0.27			

[a]USD-BRL: 3.192 (BACEN, 2022).[b] Fat and protein corrected milk.

Variable selection for the environmental production function is based on recent studies exploring the technical and environmental efficiency of dairy farms (e.g. Adenuga et al., 2020; Le et al., 2020; Mamardashvili et al., 2016; Njuki et al., 2016; Skevas et al., 2018). The *capital* variable represents the opportunity cost of capital invested in buildings and machinery, plus depreciation costs. *Purchased feed* is the sum of all feedstuffs purchased in the year including roughage, concentrates, calve feed and mineral supplements. *Other expenses* include operating expenses with fertilisers, veterinary services, medicines, artificial insemination costs and overheads. *Land* is the area available for feed production, i.e., forage and grain. *Labour* is measured in terms of working units per year. *Lactating cows* represents the number of lactating cows in the herd. *Methane* is annual amount of methane emitted on the farm from enteric fermentation and manure sources (see section 2.2. for details). All monetary values have been converted to 2017 US dollars by applying the USD-BRL exchange rate of 3.192 (BACEN, 2022).

Furthermore, to investigate the influence of year-specific climate elements on environmental efficiency, we include the annual climate type (ACT) in our model (Dubreuil et al., 2019). The ACT relies on the Köppen-Geiger climate classification algorithm, which accounts for seasonal temperature and precipitation variations for grouping climatic types and regions (Trewartha and Horn, 1980). Climatology data for each municipality have been retrieved from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resource (POWER) project.[5] The 'ClimClass' R package (Eccel et al., 2016) was employed to derive two levels of Köppen ACTs (see Table 2).

Table 2. Annual climate types (ACTs), number of farms by ACT, and summary of climate elements for 2017

Köppen ACT	Farms	P_total*	P_winter	P_summer	T_avg	T_w.m	T_c.m
Aw[a]	87	938.6	322.4	616.2	23.6	26.6	19.2
Cw[b]	100	967.6	211.3	756.2	20.9	23.3	16.4
Cs[c]	11	931.6	264.6	667.0	20.9	23.5	16.3
BS[d]	10	550.9	239.2	311.8	23.3	25.8	18.5

[a]Aw: tropical with dry winter; [b]Cw: humid subtropical with dry winter; [c]Cs: humid subtropical with dry summer; [d]BS: dry semi-arid; *P_total: total precipitation depth (mm); P_winter: precipitation depth in the six coldest months (mm); P_summer: precipitation depth in the six warmest months (mm); T_avg: average temperature (°C); T_w.m: average temperature of the warmest month (°C); T_c.m: average temperature of the coldest month (°C).

2.4 Empirical model

We estimate the stochastic version of the translog HDF (Cuesta et al., 2009). Stochastic frontier analysis was proposed independently by Meeusen and van Den Broeck (1977) and Aigner et al. (1977) and enables separating technical inefficiency from random disturbances beyond the control of the producers (Kumbhakar and Lovell, 2003).

Our model considers three outputs – including one undesirable – and six inputs. Letting i = 1, 2…N represent the number of dairy farms, the main desirable output is represented by annual fat and protein corrected milk (FPCM) production (y_M), and the secondary desirable output is the income of animals sold (y_S). The undesirable output is methane emissions (b). The six inputs are capital (x_1), lactating cows (x_2), labour (x_3), land (x_4), feed (x_5), and other expenses (x_6). The ACT

[5] https://power.larc.nasa.gov/data-access-viewer/

(c) is a four-levels controlling variable intended to gain insights into the ACT effect on environmental efficiency. We set the ACT (Aw) as the reference, since it presents the highest mean temperature throughout the year. The final specification for the HDF to be estimated is presented in eq. (10). We scaled the variables by their geometric mean before taking logarithms.

$$
\begin{aligned}
-lny_{Mi} = \alpha_0 + \sum_{k=1}^{6}\alpha_k ln(x_{ki}) + \frac{1}{2}\sum_{k=1}^{6}\sum_{l=1}^{6}\alpha_{kl} ln(x_{ki}) ln(x_{li}) \\
+ \beta_0 ln(b_i^*) + \frac{1}{2}\beta_{00} ln(\, b_i^*)^2 + \sum_{k=1}^{6}\chi_{k0} ln(x_{ki}) ln(\, b_i^*) \\
+\delta_2 ln(\, y_{si}^*) + \frac{1}{2}\delta_{22} ln(\, y_{si}^*)^2 + \sum_{k=1}^{6}\gamma_{k2} ln(x_{ki}) ln(\, y_{si}^*) \\
+\rho_{20} ln(\, y_{si}^*) ln(b_i^*) + \omega_0 c_i + v_i + u_i
\end{aligned}
\qquad (10)
$$

Where $b_i^* = b_i \times y_{Mi}; y_{si}^* = y_{si}/y_{Mi}$. The composite error term is $\varepsilon_i = v_i + u_i$, where v_i is the error term, which captures random noise and has a normal distribution $v_i\ N{\sim}(0, \sigma_{vi}^2)$, and $u_i = -lnHE_i$ is the hyperbolic inefficiency term following a half-normal distribution. Additionally, we considered heteroskedasticity in both v_i (eq.(11)) and u_i, (eq.(12)) (Caudill et al., 1995; Wang, 2002).

$$\sigma_{ui}^2 = e^{z_i' \zeta} \quad (11)$$

$$\sigma_{vi}^2 = e^{w_i' \tau} \quad (12)$$

Where z_i is a farm-specific vector of variables that affect the variance of the inefficiency term, while w_i is a farm-specific vector of variables that affect the variance of the noise term, and ζ and τ are parameters to be estimated. A positive sign of σ_{ui}^2 indicates that the variable z_i under consideration has a positive effect on inefficiency. Similarly, if σ_{vi}^2 displays a positive sign, it suggests that the variable w_i under consideration increases production uncertainty (risk) (Mamardashvili et al., 2016; Wang, 2002).

We follow the recent literature and the availability of data variables to select *z* and *w* variables. Table 3 presents the *z* and *w* variables considered in the model and the respective expected signs.

Table 3. Variables and expected signs for evaluating heteroskedasticity

Variable	σ_{ui}^2	sign	σ_{vi}^2	sign
Buyer	z_1	+	w_1	-
Milk yield	z_2	-	w_2	+/-
Time farming	z_3	+		
Improved pasture	z_4	+/-		
Cows in the herd	z_5	-		
Tech. support	z_6	-	w_3	-
Bull in the herd	z_7	+	w_4	+/-
Hired labour	z_8	+	w_5	-
Rent land	z_9	+	w_6	+/-

Following Battese and Coelli (1988), farm-specific point estimate hyperbolic efficiency (HE_i) scores are calculated according to the conditional distribution of u given ε:

$$HE_i = \mathrm{E}\,[e^{-u_i} |\, \varepsilon_i]. \quad (10)$$

The estimation of the distance function parameters is conducted by maximum-likelihood using the R software (R Core Team, 2019) and the 'npsf' package (Badunenko et al., 2020).

3 Results and discussion

3.1 Production technology

The first-order maximum-likelihood estimates for the production technology, determinants of environmental inefficiency and associated standard errors are presented in Table 4. The complete list of coefficients is presented in Appendix B, Table B1. All first-order coefficients presented the expected signs, with the exception of labour, which was not statistically significant. Moreover, the coefficient of undesirable output has a negative sign, confirming the existence of trade-offs between desirable and undesirable outputs.

The first-order coefficients in the translog HDF may directly be interpreted as elasticities (Cuesta et al., 2009). Thus, we observe that the number of lactating cows has the largest distance elasticity, followed by feed and other expenses. Land and capital exhibit very low elasticities when compared with the other inputs. This is in line with most recent studies evaluating environmental efficiency in dairy farming (e.g., Adenuga et al., 2020, 2019; Mamardashvili et al., 2016; Skevas et al., 2018). In terms of outputs, we observe that the desirable by-product income from livestock sold has a small contribution to the production function, which is expected in dairy enterprises (e.g., Le et al., 2020). In addition, the undesirable output presents a large elasticity and the expected negative sign, indicating that increases in methane emissions will shift farms away from the production frontier, consequently reducing their environmental efficiency (Skevas et al., 2018).

Table 1. First-order parameters and heteroskedasticity model estimates

Technology	D_H [a]		SE
α_0 (Intercept)	-0.218	***	0.040
α_1 (Capital)	-0.043	***	0.012
α_2 (Lactating cows)	-0.207	***	0.051
α_3 (Labour)	0.012		0.023
α_4 (Land)	-0.019	*	0.009
α_5 (Feed)	-0.154	***	0.028
α_6 (Other expenses)	-0.111	***	0.024
β_1 (Methane)	-0.257	***	0.029
δ_2(Animals sold)	0.005	**	0.002
ω_1 (Cw)	-0.042	**	0.013
ω_2 (Cs)	-0.034	*	0.015
ω_3 (BS)	-0.031		0.024
Heteroskedasticity in σ_u^2			
ζ_0 (Intercept)	3.881	**	1.425
ζ_1 (Buyer)	0.092		0.059
ζ_2 (Milk yield)	-0.481	***	0.074
ζ_3 (Time farming)	-0.015		0.010
ζ_4 (Improved pasture)	-1.773	*	0.880
ζ_5 (Cows in the herd)	-3.807	*	1.631
ζ_6 (Tech. support)	-0.055		0.036
ζ_7 (Bull in the herd)	0.239		0.312
ζ_8 (Hired labour)	0.695	*	0.370
ζ_9 (Rent land)	-0.107		0.342
Heteroskedasticity in σ_v^2			
τ_0 (Intercept)	-16.849	***	2.457
τ_1 (Buyer)	0.335	*	0.137
τ_2 (Milk yield)	0.683	***	0.123
τ_3(Tech. support)	0.014		0.065
τ_4 (Bull in the herd)	-1.905	**	0.065
τ_5 (Hired labour)	-0.721		0.629
τ_6 (Rent land)	1.110	*	0.642
Log_Likelihood	236.15		
Mean EE	0.9141		
Std.Dev	0.0873		

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; [a] Since the estimation of the production function is based on a distance function, the expected signs for first-order input variables are expected to be negative while outputs are expected to be positive.

Despite the contrasting characteristics of Aw and BS (dry semi-arid) in terms of precipitation, we find no differences between the two climate types. The mean annual rainfall in the municipalities classified as BS was 58% of the volume of rain received by farmers in Aw (see

Table 2). However, in terms of temperature, the two climate types are similar, presenting a difference of 0.3°C in the annual average temperature.

It is also noteworthy that we identified BS ACT in MG. Previous studies using older Climate Normals data found no semi-arid climate types in the state (e.g., Alvares et al., 2013). However, in our updated Köppen-Geiger model, we determine municipalities that presented dry semi-arid conditions. These results are consistent with more recent climatology studies, which also identify BS climate types in MG (e.g., Dubreuil et al., 2019; Martins et al., 2018). The presence of BS climate types in MG can be seen as evidence of climate change unfolding in the northern region of the state (Dubreuil et al., 2019). This trajectory is likely to continue for the coming years and further pressure milk productivity and environmental efficiency in the region.

3.2 Technical-environmental performance and determinants

The mean environmental efficiency of the sample is depicted in Figure 2 and was 0.91, ranging from 0.61 to 0.99, indicating that most farmers in the sample exhibit high environmental efficiency. These results suggest that on average, farmers can increase outputs by 9.4% (1/0.91) while simultaneously reducing methane emissions by 8.7% (1-0.91). By reducing inefficiency, farmers could meaningfully contribute to national commitments for reducing methane emissions and still benefit by increasing farm output at the same time. For instance, if the farmers in our sample completely eliminate inefficiency, it would represent an annual reduction of methane emissions of 86 tonnes. Moreover, since the farmers in our sample are already engaged in a programme intended to improve farm productivity, we expect that improving the performance of the average smallholder milk producer in MG can achieve higher contributions to mitigating methane emissions.

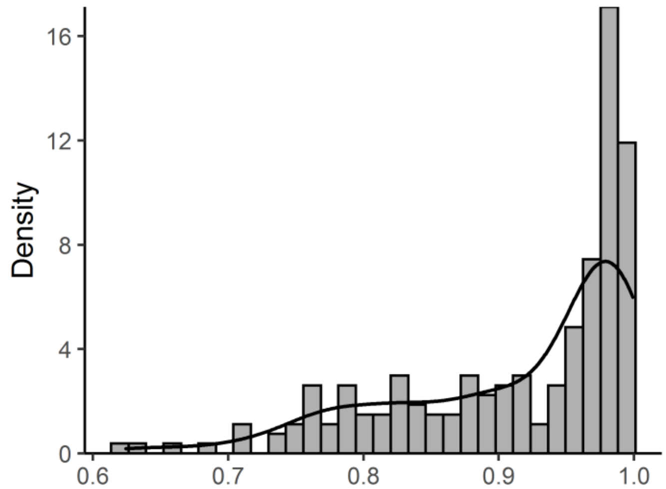

Figure 1. Environmental efficiency scores of dairy farms from Minas Gerais

To put in perspective the effect of the exogenous variables on environmental inefficiency, we present their marginal effects in Table 5.

Table 2. Marginal effects of determinants of inefficiency

Variable	Mean	Std.Dev	Min	Max
Buyer	0.005	0.004	0.000	0.024
Milk yield[a]	-0.024	0.022	-0.127	-0.001
Time farming	-0.001	0.001	-0.004	0.000
Improved pasture	-0.088	0.083	-0.468	-0.004
Cows in the herd	-0.188	0.178	-1.006	-0.009
Technical support	-0.003	0.003	-0.014	0.000
Bull in the herd	0.012	0.011	0.001	0.063
Hire labour	0.034	0.032	0.002	0.184
Rented area	-0.005	0.005	-0.028	0.000

[a] Variables in bold presented significance in the heteroskedasticity model, $p < 0.1$.

Milk yield presents a negative significant influence on environmental inefficiency, which is expected and in line with previous literature (Le et al., 2020; Mamardashvili et al., 2016; Reinhard et al., 2002; Shortall and Barnes, 2013), and can be associated to some extent with the genetic quality of the herd (Le et al., 2020). Therefore, our results confirm the evidence that increasing milk yield per cow is crucial for both the economic and environmental efficiency of dairy farms. Low-yield dairy cows in LMICs is one of the most pressing issues regarding the sustainability of dairy farms (González-Quintero et al., 2022; Novo et al., 2013; Vogel and Beber, 2022). Nevertheless, improving dairy farms in practice warrants a systems-thinking approach. For instance, the successful adoption of high-productive breeds depends on several factors, such as suitable feed supply, climate and rearing conditions that attend the requirements of the selected breed, and farmers with know-how to manage high-yielding animals (Novo et al., 2015).

The share of improved pasture has a negative influence on environmental inefficiency. This is expected since improved pastures produce more forage per unit of land, thus reducing land use. Additionally, improved pastures tend to have higher digestibility and lower natural detergent fibre, which in turn contributes to a lower feed conversion rate (FCR) and methane production from enteric fermentation. It is unsurprising that pasture improvement ranks first in the list of activities that farmers shall focus on to improve farms' sustainability in the FB programme (Novo et al., 2015). Our results are supported by a considerable body of literature providing evidence that sustainable intensification of degraded and low-quality pastures positively contributes to land sparing, soil carbon storage, and reduction of GHG intensity of beef and dairy cattle (IPCC, 2019c; O'Brien et al., 2016; Oliveira et al., 2021; Ruviaro et al., 2015).

The share of lactating cows among cows in the herd has a negative effect on inefficiency. This result provides evidence that adjusting herd structure to reach the best productive performance possible also improves the environmental efficiency of dairy farms. Fundamentally, this is a key indicator in dairy farms and should ideally be around 84% (Bachman and Schairer, 2003; Kuhn et al., 2006). Nonetheless, most dairy farms in Brazil are short of reaching this level.

We find that contracting labour has a significant positive effect on farms' inefficiency. This somewhat confirms the entrepreneurial view that farms exclusively run by the family receive better care, leading to higher efficiency. Family labour is also less expensive as it is normally informal and does not include social security expenses. The traditional efficiency literature reports no pattern regarding the influence of the share of family labour on efficiency (Zhu and Lansink, 2010).

Remarkably, we observe the existence of trade-offs between production efficiency and risk for some variables. Milk yield presented a significant negative sign in the z-model and a significant positive sign in the v-model, suggesting that adopting more productive cows increases efficiency but also production risk. There are many factors that can contribute to these results, such as the fact that animals with higher production are more susceptible to diseases and metabolic disorders, inflicting abrupt and unexpected drops in production and increasing expenses with treatments (Brito et al., 2021; Knaus, 2009). They are also more demanding in terms of diet, requiring a higher level of managerial skills to provide a balanced diet year-round, according to animals' categories and productive cycle (Brito et al., 2021; Hoischen-Taubner et al., 2021). Moreover, the capital invested in more productive animals is higher, which also increases losses in case of unexpected culling (Hoischen-Taubner et al., 2021). The same pattern was found for renting land, which significantly increases production risk but is beneficial to production efficiency. While renting land is associated with contractual expenses, we expect that farmers use rented land to produce high-quality pasture or silage, such that it improves farm environmental efficiency. Conversely, the presence of breeding bulls in the herd significantly reduces risk, but at the same time has a negative effect on environmental efficiency.

3.3 Shadow price of methane emissions

The farm-specific shadow price for methane emissions is calculated with respect to the desirable output milk by using the sample mean of milk price. Since input and output variables have been normalised to estimate the production frontier, we adjust the shadow price by multiplying the result of eq. (9) by the ratio of the desirable output by the undesirable output (Mamardashvili et al., 2016). The resulting mean shadow price value is US $2,254, suggesting that the opportunity cost of reducing an extra tonne of methane emitted in terms of foregone milk production would be around 6.2 t FPCM. Moreover, to compensate for all methane emitted by the farms in our sample, it would cost on average $11,160 per farm. These results indicate that compensating costs are high, representing almost one-quarter of farms' revenue. Therefore, under the present technology, improving farming efficiency is the most cost-effective path to mitigate the emissions of dairy farms. Notwithstanding, the shadow price calculation assumes that farms are operating on the production boundary, and thus shadow price values for inefficient farms may be overestimated (Adenuga et al., 2019).

To the best of our knowledge, this is the first study to apply the HDF to derive the shadow price of methane from dairy farms, making a cross-study comparison very limited. Scaling our results to CO_2eq. by applying the conversion factor of 27.2 (Masson-Delmotte et al., 2021), we reach a value of US $83 per one tonne of CO_2eq. The results from studies evaluating whole-farm CO_2eq. emissions considerably vary. For instance, Njuki and Bravo-Ureta (2015) reported values ranging from US $43 to US $950 per tonne of CO_2eq. for US dairy production. The mean value reported for milk production in Germany was 165 € (US $186)[6] per tonne of CO_2eq. (Wettemann and Latacz-Lohmann, 2017), while Le et al. (2020) reported a value of Can $308.29 (US $230) [7] per tonne of CO_2eq. in Canada. Naturally, direct comparisons are not only limited by differing environmental efficiency models but also by regional milk prices and assumptions in modelling GHG emissions, which considerably differ across studies.

4 Policy implications

Dairy farming is a key agricultural activity to support several SDGs in rural areas. More specifically, it can contribute to achieving the targets from SDG 1 (no poverty), 2 (zero hunger), 12 (responsible consumption and production) and 13 (climate action). In the present study, we evaluate dairy farmers' capability to manage their activities towards higher productivity and lower methane emissions. Reducing methane and other GHG emissions from dairy farming is a priority for meeting long-term climate goals (Gerber et al., 2013; IPCC, 2019c; Key and Tallard, 2012; Reisinger et al., 2021). However, this cannot be achieved at the expense of reducing milk production and availability, especially in LMICs, where milk plays a fundamental role in infant nutrition, food security and income generation (FAO, 2019; Grenov and Michaelsen, 2018; Hemme and Otte, 2010; Tricarico et al., 2020). Therefore, developing policies and mechanisms that reach these goals simultaneously is highly desirable.

There is a growing body of literature supporting the notion that the higher environmental efficiency of dairy farms can be achieved across countries and production systems. However, it is in LMICs where the greatest benefits (marginal effects) can be achieved in terms of both reduced GHG emissions and increased food production (FAO and GDP, 2018; Gerber et al., 2013). The present study adds to this literature by identifying simple management decisions that could improve the environmental efficiency of pasture-based dairy farms (e.g., increasing the share of improved pastures at the farm and adjusting herd composition). These results are very likely to be true across other regions and countries with similar production systems. For example, Ravichandran et al. (2020) identified that many smallholder producers in India did not adopt such simple technologies as feeding troughs and practices such as chopping of forage. While production technologies and knowledge to overcome such production barriers exists and are already available in Brazil and

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[6] https://www.exchangerates.org.uk/EUR-USD-spot-exchange-rates-history-2017.html
[7] https://www.exchangerates.org.uk/CAD-USD-spot-exchange-rates-history-2020.html

many other countries, there remains a huge gap between availability and adoption. Therefore, incentive mechanisms and research focusing on context-specific technology and knowledge transfer is urgently required to bridge this gap in LMICs. Moreover, while there are technologies and practices towards low-carbon dairy farming that could be adopted by farmers with zero or very low expenses, e.g., rotational grazing, others will inevitably require affordable financing instruments, e.g., pasture improvement through seeding of more productive and nutritive grass species or genetic improvement of herds.

Furthermore, our results indicate that increasing the milk production of cows improves the environmental efficiency of dairy farming. This is considered one of the most important achievements that dairy farmers should seek to reduce the carbon footprint intensity of milk (Gerber et al., 2011; Herrero et al., 2016). This goal can be reached based on two pathways: first, to increase the milk production of the actual herd by increasing the quality of cows' diet, and improving herd and animal management; and second, the adoption of animals with higher genetic merit for producing milk, which can be achieved by either crossing the actual herd with more productive animals – normally through artificial insemination – or replacing animals in the herd with more productive animals (Novo et al., 2015; Ravichandran et al., 2020). Replacing low-producing animals with more productive ones is very appealing in terms of both increasing food production and reducing GHG emissions. However, policy-makers should be aware that promoting the adoption of high-productive breeds does not solve the problem per se. Improving smallholder dairy farming must follow a planned sequence of steps based on a system thinking approach. Therefore, programmes aimed at the sustainable intensification of dairy farming. For example, Full Bucket in Brazil (Novo et al., 2015) and MilkIT in India and Tanzania (Ravichandran et al., 2020) normally first opt to implement strategies to improve the production of the actual herd through feeding, herd management, animal sanity and proper manure handling (Beber et al., 2019; Vogel and Beber, 2022). This approach takes some time to implement, requiring farmers to acquire the know-how to manage and feed more productive and demanding animals, which are promoted in a next step in the intervention cycle (Novo et al., 2015).

In the case of the Full Bucket programme, the transformation of dairy farms into showcase units (model farms) is a key strategy for creating learning clusters at the village level. In addition, technicians are trained to provide farmers with tailored support, developing strategies based on the actual farm endowments and accounting for the socioeconomic characteristics of the household.

This and similar programmes are considered successful cases for the sustainable intensification of dairy farming, increasing food security, nutrition, women's empowerment, improving the overall livelihood of smallholders and reducing environmental impacts of dairy farms across LMICs (Gerber et al., 2013; Novo et al., 2013; Ravichandran et al., 2020). Despite being very effective, the implementation of programmes with this design requires some time to show satisfactory results (3+ years) (Novo et al., 2015, 2013; Ravichandran et al., 2020). Moreover, their development must be sustained by complimentary supply chain operations and market opportunities, which are sometimes limited in LMICs (Beber et al., 2019; de Mendonça et al., 2020; Ravichandran et al., 2020).

Furthermore, promoting sustainable intensification strategies at the farm level and closing efficiency gaps may not be sufficient to meet global methane emission reduction targets on time. The pledge of reducing global methane emissions by 30% from 2020 levels by 2030 will require an extra effort by countries with large livestock herds, such as Brazil and India. Pricing instruments such as carbon and methane taxes have been suggested as an alternative to drive the reduction of externalities in the livestock sector (Key and Tallard, 2012). The shadow price found in the present study provides an indication of the abatement cost for methane emitted by pasture-based dairy farms in Brazil, which can support research for understanding the impacts of implementing pricing instruments in the dairy sector in the tropics. Nonetheless, the implementation of emission taxes in LMIC should be considered last, since the heterogeneity across farms may render the implementation of non-discriminatory emissions taxes. Moreover, advanced certification and monitoring platforms would be necessary to implement methane taxes while avoiding negative spill overs in terms reducing food security (FAO, 2019; Key and Tallard, 2012). Given the possible issues associated with the adoption of methane taxes, policy measures of incentivisation should be prioritised, e.g., payments for environmental services and other conservation-inducing incentives.

Another set of solutions that have gained importance in recent years concerns on-farm carbon storage (Brazil, 2021b; COWI et al., 2020; IPCC, 2019c). Pasture improvement is at the centre of this approach for less productive dairy farms, as it generates important synergies. For instance, pasture improvement promotes carbon storage in biomass and soil as well as the production of forage with higher digestibility, consequently favouring animal productivity and the reduction of methane emissions from livestock (Congio et al., 2018; Cortner et al., 2019; O'Brien et al., 2016). Following pasture improvement, the adoption of integrated production systems has also been promoted as an important carbon farming strategy (e.g., silvopastoral, livestock-forestry and crop-livestock-forestry). The use of fast-growing trees species on farms can also create synergies in many ways. They have strong potential to capture carbon in biomass through photosynthesis. In addition, experimental studies in Brazil have shown that implementing trees on pastures creates microclimates that protect pastures from heat and frost. This microclimate also improves animals' thermal comfort, reducing energy use for maintenance and increasing milk production (Brazil, 2021a; Cortner et al., 2019; Resende et al., 2020; Salton et al., 2014). This set of actions has been extensively supported by financing incentives in Brazil through the Low Carbon Agriculture (ABC) plan (Brasil, 2012; Brazil, 2021b).

The ABC plan has led to significant reductions in GHG emissions in the country, the development of low-carbon and adaptation research and successful certifications schemes, e.g., Low Carbon Brazilian Beef (Brazil, 2021b, 2021a; Resende et al., 2020). Despite the effectiveness of the cases developed in Brazil, the low rate of adoption of financial incentives for adopting low-carbon practices in the country is a sign of lacking governance to couple financial incentives and technological transfer at the farm level (Cortner et al., 2019). Moreover, implementing silvopastoral and forestry integration on dairy farms may require on-farm structural changes, increasing the complexity of the farming systems. This in turn will require even higher technical and managerial skills as well as financial resources for farmers. This clearly indicates the need to develop and expand technology and knowledge transfer programmes based on holistic approaches guided by multidisciplinary teams, as well as the access to credit to improve feeding strategies and genetics of the dairy herd to reach satisfactory levels of productivity and reduction of GHG emissions.

Given the stark heterogeneity of dairy farms across countries and regions, defining and benchmarking satisfactory levels of productivity must take into account regional pedoclimatic conditions for milk production as well as the socioeconomic conditions of farmers in the region (FAO and GDP, 2018; Gerber et al., 2011; Vogel and Beber, 2022). The greatest benefits from increasing dairy cow productivity can be achieved in systems with animals producing less than 2 tonnes FPCM year. Gains are still significant in systems producing between 2 and 5 t FPCM per year, while increasing productivity above 5 tonnes FPCM per cow per year will produce only small marginal reductions in the carbon footprint of milk (FAO and GDP, 2018; Gerber et al., 2011). Farms in our sample presented a production of ~3.7 t FPCM per cow per year, which is about one tonne higher than the national average (IBGE, 2018). Thus, we can infer that commercial pasture-based farms in Brazil striving to achieve 5 t FPCM per cow per year could remarkably increase milk outputs while reducing the GHG intensity of milk.

5 Conclusion

Dairy farming has a crucial function in generating farm income, providing food security and employment, as well as safeguarding livelihoods in rural areas in many LMICs. Nevertheless, dairy farming is also an important contributor to GHG emissions, which is an externality of global concerns. Low productive cows in adverse climate settings as much as inadequate management practices compromise farm productivity and are also likely to affect their environmental performance. However, research on the environmental performance of dairy farming is limited to developed countries and high-productive systems. In this paper, we have addressed this gap and analysed the environmental performance of pasture-based dairy production in MG state in Brazil. The stochastic translog HDF was applied considering methane emissions as an undesirable output. This approach allowed us to derive farms' specific environmental efficiency scores, identify key variables that affect efficiency and risk in milk production, and derive the economic/environmental trade-off in the form of the shadow price for methane.

Therefore, this study concludes that farmers can improve farms' environmental performance by increasing milk and animal liveweight outputs while simultaneously reducing methane emissions and thus contribute to the Brazilian commitments for reducing methane emissions simply by becoming more efficient in the use of current level of inputs. On average, farmers can improve the environmental efficiency of their farms by increasing the milk yield of cows, increasing the share of improved pastures on farms and adjusting the herd structure. The study also provides evidence that dairy farmers operating in tropical and semi-arid climates are at a disadvantage compared with farmers from areas with a humid subtropical climate. These results reinforce the necessity of considering regional climate types for designing agri-environmental policies and instruments. The shadow price found in this study is within the range reported in the literature and was considerably high in terms of farm revenue, suggesting that mechanisms other than pricing should be given priority for reducing methane emissions in dairy farms. Given the importance and sensitivity of dairy farming for food security and infant nutrition in LMICs, climate policies for the dairy sector must take a precautionary approach in this regard. While the development of dairy farming in LMICs must be driven by multiple strategies, providing long-term technical support and knowledge transfers must be at the core of policy strategies.

Finally, we discuss some limitations of our study. Our sample exclusively comprised farmers taking part in a voluntary opt-in programme designed to improve farm efficiency, and thus extrapolating our results for the whole population of dairy farmers in Brazil warrants caution due to possible selection bias issues. Nonetheless, given the actions promoted by the FB program, we expect that smallholder farmers not engaged in the programme will on average display lower environmental performance than those who participate. The cross-sectional characteristic of our database did not allow us to explore the dynamics in climate and annual extreme weather conditions faced by farmers in MG. Moreover, due to the limited number of observations, we derived a two-level ACT, which includes a main climate group and the seasonal precipitation characteristics. Further studies considering three-level ACT classification are expected to provide further insights into the climate influence on the efficiency of dairy farms. Due to the lack of feasible measurement techniques, it was necessary to calculate methane emissions indirectly and based on assumptions, e.g., manure deposition. This certainly added some uncertainty to our results. Finally, this study focused exclusively on methane, which is currently the most concerning externality in the Brazilian dairy sector, and it is necessary to further explore trade-offs between methane and other undesirable outputs in future studies in the Brazilian conditions.

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Appendix A

Table A1
Forage characteristics

Name	Type	DM	NDF	TDN	CP
Zea mays	Silage	31.2	54.0	63.2	7.2
Saccharum officinarum L.	Fresh forage	28.9	53.5	62.8	2.8
Brachiaria.spp	Fresh forage	35.4	71.5	50.1	6.4
Cynodon spp.	Fresh forage	27.9	75.6	59.1	12.1
Panicum spp.	Fresh forage	28.0	70.4	58.0	10.2
Pennisetum purpureum Schum.	Fresh forage	22.04	64.91	63.66	10.78
Generic Intensive	Fresh forage	25.98	70.31	60.26	11.04

DM: dry matter (% fresh matter); NDF: neutral detergent fiber (%DM); TDN: total digestible nutrients (% DM); CP: crude protein (%DM). Based on Valadares Filho et al. (2020).

Table A2
Concentrate ration formulation for lactating cows and other cattle

Ingredient	Lactating cows	Other cattle
Maize meal (%)	63.00	40.00
Soybean meal (%)	24.28	20.00
Soybean hulls (%)	2.00	5.00
Rice meal (%)	6.75	32.58
Dicalcium phosphate (%)	1.12	1.53
Limestone (%)	1.07	0.00
Salt (%)	0.79	0.78
Urea (%)	1.00	0.10

Appendix B

Table B1
Parameter estimates of the hyperbolic distance function

Technology	D_H CH_4		SE
α0 (Intercept)	-0.218	***	0.040
α1 (Capital)	-0.043	***	0.012
α2 (Lactating cows)	-0.207	***	0.051

α3 (Labour)	0.012		0.023
α4 (Land)	-0.019	*	0.009
α5 (Feed)	-0.154	***	0.028
α6 (Other expenses)	-0.111	***	0.024
β1 (Methane)	-0.257	***	0.029
β00	0.239		0.236
α11	0.054	***	0.016
α22	2.518	***	0.581
α33	-0.023		0.117
α44	-0.004		0.011
α55	0.001		0.084
α66	0.060		0.053
α12	-0.103	*	0.059
α13	0.005		0.029
α14	0.023	*	0.011
α15	0.010		0.031
α16	0.129	***	0.033
α23	-0.265		0.173
α24	-0.026		0.064
α25	-0.863	***	0.178
α26	0.051		0.144
α34	0.025		0.023
α35	-0.323	***	0.063
α36	0.105	*	0.047
α45	0.051	*	0.021
α46	-0.057	**	0.019
α56	0.102	*	0.052
δ2(Animals sold)	0.005	**	0.002
δ22	0.001	**	0.001
χ10	-0.043		0.029
χ20	-0.682	*	0.348
χ30	0.230	*	0.094
χ40	0.005		0.037
χ50	0.317	**	0.114
χ60	-0.152		0.093
γ12	0.002	*	0.001
γ22	0.016	***	0.005
γ32	-0.011	***	0.002
γ42	0.003	***	0.001
γ52	0.001		0.003
γ62	0.005	**	0.002
ρ20	-0.008	***	0.003
ω2	-0.042	**	0.013
ω3	-0.034	*	0.015
ω4	-0.031		0.024

Heteroskedasticity in σ_u^2

ζ0 (Intercept)	3.881	**	1.425
ζ1 (Buyers)	0.092		0.059
ζ2 (Milk yield)	-0.481	***	0.074
ζ3 (Time farming)	-0.015		0.010
ζ4 (Intensive pasture)	-1.773	*	0.880
ζ5 (Cows in the herd)	-3.807	*	1.631
ζ6 (Tech. support)	-0.055		0.036
ζ7 (Bull in the herd)	0.239		0.312
ζ8 (Hire labour)	0.695	*	0.370
ζ9 (Rent land)	-0.107		0.342
Heteroskedasticity in σ_v^2			
τ0 (Intercept)	-16.849	***	2.457
τ1 (Buyers)	0.335	*	0.137
τ2 (Milk yield)	0.683	***	0.123
τ3 (Bull in the herd)	0.014		0.065
τ4 (Hire labour)	-1.905	**	0.629
τ5 (Rent land)	-0.721		0.642
Log_Likelihood	236.15		
Mean EE	0.9141		
Std.Dev	0.0873		