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Environmental efficiency and methane abatement costs of dairy farms from Minas Gerais, Brazil

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2
3 Abstract

4
5 Increasing dairy farm productivity while simultaneously mitigating greenhouse gases emissions is
6 a common policy goal in many countries. In this paper, we assess trade-offs and synergies between
7 these goals for pasture-based dairy farms in Brazil. We apply stochastic frontier analysis within a
8 translog hyperbolic distance function specification, including methane emissions as an undesirable
9 output and accounting for annual climatic types. Our results indicate that on average, farmers can
10 improve their production by 9.4% while simultaneously reducing methane emissions by 8.7%. The
11 adoption of more productive cows and improved pastures have a positive effect on the
12 environmental efficiency of the farms. Farmers operating in warmer and dryer climate types tend
13 to have lower environmental efficiency. Calculating shadow prices for methane emitted on farms
14 indicates that the mean abatement costs of methane are US \$2,254 per tonne. Overall, by reducing
15 inefficiency, dairy farmers can significantly increase farm production while simultaneously
16 reducing emissions and thus contribute to national commitments to eradicate hunger and mitigate
17 methane emissions.

18
19 **Keywords:** shadow price, technical efficiency, eco-efficiency, GHG mitigation, Balde cheio,
20 Köppen classification

33 **1 Introduction**

34 Dairy farming is fundamental to the economy of many countries, markedly low- and
35 middle-income countries (LMICs), where it plays a pivotal role in employment generation,
36 livelihoods and food security in rural areas (FAO, 2010; OECD-FAO, 2021). Estimates indicate
37 that worldwide 133 million farm holdings keep dairy animals (FAO and GDP, 2018). In LMICs,
38 smallholder famers also rely on milk production for a less risky and regular source of income and
39 food, adding to the income of seasonal crop harvests. Moreover, dairy activities are traditionally
40 conducted by women in many of these countries, contributing to their empowerment, income and
41 household food security (FAO et al., 2020; Ravichandran et al., 2020), especially in households
42 where men outmigrate seeking work in other regions (Ravichandran et al., 2020). In terms of
43 nutrition, milk serves as a high-quality source of protein, vitamins and minerals for humans,
44 playing an indispensable role for nutrition in LMICs, where the rate of undernourished children
45 remains high. For instance, there is strong evidence that the consumption of cow's milk and
46 products by undernourished children has positive effects on their growth (FAO, 2013; FAO et al.,
47 2020; Weaver et al., 2013), while households owning dairy cattle also have children with higher
48 growth and lower rates of undernourishment (FAO et al., 2020). Moreover, dairy is critically
49 important for sustain local food security in rural areas during commercial food shortages, e.g., due
50 to pandemics (OECD-FAO, 2021).

51 Concurrently, dairy farming contributes to greenhouse gas (GHG) emissions, which are
52 major drivers of global warming. Globally, the dairy herd is responsible for emitting around 2.1 Gt
53 of CO₂eq.¹, representing ~ 30% of all emissions in the livestock sector (Gerber et al., 2013; Herrero
54 et al., 2016). These emissions comprise carbon dioxide, nitrous oxide and remarkably methane,
55 which represents more than 50% of all emissions. GHG emissions from dairy farming considerably
56 vary across countries and production systems, although a strong negative correlation between the
57 carbon footprint of milk and animal productivity has been identified (FAO and GDP, 2018; Gerber
58 et al., 2011; Vogel and Beber, 2022). Moreover, regions that present milk with a higher carbon
59 footprint (or lower productivity) are also those with higher rates of undernourished children and
60 people suffering from chronic food deprivation (FAO and GDP, 2018; Gerber et al., 2011). These

¹Carbon dioxide equivalent (CO₂eq.) based on the Global Warming Potential 100 years-time horizon (GWP₁₀₀).

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

65 Globally, policy-makers face the challenge of designing strategies to mitigate GHG
66 emissions to comply with international climate commitments and national laws while maintaining
67 and improving socioeconomic and ecosystem services provided by dairy farms (Brazil, 2021a;
68 Clay et al., 2020; Gerber et al., 2013; Ravichandran et al., 2020). However, the implementation of
69 such strategies at farms is complex and context-specific, generating outcomes that are likely to
70 produce synergies as much as trade-offs (Campbell et al., 2018; Clay et al., 2020; Novo et al.,
71 2015). Unveiling these complexities and finding the most suited strategies is keen for the design of
72 adapted policies to promote the dairy sector and contribute to development goals in LMICs.

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

83 The Brazilian dairy farming is rapidly evolving and has become one of the main
84 components of the national agri-food sector. According to the most recent agricultural census, in
85 the 2006-2017 period the number of dairy farms in the country decreased from 1.35 M to 1.17 M
86 farms (13%), while the number of milked animals declined by 9% from 12.7 M to 11.5 M cows,
87 and conversely milk production increased by 70% in the same period. In 2020, national milk
88 production reached 36.5 Mt, generating around US \$12 billion in value for farmers and placing
89 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>).

90 Moreover, national dairy production contributes to local food security in rural areas. For instance,
91 more than one-quarter of the milk produced in the country does not enter the dairy processing
92 industry (IBGE, 2018), indicating that it is either consumed directly by the household or
93 commercialised locally through short supply chains. On the environmental side, Brazilian dairy
94 farms play an important role in the conservation of grassland and key biodiversity areas in the form
95 of Legal Reserve and Permanent Preservation Areas, which are spared on farms (Embrapa
96 Territorial, 2020). Nevertheless, by hosting one of the largest dairy herds in the world, the country
97 substantially contributes to GHG emissions. In 2019, dairy farming in Brazil was responsible for
98 emitting 53.8 Mt CO₂eq., representing 2.5% of the national and 9.3% of the agri-food sector CO₂eq.
99 emissions (SEEG, 2020). Overall, the national dairy herd presents low productivity and high GHG
100 intensity, with methane accounting for almost three-quarters of all emissions (SEEG, 2020).

101 A number of studies have analysed the environmental efficiency of dairy farms. Early
102 approaches treated externalities as inputs in the production function, focusing on farmers' ability
103 to minimise the surplus of nitrogen (N) and phosphorus (P) compounds in Dutch dairy farming
104 (Reinhard et al., 2002, 2000, 1999). Mamardashvili et al. (2016) investigated the environmental
105 efficiency and abatement costs of N surplus in Swiss dairy farms located in mountainous areas.
106 The authors applied hyperbolic and enhanced hyperbolic distance functions to investigate the
107 farmers' ability to expand the production of desirable outputs while reducing Nitrogen N pollution.
108 Applying a similar approach, Skevas et al. (2018) revisited the Dutch case to investigate the effects
109 of agri-environmental policies and production intensification on the environmental efficiency of
110 dairy farms. Adenuga et al. (2019) compared the environmental efficiency and abatement costs of
111 N surplus for dairy farms on the island of Ireland. In terms of P surplus, March et al. (2016) applied
112 the non-parametric data envelopment analysis (DEA) to assess the environmental efficiency of
113 dairy farms in Scotland, while Adenuga et al. (2020) compared farmers from Northern Ireland by
114 applying the stochastic hyperbolic distance function. Studies evaluating the environmental
115 efficiency of dairy farmers in terms of GHG emissions have also gained attention in the dairy
116 sector. A pioneering study considering GHGs in the environmental efficiency of dairy farms was
117 proposed by Njuki and Bravo-Ureta (2015), who employed a quadratic directional distance
118 function with a CO₂eq. pollution index to investigate the impacts of GHG regulations in the US
119 dairy sector. The same approach was applied by Njuki et al. (2016) to study the effects of dairy
120 enterprise size on the environmental efficiency and abatement costs of CO₂eq. of dairy farms in the

121 northeastern US. Wettemann and Latacz-Lohmann (2017) applied DEA techniques to derive
122 ranges of efficiencies and abatement costs for specialised dairy farms in northern Germany. Le et
123 al. (2020) employed the stochastic hyperbolic distance function to compare technical and
124 environmental efficiency and calculate CO₂eq. abatement costs for dairy production in Alberta,
125 Canada.

126 We expand the literature on environmental efficiency of dairy farms in multiple directions.
127 First, most studies thus far have evaluated intensive high-productive systems in developed
128 countries (e.g., Adenuga et al., 2019; Le et al., 2020; Njuki et al., 2016; Reinhard et al., 1999;
129 Skevas et al., 2018; Wettemann and Latacz-Lohmann, 2017). By contrast, we analyse pasture-
130 based dairy production in Brazil, where dairy farms on average present low yields, operate with
131 limited access to technology and face different policy incentives. Second, instead of evaluating a
132 CO₂eq. index, we focus exclusively on methane emissions as an undesirable output. Thus, we
133 provide a better understating of the environmental efficiency of dairy farms in terms of the most
134 important GHG emitted in the dairy sector. In this approach, we also calculate methane-specific
135 shadow prices, providing an indication of the abatement costs of this GHG for dairy farms in Brazil.
136 This might hold interest for national policy design, particularly given the recent commitments that
137 the Brazilian government assumed to cut methane emissions as a signing party of the Global
138 Methane Pledge.³ Finally, we include the annual climate type concept in our production function
139 to evaluate the effects of climatic regions on farms' environmental efficiency. This approach is
140 based on the Köppen-Geiger climate classification and might be relevant since there is increasing
141 evidence of the impact of climatic elements on the technical (Gori Maia et al., 2021; Perez-Mendez
142 et al., 2019) and environmental efficiency (Le et al., 2020; Njuki et al., 2016; Njuki and Bravo-
143 Ureta, 2015) of dairy farms.

144 **2 Methods**

145 **2.1 Theoretical framework**

146 The theoretical foundations for investigating production in a dynamic environment where
147 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).

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

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

169 Another approach to estimate the environmental efficiency is the hyperbolic distance
170 function (HDF) proposed by Färe et al. (1989), based on the work of Färe et al. (1985). Instead of
171 projecting a straight line towards the frontier, the graph representation follows a hyperbolic path
172 allowing inputs and outputs to be treated asymmetrically (Färe et al., 1985). Färe et al. (1989)
173 developed their framework applying the non-parametric DEA approach. The parametric stochastic
174 framework considering the HDF was proposed by Cuesta and Zofío (2005), while proper
175 adjustments to accommodate undesirable outputs were amended by Cuesta et al. (2009). The HDF
176 satisfies the commensurability property (Skevas et al., 2018) and overcomes the arbitrariness of
177 selecting a directional vector. Moreover, the HDF also enables calculating shadow prices for non-
178 marketable by-products. One limitation often associated with the HDF is that by relying on the

179 weak disposability assumption, it may not comply with the mass balance principle, i.e., the first
 180 law of thermodynamics. A number of developments have been undertaken to address this limitation
 181 (e.g., Dakpo et al., 2016; Førsund, 2021; Murty et al., 2012; Murty and Nagpal, 2020). Nonetheless,
 182 these developments also have constraints that are not completely solved (see Ang and Dakpo, 2021;
 183 Dakpo et al., 2016; Murty and Russell, 2021). In addition, HDF has been used in a variety of case
 184 studies examining environmental performance and efficiency in dairy production systems, which
 185 thus enables comparability with similar work.

186 To characterise the technology set with undesirable by-products, an additional vector
 187 representing undesirable outputs is appended to the traditional representation. It is then represented
 188 by a feasible combination of vectors of inputs $x = (x_1, x_2, \dots, x_n)$, desirable outputs $y =$
 189 (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
 190 technology can be represented by the graph set

191

$$192 \quad T = \{(x, y, b): x \in R_+^K, y \in R_+^M, b \in R_+^R, x \text{ can produce } (y, b)\}. \quad (1)$$

193

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

198

$$199 \quad D_H(\mathbf{x}, \mathbf{y}, \mathbf{b}) = \min \left\{ \theta > 0: \left(\mathbf{x}, \frac{\mathbf{y}}{\theta}, \mathbf{b}\theta \right) \in T \right\} \quad (2)$$

200 $D_H(\mathbf{x}, \mathbf{y}, \mathbf{b})$ ranges between 0 and 1. If a farm presents $D_H(\mathbf{x}, \mathbf{y}, \mathbf{b}) = 1$, it is located at the boundary
 201 of the production possibility set and is considered environmentally-adjusted technical efficient
 202 (Dalheimer, 2020). If the technology satisfies the traditional axioms, then our HDF satisfies the
 203 properties P1 to P4 below (Cuesta et al., 2009; Cuesta and Zofío, 2005; Färe et al., 1985).

204

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

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

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

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

209

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

$$212 \quad D_H\left(\mathbf{x}_i, \frac{\mathbf{y}_i}{y_M}, \mathbf{b}_i y_M\right) = \frac{1}{y_M} D_H(\mathbf{x}_i, \mathbf{y}_i, \mathbf{b}_i). \quad (3)$$

213

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

$$215 \quad \ln D_H(\mathbf{x}_i, \mathbf{y}_i, \mathbf{b}_i) = \ln D_H\left(\mathbf{x}_i, \frac{\mathbf{y}_i}{y_M}, \mathbf{b}_i y_M\right) + \ln y_{Mi}. \quad (4)$$

216

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

$$219 \quad -\ln y_{Mi} = \ln D_H\left(\mathbf{x}_i, \frac{\mathbf{y}_i}{y_M}, \mathbf{b}_i y_M\right) - \ln HE_i + v_i. \quad (5)$$

220 **2.1.1 Shadow price**

221 The shadow price can be interpreted as the production of desirable output that must be
 222 foregone to reduce one unit of the undesirable output under analysis (Färe et al., 2005; Zhou et al.,
 223 2014). Shadow prices are particularly relevant for studying production systems where by-products
 224 are not marketable. An ingenious approach to calculating shadow prices is based on the duality
 225 between the HDF and the profitability (Return to the dollar) function (Färe et al., 2002; Färe and
 226 Grosskopf, 1998).

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

229

$$231 \quad \prod(x, p_y, p_b) = \max_{x, y} \left\{ \frac{p_y y}{p_b b} : D_H(x, y, b) \leq 1 \right\} \quad (6)$$

230

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

234

$$235 \quad \frac{p_y y}{p_b b} = \lambda \frac{\partial D_H}{\partial y} y = \lambda \left(\frac{\partial \ln D_H}{\partial \ln y} \right) D_H \quad (7)$$

236

$$238 \quad \frac{p_y y}{p_b b} = -\lambda \frac{\partial D_H}{\partial y} b = -\lambda \left(\frac{\partial \ln D_H}{\partial \ln b} \right) D_H. \quad (8)$$

237

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

241

$$242 \quad -p_y \frac{\frac{\partial D_H}{\partial b}}{\frac{\partial D_H}{\partial y_M}} = p_y \frac{dy_M}{db} \Big|_{D_H=1} \quad (9)$$

243

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

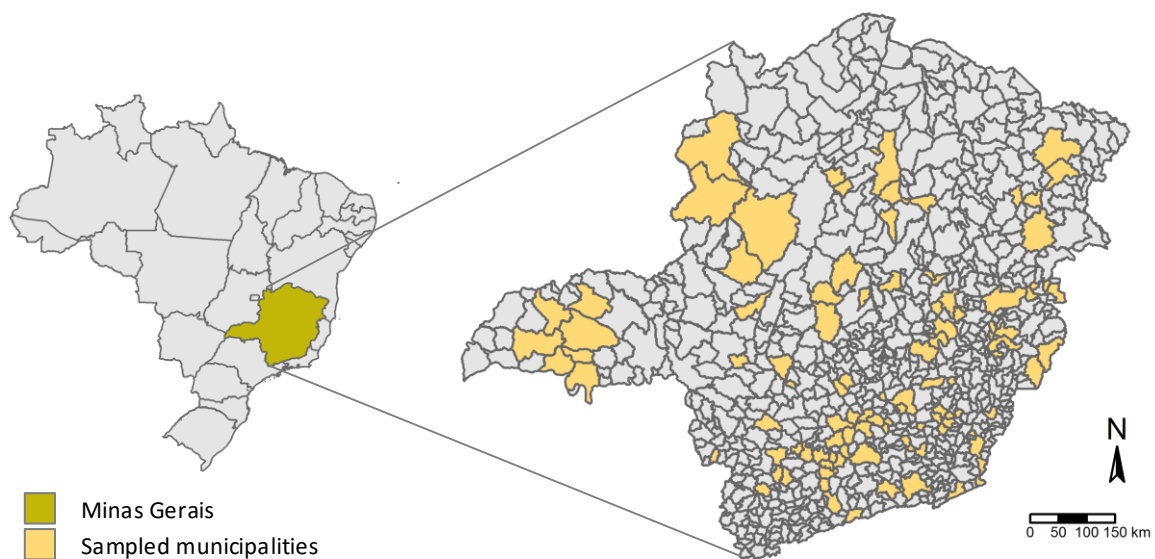
246 **2.2 Methane emissions**

247 Given that direct measurement of methane emissions is complex and expensive, we
248 estimate the emissions following the Guidelines for National Greenhouse Gas Inventories (IPCC,
249 2019a). Methane originated from enteric fermentation and manure management are the two sources
250 considered in the guidelines. Enteric fermentation emissions are derived based on the daily feed
251 intake of the herd. We calculate the daily gross energy (GE) intake and apply the simplified tier 2
252 method to calculate the daily dry matter intake (DMI) for each animal category declared by the
253 farmers (i.e., cows, calves, heifers, bulls) (IPCC, 2019b). Finally, we apply the equations for
254 predicting enteric methane based on DMI described by Ribeiro et al. (2020). Forage and
255 concentrate ration information are presented in Appendix A, Tables A1 and A2, respectively.

256 Methane originated from manure is derived from information on manure volatile solids
257 (VS) content and manure management system. The VS excretion is calculated based on the daily
258 GE intake of the animals and feed quality (IPCC, 2019a). Based on expert information, we assume
259 that 80% of the manure from animals handled on a daily basis was deposited on pastures, while the
260 remaining 20% was deposited onto barns, milking parlour or handling areas, and thus entered the
261 storage system. The default value of $0.19 \text{ m}^3 \text{ CH}_4 (\text{kg VS})^{-1}$ is adopted as the maximum methane
262 producing capacity of VS excreted (IPCC, 2019a).

263 **2.3 Study area and data**

264 We analyse a sample of 208 dairy farms distributed across the state of Minas Gerais (MG)
265 in south-eastern Brazil (see Figure 1). MG has an area of ~586,522 km² and is covered by three out
266 of six Brazilian biomes (IBGE, 2021). The state has a long tradition in milk production and is the
267 largest milk producer in Brazil (IBGE, 2018). In 2021, MG produced a total of 9.4 Mt milk,
268 representing 27% of the national production (Embrapa, 2021).
269



270

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

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

280

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>.

281 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			

^aUSD-BRL: 3.192 (BACEN, 2022).^b Fat and protein corrected milk.

282

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

295 Furthermore, to investigate the influence of year-specific climate elements on
 296 environmental efficiency, we include the annual climate type (ACT) in our model (Dubreuil et al.,
 297 2019). The ACT relies on the Köppen-Geiger climate classification algorithm, which accounts for
 298 seasonal temperature and precipitation variations for grouping climatic types and regions
 299 (Trewartha and Horn, 1980). Climatology data for each municipality have been retrieved from the
 300 National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC)
 301 Prediction of Worldwide Energy Resource (POWER) project.⁵ The ‘ClimClass’ R package (Eccel
 302 et al., 2016) was employed to derive two levels of Köppen ACTs (see Table 2).

303 Table 2. Annual climate types (ACTs), number of farms by ACT, and summary of climate elements
 304 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

305 ^aAw: tropical with dry winter; ^bCw: humid subtropical with dry winter; ^cCs: humid subtropical with
 306 dry summer; ^dBS: dry semi-arid; *P_total: total precipitation depth (mm); P_winter: precipitation
 307 depth in the six coldest months (mm); P_summer: precipitation depth in the six warmest months
 308 (mm); T_avg: average temperature (°C); T_w.m: average temperature of the warmest month (°C);
 309 T_c.m: average temperature of the coldest month (°C).
 310

311 2.4 Empirical model

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

316 Our model considers three outputs – including one undesirable – and six inputs. Letting $i =$
 317 $1, 2, \dots, N$ represent the number of dairy farms, the main desirable output is represented by annual
 318 fat and protein corrected milk (FPCM) production (y_M), and the secondary desirable output is the
 319 income of animals sold (y_S). The undesirable output is methane emissions (b). The six inputs are
 320 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/>

321 (c) is a four-levels controlling variable intended to gain insights into the ACT effect on
 322 environmental efficiency. We set the ACT (Aw) as the reference, since it presents the highest mean
 323 temperature throughout the year. The final specification for the HDF to be estimated is presented
 324 in eq. (10). We scaled the variables by their geometric mean before taking logarithms.
 325

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

326 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
 327 error term, which captures random noise and has a normal distribution $v_i \sim (0, \sigma_{vi}^2)$, and $u_i =$
 328 $-\ln HE_i$ is the hyperbolic inefficiency term following a half-normal distribution. Additionally, we
 329 considered heteroskedasticity in both v_i (eq.(11)) and u_i , (eq.(12)) (Caudill et al., 1995; Wang,
 330 2002).

331

$$332 \quad \sigma_{ui}^2 = e^{z_i \zeta} \tag{11}$$

$$333 \quad \sigma_{vi}^2 = e^{w_i \tau} \tag{12}$$

334

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

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

344 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	+/-

345

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

348
$$HE_i = E [e^{-u_i} | \varepsilon_i]. \quad (10)$$

349

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

352

353 **3 Results and discussion**

354 **3.1 Production technology**

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

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

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392 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		

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

396
397 Despite the contrasting characteristics of Aw and BS (dry semi-arid) in terms of
398 precipitation, we find no differences between the two climate types. The mean annual rainfall in
399 the municipalities classified as BS was 58% of the volume of rain received by farmers in Aw (see

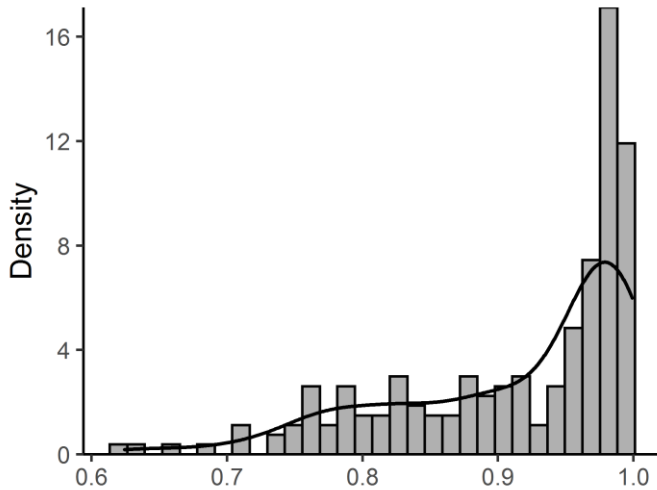
400 Table 2). However, in terms of temperature, the two climate types are similar, presenting a
401 difference of 0.3°C in the annual average temperature.

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

410 **3.2 Technical-environmental performance and determinants**

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

422



423

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

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

427

428 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

429 ^a Variables in bold presented significance in the heteroskedasticity model, $p < 0.1$.

430

431 Milk yield presents a negative significant influence on environmental inefficiency, which
 432 is expected and in line with previous literature (Le et al., 2020; Mamardashvili et al., 2016;
 433 Reinhard et al., 2002; Shortall and Barnes, 2013), and can be associated to some extent with the
 434 genetic quality of the herd (Le et al., 2020). Therefore, our results confirm the evidence that
 435 increasing milk yield per cow is crucial for both the economic and environmental efficiency of
 436 dairy farms. Low-yield dairy cows in LMICs is one of the most pressing issues regarding the
 437 sustainability of dairy farms (González-Quintero et al., 2022; Novo et al., 2013; Vogel and Beber,

438 2022). Nevertheless, improving dairy farms in practice warrants a systems-thinking approach. For
439 instance, the successful adoption of high-productive breeds depends on several factors, such as
440 suitable feed supply, climate and rearing conditions that attend the requirements of the selected
441 breed, and farmers with know-how to manage high-yielding animals (Novo et al., 2015).

442 The share of improved pasture has a negative influence on environmental inefficiency. This
443 is expected since improved pastures produce more forage per unit of land, thus reducing land use.
444 Additionally, improved pastures tend to have higher digestibility and lower natural detergent fibre,
445 which in turn contributes to a lower feed conversion rate (FCR) and methane production from
446 enteric fermentation. It is unsurprising that pasture improvement ranks first in the list of activities
447 that farmers shall focus on to improve farms' sustainability in the FB programme (Novo et al.,
448 2015). Our results are supported by a considerable body of literature providing evidence that
449 sustainable intensification of degraded and low-quality pastures positively contributes to land
450 sparing, soil carbon storage, and reduction of GHG intensity of beef and dairy cattle (IPCC, 2019c;
451 O'Brien et al., 2016; Oliveira et al., 2021; Ruviaro et al., 2015).

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

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

462 Remarkably, we observe the existence of trade-offs between production efficiency and risk
463 for some variables. Milk yield presented a significant negative sign in the z -model and a significant
464 positive sign in the v -model, suggesting that adopting more productive cows increases efficiency
465 but also production risk. There are many factors that can contribute to these results, such as the fact
466 that animals with higher production are more susceptible to diseases and metabolic disorders,
467 inflicting abrupt and unexpected drops in production and increasing expenses with treatments
468 (Brito et al., 2021; Knaus, 2009). They are also more demanding in terms of diet, requiring a higher

469 level of managerial skills to provide a balanced diet year-round, according to animals' categories
470 and productive cycle (Brito et al., 2021; Hoischen-Taubner et al., 2021). Moreover, the capital
471 invested in more productive animals is higher, which also increases losses in case of unexpected
472 culling (Hoischen-Taubner et al., 2021). The same pattern was found for renting land, which
473 significantly increases production risk but is beneficial to production efficiency. While renting land
474 is associated with contractual expenses, we expect that farmers use rented land to produce high-
475 quality pasture or silage, such that it improves farm environmental efficiency. Conversely, the
476 presence of breeding bulls in the herd significantly reduces risk, but at the same time has a negative
477 effect on environmental efficiency.

478 **3.3 Shadow price of methane emissions**

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

492 To the best of our knowledge, this is the first study to apply the HDF to derive the shadow
493 price of methane from dairy farms, making a cross-study comparison very limited. Scaling our
494 results to CO₂eq. by applying the conversion factor of 27.2 (Masson-Delmotte et al., 2021), we
495 reach a value of US \$83 per one tonne of CO₂eq. The results from studies evaluating whole-farm
496 CO₂eq. emissions considerably vary. For instance, Njuki and Bravo-Ureta (2015) reported values
497 ranging from US \$43 to US \$950 per tonne of CO₂eq. for US dairy production. The mean value

498 reported for milk production in Germany was 165 € (US \$186)⁶ per tonne of CO₂eq. (Wettemann
499 and Latacz-Lohmann, 2017), while Le et al. (2020) reported a value of Can \$308.29 (US \$230)⁷
500 per tonne of CO₂eq. in Canada. Naturally, direct comparisons are not only limited by differing
501 environmental efficiency models but also by regional milk prices and assumptions in modelling
502 GHG emissions, which considerably differ across studies.

503 **4 Policy implications**

504 Dairy farming is a key agricultural activity to support several SDGs in rural areas. More
505 specifically, it can contribute to achieving the targets from SDG 1 (no poverty), 2 (zero hunger),
506 12 (responsible consumption and production) and 13 (climate action). In the present study, we
507 evaluate dairy farmers' capability to manage their activities towards higher productivity and lower
508 methane emissions. Reducing methane and other GHG emissions from dairy farming is a priority
509 for meeting long-term climate goals (Gerber et al., 2013; IPCC, 2019c; Key and Tallard, 2012;
510 Reisinger et al., 2021). However, this cannot be achieved at the expense of reducing milk
511 production and availability, especially in LMICs, where milk plays a fundamental role in infant
512 nutrition, food security and income generation (FAO, 2019; Grenov and Michaelsen, 2018; Hemme
513 and Otte, 2010; Tricarico et al., 2020). Therefore, developing policies and mechanisms that reach
514 these goals simultaneously is highly desirable.

515 There is a growing body of literature supporting the notion that the higher environmental
516 efficiency of dairy farms can be achieved across countries and production systems. However, it is
517 in LMICs where the greatest benefits (marginal effects) can be achieved in terms of both reduced
518 GHG emissions and increased food production (FAO and GDP, 2018; Gerber et al., 2013). The
519 present study adds to this literature by identifying simple management decisions that could improve
520 the environmental efficiency of pasture-based dairy farms (e.g., increasing the share of improved
521 pastures at the farm and adjusting herd composition). These results are very likely to be true across
522 other regions and countries with similar production systems. For example, Ravichandran et al.
523 (2020) identified that many smallholder producers in India did not adopt such simple technologies
524 as feeding troughs and practices such as chopping of forage. While production technologies and
525 knowledge to overcome such production barriers exists and are already available in Brazil and

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>

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

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

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

557 This and similar programmes are considered successful cases for the sustainable intensification of
558 dairy farming, increasing food security, nutrition, women's empowerment, improving the overall
559 livelihood of smallholders and reducing environmental impacts of dairy farms across LMICs
560 (Gerber et al., 2013; Novo et al., 2013; Ravichandran et al., 2020). Despite being very effective,
561 the implementation of programmes with this design requires some time to show satisfactory results
562 (3+ years) (Novo et al., 2015, 2013; Ravichandran et al., 2020). Moreover, their development must
563 be sustained by complimentary supply chain operations and market opportunities, which are
564 sometimes limited in LMICs (Beber et al., 2019; de Mendonça et al., 2020; Ravichandran et al.,
565 2020).

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

581 Another set of solutions that have gained importance in recent years concerns on-farm
582 carbon storage (Brazil, 2021b; COWI et al., 2020; IPCC, 2019c). Pasture improvement is at the
583 centre of this approach for less productive dairy farms, as it generates important synergies. For
584 instance, pasture improvement promotes carbon storage in biomass and soil as well as the
585 production of forage with higher digestibility, consequently favouring animal productivity and the
586 reduction of methane emissions from livestock (Congio et al., 2018; Cortner et al., 2019; O'Brien
587 et al., 2016). Following pasture improvement, the adoption of integrated production systems has

588 also been promoted as an important carbon farming strategy (e.g., silvopastoral, livestock-forestry
589 and crop-livestock-forestry). The use of fast-growing trees species on farms can also create
590 synergies in many ways. They have strong potential to capture carbon in biomass through
591 photosynthesis. In addition, experimental studies in Brazil have shown that implementing trees on
592 pastures creates microclimates that protect pastures from heat and frost. This microclimate also
593 improves animals' thermal comfort, reducing energy use for maintenance and increasing milk
594 production (Brazil, 2021a; Cortner et al., 2019; Resende et al., 2020; Salton et al., 2014). This set
595 of actions has been extensively supported by financing incentives in Brazil through the Low Carbon
596 Agriculture (ABC) plan (Brasil, 2012; Brazil, 2021b).

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

610 Given the stark heterogeneity of dairy farms across countries and regions, defining and
611 benchmarking satisfactory levels of productivity must take into account regional pedoclimatic
612 conditions for milk production as well as the socioeconomic conditions of farmers in the region
613 (FAO and GDP, 2018; Gerber et al., 2011; Vogel and Beber, 2022). The greatest benefits from
614 increasing dairy cow productivity can be achieved in systems with animals producing less than 2
615 tonnes FPCM year. Gains are still significant in systems producing between 2 and 5 t FPCM per
616 year, while increasing productivity above 5 tonnes FPCM per cow per year will produce only small
617 marginal reductions in the carbon footprint of milk (FAO and GDP, 2018; Gerber et al., 2011).
618 Farms in our sample presented a production of ~3.7 t FPCM per cow per year, which is about one

619 tonne higher than the national average (IBGE, 2018). Thus, we can infer that commercial pasture-
620 based farms in Brazil striving to achieve 5 t FPCM per cow per year could remarkably increase
621 milk outputs while reducing the GHG intensity of milk.

622 **5 Conclusion**

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

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

649 development of dairy farming in LMICs must be driven by multiple strategies, providing long-term
650 technical support and knowledge transfers must be at the core of policy strategies.

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

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962

963 Appendix A

964

965 Table A1

966 Forage characteristics

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

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

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970 Table A2

971 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

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977 Appendix B

978

979 Table B1

980 Parameter estimates of the hyperbolic distance function

Technology	$D_H CH_4$		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
β_{00}	0.239		0.236
α_{11}	0.054	***	0.016
α_{22}	2.518	***	0.581
α_{33}	-0.023		0.117
α_{44}	-0.004		0.011
α_{55}	0.001		0.084
α_{66}	0.060		0.053
α_{12}	-0.103	*	0.059
α_{13}	0.005		0.029
α_{14}	0.023	*	0.011
α_{15}	0.010		0.031
α_{16}	0.129	***	0.033
α_{23}	-0.265		0.173
α_{24}	-0.026		0.064
α_{25}	-0.863	***	0.178
α_{26}	0.051		0.144
α_{34}	0.025		0.023
α_{35}	-0.323	***	0.063
α_{36}	0.105	*	0.047
α_{45}	0.051	*	0.021
α_{46}	-0.057	**	0.019
α_{56}	0.102	*	0.052
δ_2 (Animals sold)	0.005	**	0.002
δ_{22}	0.001	**	0.001
χ_{10}	-0.043		0.029
χ_{20}	-0.682	*	0.348
χ_{30}	0.230	*	0.094
χ_{40}	0.005		0.037
χ_{50}	0.317	**	0.114
χ_{60}	-0.152		0.093
γ_{12}	0.002	*	0.001
γ_{22}	0.016	***	0.005
γ_{32}	-0.011	***	0.002
γ_{42}	0.003	***	0.001
γ_{52}	0.001		0.003
γ_{62}	0.005	**	0.002
ρ_{20}	-0.008	***	0.003
ω_2	-0.042	**	0.013
ω_3	-0.034	*	0.015
ω_4	-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		

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