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# Evaluating environmental and economic trade-offs in cattle feed strategies using multiobjective optimization

J G O Marques<sup>1</sup>, R de Oliveira Silva<sup>1</sup>, L G Barioni<sup>2</sup>, J A J Hall<sup>3</sup>, C Fossaert<sup>4</sup>, L O Tedeschi<sup>5</sup>, F Garcia-Launay<sup>4</sup> and D Moran<sup>1</sup>

<sup>1</sup>Global Academy of Agriculture and Food Security - University of Edinburgh, Edinburgh, UK.

<sup>2</sup>Embrapa Agricultural Informatics, Campinas, Brazil.

<sup>3</sup>School of Mathematics - University of Edinburgh, Edinburgh, UK.

<sup>4</sup>PEGASE, INRAE, Institut Agro, 35590, Saint Gilles, France.

<sup>5</sup>Department of Animal Science, Texas A&M University, College Station, Texas, USA.

Corresponding author: João Gabriel Oliveira Marques. Email: j.g.o.marques@sms.ed.ac.uk

#### 1 1 Introduction

2 Beef production systems have been implicated as the source of a significant proportion 3 of global agricultural greenhouse gas (GHG) emissions, with methane (CH<sub>4</sub>) from 4 ruminant enteric fermentation as the principal source (Gerssen-Gondelach et al., 5 2017). However, net emissions vary greatly depending on the production system and 6 levels of intensification, e.g., low input (extensive) versus feedlot finishing with high 7 energy-dense diets. The rhetoric around sustainable intensification of agriculture has 8 highlighted the advantages of feedlot systems to shorten the animal production cycle 9 and increasing animal growth efficiency (Tilman et al., 2011). Feedlot systems and on-10 pasture supplementation can also reduce net CH<sub>4</sub> emission per kilogram of beef (de 11 Oliveira Silva et al., 2015). In some regions, feedlots might decrease GHG emissions 12 intensity by 25% compared with extensive pasture-based systems (Cortez-Arriola et 13 al., 2016). In such systems, feed ingredients and diet formulation contribute 14 significantly to GHG emissions (Tilman et al., 2011). However, the extent of any 15 potential GHG reduction depends both on the impact of feed composition – on CH4 16 emissions – and of manure decomposition – on CH<sub>4</sub> and N<sub>2</sub>O emissions – from 17 different management practices, and the environmental life cycle impacts of individual ingredients. 18

19 A potential cost-effective emissions mitigation strategy is to use proper diet 20 formulation balancing economic and environmental objectives. The economic 21 optimization of feed formulation is typically achieved through a least-cost linear 22 programming diet model (Soto and Reinoso, 2012), which formulates the optimal diet 23 minimizing feeding cost subject to a set of nutritional constraints. The environmental 24 objective in feed formulation varies considerably across species with CH<sub>4</sub> production 25 from ruminants a more significant target compared to relatively negligible emissions 26 from monogastrics. In this context, Jean dit Bailleul et al. (2001) developed a 27 multiobjective model based on an least-cost model focusing solely on nitrogen (N) 28 excretion in pigs. Similarly, Hadrich et al. (2005) and Pomar et al. (2007) examined 29 reducing phosphorus (P) excretion based on an least-cost model using multiobjective 30 optimization, focusing on cattle and pigs, respectively. Later models minimizing both 31 nitrogen (N) and P production were introduced by Kikuhara et al. (2009) for dairy cattle, 32 and by Dubeau et al. (2011) for pigs. Moraes et al. (2012) represented carbon cost 33 equivalent from N and CH<sub>4</sub> emission in the least-cost model objective function.

However, their work overlooked the impact arising from the feedstuff life cycle in diet formulation, i.e., the accumulated emissions of feedstuff throughout the production cycle. Moraes et al. (2015) developed an efficiency frontier from a goal programming approach between diet costs and CH<sub>4</sub> emissions, improving the representation of economic and environmental impact trade-offs.

39 With an improved understanding of livestock nutritional dynamics and better life 40 cycle assessment (LCA) data, state-of-the-art environmental-economic diet 41 formulation models can capture the interaction between multiple environmental 42 impacts when optimizing animal diets. Integrating LCA with diet models was utilized 43 by Mackenzie et al. (2016), reducing N and P excretion in pigs, along with LCA for 44 non-renewable resource use, and combining acidification, eutrophication, and global 45 warming potentials in a combined environmental impact score. However, Garcia-46 Launay et al. (2018), noted that "they did not investigate trade-offs between economic 47 and environmental objectives", and proposed a multiobjective linear programming 48 model to minimize a weighted sum of the least-cost diet and environmental impacts 49 measured solely by the feedstuff LCA (Garcia-Launay et al. 2018). The approach 50 generates an efficiency frontier representing the trade-offs between diet cost and 51 environmental impacts. Their analysis explores multiple livestock species (pig, broiler, 52 and bulls) and environmental impacts (phosphorus demand, non-renewable energy, 53 climate change potential, and land use).

54 However, in the case of ruminants, and more specifically cattle, the Garcia-55 Launay et al. (2018) methodology has two drawbacks. First, it does not account for 56 emissions from enteric fermentation (CH<sub>4</sub>) and manure decomposition (N<sub>2</sub>O), which 57 are significant in ruminants. Second, it does not tackle profit maximization in the feed 58 formulation, a reasonable objective. One possible reason is that these factors can 59 imply a hard-to-solve nonlinear programming model, which has recently been 60 addressed by Margues et al. (2020) in relation to optimal cattle diet formulation. The 61 latter highlighted significant differences between the use of a nonlinear profit-62 maximizing diet (NLPMD) model versus least-cost for feed formulation. The NLPMD 63 model can be efficiently solved through parametric linear programming, i.e., by 64 optimizing the least-cost model for the range of feasible shrunk weight gain (SWG), 65 i.e., animal weight gain in terms of shrunk bodyweight, approximately 96% of live 66 weight. By integrating the contributions from Marques et al. (2020) and Garcia-Launay et al. (2018) and computing CH<sub>4</sub> and N<sub>2</sub>O production from enteric fermentation and
manure decomposition, it is possible to derive a more comprehensive analysis of the
environmental-economic trade-offs in feedlot beef production systems.

70 This paper uses a multiobjective method based on a nonlinear profit-71 maximizing diet model to assess the economic and environmental trade-offs in diet 72 formulation for feedlots in France. The analysis combines data from ingredients LCA 73 - from the ECOALIM database (Wilfart et al., 2016) - and Tier 2 equations for direct 74 cattle emissions derived by Escobar-Bahamondes et al. (2017) and the IPCC (2006). 75 We also analyze the impacts of using a profit-maximizing objective function in contrast 76 to using the least-cost diet, and the implications of weighting different environmental 77 impacts in the multiobjective function. The model context (outlined in section 2) is an 78 exploration of the emissions mitigation potential from French livestock production and 79 its contribution to national mitigation ambitions. Section 3 details the methodology, 80 comprising the multiobjective technique utilized to generate an efficiency frontier 81 considering: (i) feedstuff costs, (ii) revenue associated with animal SWG, (iii) 82 environmental impacts measured by LCAs for each ingredient, (iv) CH<sub>4</sub> emissions 83 from enteric fermentation, and (v) N<sub>2</sub>O emissions from manure decomposition. In 84 section 4, using a typical feedlot, we derive the efficiency frontier, the marginal GHG 85 abatement cost curve, the emission intensity per kg of carcass, the diet composition, 86 and animal performance. In section 5, we discuss the results, the environmental 87 (impact) mitigation potential, and the farm-level economic implications within the 88 French production context. We conclude our findings in section 6.

#### 89 2 Background and policy context

90 Livestock is of significant importance in the European economy, accounting for roughly 91 21.5% of the total € 41.6 billion in exports in 2019 (EUROSTAT, 2020a). European 92 beef production has been constant, ranging from 86 to 89 million heads per year since 93 2011 (EUROSTAT, 2020b). However, the average carcass weight has been 94 increasing, e.g. additional 24 kg/head between 2000 and 2015, increasing total meat 95 production over time (Hocquette et al., 2018). France is Europe's largest beef producer 96 and exporter, producing over 18 million head of cattle in 2019, which accounts for a 97 little over 20% of Europe's total (EUROSTAT, 2020a). Developments in the sector are 98 being influenced by several factors, including shifting consumer behaviours, changing

99 meat consumption per capita, and emerging environmental constraints (Hocquette et 100 al., 2018). A significant driver of change is the growing concern over the livestock 101 contribution to climate change. Many countries are therefore examining total GHG 102 emissions mitigation strategies within more or less (sustainably) intensive systems i.e., 103 seeking to reduce emissions per kg of product without compromising economic 104 performance, what would lead to reducing total emissions for the same demand level 105 of a baseline scenario. Ruminant emissions are particularly implicated in mitigation 106 strategies, accounting for a significant share of sector emissions and around 31% of 107 those arising from global food production (Ritchie, 2019), a contribution that varies 108 between countries (Tedeschi and Fox, 2020, Chapter 3.1). Many mitigation measures 109 have been proposed, with significant effort made to identify those that are cost-110 effective (Pellerin et al., 2017). Less attention has been paid to the emerging ancillary 111 effects of measures implemented alone or in combination and the issue of 112 environmental impact transference, i.e. reducing one impact metric causes increase 113 in other metrics.

114 In its National Low-Carbon Strategy (SNBC), France has set a target to reduce 115 agricultural sector emissions by 18% by 2030 compared to a 2015 baseline (MTES, 116 2020). Among other strategies, the SNBC highlights N<sub>2</sub>O and CH<sub>4</sub> emission reduction 117 by "reducing excess protein intake in animal diets" and "limiting enteric fermentation 118 through adjustments to animal feed ... " (MTES, 2020). Given this ambition, our model 119 aims to assess the emissions reduction potential (expressed in CO<sub>2</sub> equivalent -120 CO<sub>2</sub>eq) from cattle feedlots while accounting for potential environmental impact 121 transference and any trade-offs with productivity and profit.

#### 122 3 Material and methods

123 We developed an *\varepsilon*-constrained multiobjective (MO) model – solved through *\varepsilon*-124 constrained technique – defining two objectives in diet formulation: profit maximization 125 and environmental impact minimization. The  $\varepsilon$ -constrained is a MO technique, which 126 overcomes convexity issues in nonlinear programming, in contrast to the weighted 127 sum technique (Bérubé et al., 2009). We use the nonlinear profit-maximizing diet 128 model proposed by Margues et al. (2020), which is based on the predictive equations 129 of nutrient requirements from NASEM (2016) and Tedeschi and Fox (2020). Using the 130 NASEM (2016) system, the NLPMD was shown to be effectively solved through parametric linear programming, i.e., we can obtain the optimal solution by solving a finite number of linear programming models. Thus, our proposed nonlinear MO model can be solved by the same technique, from which we derive trade-offs and sensitivity analysis of emissions versus profit. Moreover, we integrated our optimization model with the data file generated by the "Ruminant Nutrition System" software (Tedeschi and Fox, 2020a, 2020b) to import all the animal requirement parameters.

#### 137 3.1 Feedstuff properties

138 We obtained the nutritional properties of feedstuffs from NASEM (2016), which has a 139 library with over 200 feeding ingredients. The mathematical model developed by 140 Margues et al., (2020) requires the following properties to evaluate the nutritional 141 requirements: metabolizable protein (MP), physically effective neutral detergent fiber 142 (peNDF), fat content (FAT), ruminally degradable protein (RDP), crude protein (CP), 143 net energy for maintenance and gain (CNEm and CNEg), and dry matter (DM) to "as 144 fed" (AF) conversion for each ingredient. We obtained LCA information of each 145 ingredient from the ECOALIM database (Wilfart et al., 2016). Analogous to Garcia-146 Launay et al. (2018), we considered the following environmental impacts: phosphorus 147 demand (PD, in kg P/kg of ingredient DM), non-renewable energy (NRE, MJ/kg of 148 ingredient DM), climate change potential (CC, in kg CO<sub>2</sub>eg/kg of ingredient DM), 149 acidification potential (AC, in mol H<sup>+</sup>-eq/kg of ingredient DM), eutrophication potential 150 (EU, in kg PO<sub>4</sub><sup>3</sup>-eq/kg of ingredient DM) and land occupation (LO, m<sup>2</sup> year/kg of 151 ingredient DM).

152 The CH<sub>4</sub> emission from enteric fermentation is calculated using a linear-153 equivalent equation from Escobar-Bahamondes et al. (2017) and that from manure 154 management uses the IPCC Tier 2 (IPCC, 2006). Both equations can be split into the 155 contribution of each ingredient *j*, considering their partial nutritional composition, thus 156 being integrated linearly into the model. For simplification, the CH<sub>4</sub> equation had its fat 157 factor adjusted to utilize the first rather than the third power, with  $R^2 \leq 0.99$ . Moreover, 158 we consider the constraint that the feedlot-fed cattle diet typically has less than 65% 159 DM forage content. We used the conversion factor of 34 kg CO<sub>2</sub>eg / kg CH<sub>4</sub> (IPCC, 160 2013). For the N<sub>2</sub>O emissions, we use the IPCC Tier 2, which also does not affect the 161 structure of the mathematical model; i.e., it can still be solved using the same 162 technique. For N<sub>2</sub>O, we consider the animal's final weight in a dry lot system (0.02 kg 163 N<sub>2</sub>O / kg Nitrogen excreted), N<sub>retention frac</sub> of 7% and conversion rates of 298 kg CO<sub>2</sub>eq 164 / kg N<sub>2</sub>O (IPCC, 2013), and 1.57 kg N<sub>2</sub>O-N / kg N<sub>2</sub>O (IPCC, 2006). The equations are
165 shown in appendix Equations A.1.

#### 166 3.2 *Multiobjective approach*

167 The NLPMD model (Margues et al., 2020) has the advantage of being solved through 168 linear parametric programming. This advantage derives from the fact that while the 169 NLPMD is solved for a variable SWG and ingredient inclusions  $x_i$  for each feed  $i \in J$ , 170 fixing a value for SWG reduces the NLPMD to the least-cost model, which is a linear 171 model. Thus, parameterizing SWG allows us to find the optimal NLPMD and the 172 respective optimal SWG. The parametrically linearized objective function in (1) 173 computes profit as a function of feeding time T (days), animal selling price S ( $\in$  / kg 174 SW), dry matter intake DMI (kg of feed/day), initial shrunk bodyweight  $SBW_0$  (kg SW), 175 purchase price  $p_0$  ( $\in$  / kg SW), the parametric variable shrunk weight gain SWG (kg 176 SW / day), and for each feed  $j \in J$  their respective costs  $c_i$  ( $\in$  / kg of feed DM), and 177 inclusion in the diet  $x_i$  (%DM). We can simplify equation (1) by considering that the 178 purchase price  $p_0$  and selling price S are equal; thus, profit is given by growth minus 179 the diet cost during the feeding period.

$$Z(SWG, \mathbf{x}) = T \left[ S \times SWG - DMI \sum_{j \in J} c_j x_j \right] - SBW_0 \times (p_0 - S)$$
(1)

180 We can assemble the objective function of the six environmental impacts  $k \in K=\{PD, d\}$ 181 NRE, CC, AC, EU, LO} into a single environmental impact metric (EI) as shown in (2). 182 The LCA<sub>ik</sub> for each feed  $j \in J$  and environmental impact  $k \in K$  is weighted by a 183 coefficient  $\beta_k$ , such that  $\sum_{k \in K} \beta_k = 1$ . This coefficient balances the relative "importance" 184 of each LCA in the objective function. In practice, the weights must be chosen in a way 185 that avoids environmental impact transference. That is, the propensity for reducing 186 one impact at the cost of increasing others. The first part of equation (2) is identical to 187 Garcia-Launay et al., (2018). The second includes the CH<sub>4</sub> and N<sub>2</sub>O emission 188 contribution from each ingredient converted to (kg CO<sub>2</sub>eq/kg of ingredient DM). Both 189 are subject to the exact weighting for climate change potential ( $\beta_{CC}$ ). For mathematical 190 purposes, we use normalized LCA values in (2) and convert them back to marginal 191 values to present the results. This approach does not change the optimal solution in 192 the model.

$$EI(\mathbf{x}) = T \times DMI\left(\sum_{k \in K} \beta_k \left(\sum_{j \in J} x_j \, LCA_{jk}\right) + \beta_{CC}\left(\sum_{j \in J} x_j \, CH4_j + \, N2O_j\right)\right)$$
(2)

193 The multiobjective function is the convex combination of functions (1) and (2): 194 MO( $\lambda$ , SWG, **x**) =  $\lambda \times Z(SGW, \mathbf{x}) - (1 - \lambda) \times EI(\mathbf{x})$ , such as  $\lambda \in [0; 1]$ . When  $\lambda = 1$ , we 195 are maximizing only the profit function, for which we can compute the reference 196 (maximum) environmental impact El<sub>REF-ub</sub>, using (2). Conversely, for  $\lambda = 0$ , we can find 197 the minimum environmental impact El<sub>REF-lb</sub>. The functions (1) and (2) can have the 198 time parameter T replaced by a target weight, and be written as a function of SWG, 199 as T = (SBW<sub>f</sub> - SBW<sub>0</sub>) / SWG. We used the  $\varepsilon$ -constrained method instead of the 200 weighted sum since the latter can skip solution points in the solution frontier of 201 nonlinear problems (Bérubé et al., 2009). With the combined function, we can 202 generate the complete solution frontier for the nonlinear MO problem using the ε-203 constrained method. In Algorithm 1 we show how to obtain the efficient frontier 204 defined by the nutritional constraints in the NLPMD. In Algorithm 1, line 2, by solving 205 the NLPMD model we calculate the upper bound environmental impacts (EI<sub>REF-ub</sub>), i.e., 206 the impacts when the objective is only to maximize profit. Alternatively, replacing the 207 objective function of the NLPMD by minimizing (2), we compute the minimum possible 208 environmental impact (EIREF-Ib), i.e., the lower bound, in line 3. To generate a frontier 209 with N points, in line 4 we compute the step value  $\varepsilon = (EI_{REF-ub} - EI_{REF-lb})/N$ , and then 210 solve the nonlinear model (NLPMD) N times with the additional constraint  $EI(x) = EI_{REF}$ 211  $_{\rm lb}$  +  $\epsilon$  × s, where  $s \in \mathbb{Z}_0^+ \leq N$  (lines 5 to 7).

Each step *s* requires solving the nonlinear profit-maximizing model, thus the value N is defined depending on the desired granularity of the efficiency frontier and the available computational power. Marques (2020) highlights that using the golden section search algorithm instead of brute force to solve the parametric linear programming model (NLPMD), reduces time complexity from O(n) to O(log n). Such reduction assumes a precision of  $10^{-3}$  and N = 100, this choice reduces the resolution of 240,250 models to 1,465.

Algorithm 1: Pseudo-code procedure to build the efficiency frontier.

input: animal characteristics, Ingredients parameters, environmental impact
 LCAs, interval (N)

2	El <sub>REF-ub</sub> ← El( <b>x*</b>   {Ma>	<: MO(λ = 1, SWG, <b>x</b> ) })
3	EI <sub>REF-lb</sub> ← EI( <b>x*</b>   {Max	: MO(λ = 0, SWG, <b>x</b> ) })
4	ε = (EI <sub>REF-ub</sub> - EI <sub>REF-lb</sub> )/I	N
5	for s = 0 to N do	
6	solve NLPMD:{	Max: MO( $\lambda$ = 1, SWG, <b>x</b> ),
		s.t.: $EI(x) \le EI_{REF-lb} + \epsilon \times s$ }
7	end for	

#### 220 3.3 Analysis and scenarios

221 We use one typical feedlot input in the French production system: Charolais steers 222 fattened from 350 kg to 620 kg (live weight) with body condition score 5, sold at €3.73 223 (2015 reference) per kilogram of carcass weight equivalent (CWE), or €2.46 per kg 224 SWG (IDELE, 2016) - note that CWE is approximate 0.66 × SWG (Tedeschi and Fox, 225 2020a, 2020b). We use typical ingredients available in France to compose the diet, 226 presented in Table 1. The table contains ingredient cost, minimum and maximum 227 inclusion levels in the diet, and their respective LCA. Such values are the same as 228 those used by Garcia-Launay et al. (2018), allowing us to compare the results. We 229 extracted the properties of the ingredients used in the mathematical model from the 230 RNS model (Tedeschi and Fox, 2020a, 2020b), generating the RData file used to run 231 the model. The model and respective data used are available in Marques (2021). We 232 estimate animal full-cycle GHGs and assume in both the scenarios that the animals 233 bring an overhead emission (i.e. emissions accumulated prior to the current process 234 of interest) of 14.3 kg CO<sub>2</sub>eq / kg LW (12.24 kg CO<sub>2</sub>eq / kg CWE, at the final live weight 235 of 620kg) from birth and raise before being moved to the feedlot growing phase 236 (Desjardins et al., 2012).

- 237 Table 1 Ingredients' prices and nutritional properties used in the computational
- simulation.

Feed	Cost (€/kg DM)	Forage (%DM)	DM (%AF)	CP (%DM)	Fat (%DM)	NDF (%DM)	TDN (%DM)	NEma (Mcal/kg)	NEga (Mcal/kg)	RUP (%CP)	peNDF (%NDF)
Urea	0.39	0	99.0	281.0	0	0	96.6	2.42	1.7	0	0
Sugar beet pulp dehydrated	0.23	0	91.0	9.8	1.43	44.6	71.8	1.69	1.07	52	60
Corn gluten feed	0.23	0	89.6	24.0	4.2	34.64	74.5	1.77	1.15	24	40
Corn gluten meal (gluten 60)	0.78	0	92.7	65.5	2.6	11	84.2	2.06	1.4	47	40

Molasses	0.23	0	75.0	8.5	1	0	79.4	1.92	1.28	0	0
Rapeseed meal	0.27	0	90.1	41.5	4.77	27.66	73	1.73	1.11	31	40
Rapeseed oil	0.92	0	99.0	0	100	0	193.5	5.3	3.94	0	0
Sunflower meal without dehulling	0.18	0	93.0	26.3	2.6	42	60.5	1.32	0.75	23	50
Sunflower oil without dehulling	0.89	0	99.0	0	100	0	193.5	5.3	3.94	0	0
Wheat bran	0.13	0	88.7	17.0	4.5	44	71.5	1.68	1.06	23	45
DDGS Wheat	0.31	0	92.6	29.0	8	50.1	74.4	1.77	1.14	54	40
Wheat feed flour	0.22	0	95.0	10.0	1.3	6	86.1	2.12	1.45	17	5
Wheat gluten feed	0.20	0	88.5	20.1	4.09	27	81.2	1.98	1.32	15	10
Wheat middlings	0.16	0	89.0	18.4	5	38	74.7	1.78	1.15	14	15
Baled grass	0.09	100.0	89	10	3	67	59.5	1.29	0.72	34	95
Sunflower meal low dehulling	0.25	0	93.0	40.2	3	38	62.3	1.38	0.8	23	45
Sunflower meal high dehulling	0.30	0	93.0	48.9	3.3	35	65.9	1.5	0.91	23	40
Maize silage	0.10	100.0	35.0	8.0	3.18	41	72.7	1.71	1.1	21	82
Grass silage	0.11	100.0	35.0	14.7	5.4	57	62.8	1.4	0.82	24	80

240 We analyze two trade-off dynamic scenarios with different environmental 241 impact weights β: "RCS" (reduced carbon scenario), and "BIS" (balanced impacts 242 scenario). These scenarios offer alternative perspectives on sustainable intensification; 243 the first focusing solely on GHG mitigation, the second targeting GHG mitigation that 244 avoids impact transference. In the RCS, we run the multiobjective model with weights 245 1 for  $\beta_{CC}$  and 0 for the rest. This allows us to estimate maximum carbon abatement 246 and respective costs in the context of a typical French feedlot. In the BIS we use the 247 same arbitrary weights as Garcia-Launay et al., (2018): 0.4 for  $\beta_{CC}$ , 0.2 for  $\beta_{PD}$ ,  $\beta_{NRE}$ , 248 and  $\beta_{LO}$ , and 0 for  $\beta_{AC}$ ,  $\beta_{EU}$ . In this scenario, we normalize the impact values before 249 running the model. We run sensitivity analysis on each environmental output to 250 analyze the environmental transference impacts based on the inputs  $\beta_k$ , for  $k \in K$ , and 251 the MO convex weight  $\lambda$ .

#### 252 4 Results

The NLPMD solution frontier for the balanced impacts scenario (BIS) and the reduced carbon scenario (RCS) minimization are shown in Figure 1, which shows the relative change in environmental impacts related to change in profit, both using the maximum profit solution as baseline (El<sub>REF-ub</sub>). At this point, the absolute environmental impact 257 is the same for both scenarios since their objective function is essentially equal, given 258 by equation (1). In contrast, EIREF-Ib is given by equation (2); thus, the objective 259 functions BIS and RCS differ in direction due to the differing weights of coefficient  $\beta_k$ . 260 The x-axis is expressed as a percentage reduction of the maximum profit of €1139.00 261 (GHG reduction = 0%), the minimum weighted environmental impact is obtained for 262 the BIS and RCS on the right-hand side of the graph at (a) €992.05 (GHG reduction = 263 44.7%, equivalent to 483 kg CO<sub>2</sub>eq) and (b)  $\in$  1024.34 (GHG reduction = 36.4%, equivalent to 392 kg CO<sub>2</sub>eq), respectively. In the BIS the minimum impact scenario is 264 265 not the minimum CO<sub>2</sub>eq emissions solution. Furthermore, the global minimum CO<sub>2</sub>eq 266 solution is only found on the RCS for a high reduction in profit.

267



Figure 1 – Efficient solution frontier for (a) reduced carbon scenario and (b) balanced impacts scenario. Each solution (mark) is associated with a decrease in profit (x-axis) and was plotted with its associated percentage change in each of the environmental impacts (y-axis) calculated in relation to El<sub>REF-ub</sub>, i.e., maximizing profit, which is the same for both scenarios. The percentage change is measured in relation to the feedlot baseline, not accounting for impacts generated prior to this feeding phase.

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Figure 2 shows the marginal GHG abatement cost (€ / kg CO<sub>2</sub>eq / kg CWE) for
the balanced impacts scenario (BIS), and the reduced carbon scenario (RCS). The
total emissions intensities – i.e., pre-feedlot accumulated GHGs (14.3 kg CO<sub>2</sub>eq / kg
LW, at 350 kg LW) plus feedlot phase GHGs – vary from the maximum 14.99 kg CO<sub>2</sub>eq
/ kg CWE, in both scenarios, to a minimum of 13.98 kg CO<sub>2</sub>eq / kg CWE for the BIS,

and 13.76 kg CO<sub>2</sub>eq / kg CWE in the RCS. The marginal abatement cost computes,
in relation to the baseline (EI<sub>REF-ub</sub>), the marginal profit loss per unit reduction in CO<sub>2</sub>eq
emissions. This cost solely reflects improvements in the feedlot operation, regardless
of the initial carbon footprint associated with the animals. Hence, the reduction of 1.23
kg CO<sub>2</sub>eq / kg CWE (RCS) represents the 44.7% GHG reduction shown in the far left
of Figure 1 (a). The equivalent maximum reduction for the BIS is 1.20 kg CO<sub>2</sub>eq / kg
CWE, achieved with a profit reduction of 5.7%.



288

Figure 2 – The marginal abatement cost and its respective total emissions in the animal life cycle (including initial footprint) are shown for the RCS (reduced carbon scenario) and BIS (balanced impact scenario). Total emissions include overhead before the feedlot-optimized phase of 12.74 kg CO<sub>2</sub>eq / kg CWE.

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Figure 3 – Solution frontier of the climate change emission sources in the diet for the RCS (reduced carbon scenario). Along with the marginal contribution of each source (area graph), we also present the respective fraction of each source (lines) that contributes the total feedlot emission. The x-axis shows the respective marginal abatement obtained from the GHG reduction targets in the multiobjective model.

301 The contribution of each climate change factor, i.e., indirect emissions (diet 302 LCA), and direct animal emissions (CH<sub>4</sub> and N<sub>2</sub>O) are shown in Figure 3 for the RCS 303 (BIS results are included in supplementary material). Figure 3 shows that diet LCA, 304 CH4, and N2O represent, 58%, 32%, and 11% of the total carbon footprint in the 305 maximum profit solution. The RCS emissions start at a maximum of 1.57, 0.88, and 306 0.30 kg CO<sub>2</sub>eq / kg CWE, for diet, CH<sub>4</sub>, and N<sub>2</sub>O contributions, respectively. In the 307 minimum emissions solution, these values fall to 0.78, 0.50, and 0.25 kg CO<sub>2</sub>eg / kg 308 CWE (reductions of 54%, 32%, and 17%, respectively). The sum of these individual 309 contributions adds to the initial carbon footprint of 12.74 kg CO<sub>2</sub>eq / kg CWE, 310 representing the emissions decrease shown in Figure 2. Hence, these values and 311 behavior represent only the feedlot feeding phase.



Figure 4 – Diet composition for each multiobjective model solution for the balanced impact scenario (BIS), showing solution respective shrunk weight gain (SWG) on the secondary axis (right-hand side). Each optimal diet composition in the multiobjective solution space is presented in relation to its consequential marginal CO<sub>2</sub>eq abatement. Only ingredients with inclusion greater than 0% in at least one multiobjective solution are displayed.

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320 Figure 4 presents the optimal diet composition for the efficient solution frontier. Each 321 optimal solution in the figure is characterized by the respective profit reduction and 322 marginal CO<sub>2</sub>eg abatement, which can be related to the results presented in Figure 3. 323 The feedstuff not shown in Figure 4 (included in Appendix Table A2) have entry-level 324 equals to zero throughout the whole MO solution space. Thus from the 19 ingredients 325 available, only 7 are used in at least one optimal solution of the efficient frontier. The 326 maximum and minimum values for SWG are 1.38 kg SW per day (at 1.23 kg CO<sub>2</sub>eq / 327 kg CWE abatements) and 1.15 kg SW per day (at zero abatements), respectively. This 328 change in daily weight gain is reflected on the feeding days until the animal is finished, 329 lowering from 225 days in the maximum profit solution to a minimum of 187 days in 330 the minimum GHG emissions solution. The resulting tables used to create all the 331 graphs are included in the supplementary materials.



**Figure 5** – Sobol sensitivity analysis of the environmental impacts outputs as a function of the multiobjective function weights. While the outputs are the measurements of the total impact in the solutions, the legend represents the weights  $\beta_k$ , for  $k \in K = \{PD, NRE, CC, AC, EU, LO\}$ , and the multiobjective weight  $(1 - \lambda)$  is represented by "EI". The impacts are: AC, acidification potential; CC, climate change potential; EU, euthrophication potential; LO, land occupation; NRE, non-renewable energy usage; PC, phosphorus comsumption.

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341 Finally, Figure 5 shows the first and total order indices of the Sobol sensitivity analysis 342 for each of the environmental impacts. The first order indices show the highest volatility 343 of the NRE impact, highly associated with the  $\beta_{CC}$  and  $\beta_{EU}$  weights. In contrast, the AC 344 impact has the least variability when varying the inputs. The total order indices shows 345 that the relative variance with combined change of the weights is highest for the NRE 346 and similar for all other outputs. Moreover, although  $\beta_{CC}$  causes the least variability in 347 the outputs (except for NRE) in the first order, the total order indices show that  $\beta_{PC}$ 348 and  $\beta_{\text{NRE}}$  are the impacts with least influence on the variability of others when changing 349 an arbitrary combination of weights. These results partially incorporate the behaviour 350 shown in Figure 1, especially of the NRE impact, which does not follow the same rate 351 of decrease as the other impacts in the MO efficient frontier.

352

#### 353 5 Discussion

354 Feeding strategies to reduce GHG emissions observed in these results accord with 355 other studies, namely reduction of forage in the diet (Koscheck et al., 2020), reduction 356 of diet LCA (Garcia-Launay et al., 2018), and improved animal performance (Pashaei 357 Kamali et al., 2016). Values obtained for SWG and the diet profiles are also consistent 358 with the literature (IDELE, 2011). The environmental impact values we obtained are 359 on average consistent with those reported by Garcia-Launay et al. (2018) and Wilfart 360 et al. (2019). Any difference in impact values is expected and arises from a 361 combination of choice of available ingredients and the use of the profit-maximizing 362 objective function. Compared to the least-cost model, the NLPMD has a broader 363 solution space, which allows for a greater variety of results regarding both diet cost, 364 profit, and environmental impacts.

365 Our results indicate that the optimal GHG mitigation strategy for the growing 366 feedlot phase (350 kg LW to 620 kg LW) is a combination of three sub-strategies: (i) 367 reducing diet footprint, (ii) reducing animal CH<sub>4</sub> and N<sub>2</sub>O emissions, and (iii) increasing 368 animal performance. For the RCS, Figure 1a shows that the mitigation strategy can 369 be divided into three different groups, defined by the cost-effectiveness and maximum 370 CO<sub>2</sub>eg reduction achievable. In the first group, high emission reduction is achieved 371 (up to 0.62 kg CO<sub>2</sub>eq / kg CWE, for the RCS) mostly by reducing the diet LCA footprint, 372 as seem in Figure 3. This is combined with a steady increase in animal performance, 373 from 1.15 kg SW per day to 1.21 kg SW per day, shown in Figure 4. Note that this 374 initial mitigation strategy is the cheapest, with a roughly constant cost of  $22 \in /$  (kg 375 CO<sub>2</sub>eq / kg CWE), shown in Figure 2. This 24% emission reduction in the feedlot 376 feeding phase – i.e. not accounting for overhead – in relation to the maximum profit 377 baseline is consistent with the results of Garcia-Launay et al. (2018). However, to 378 achieve higher marginal mitigation per kg CWE, the optimal solution is a combination 379 of the sub-strategies, defining an intermediate group with emissions from 0.62 to 1.20 380 kg CO<sub>2</sub>eq / kg CWE. Here, considering the CO<sub>2</sub>eq emissions reduction in the feeding 381 phase ( $\Delta_{ERFP}$ ), the increase of animal performance,  $\Delta_{SWG} / \Delta_{ERFP} = 0.27$  (Figure 4), 382 and constant reductions of CH<sub>4</sub>,  $\Delta_{CH4}$  /  $\Delta_{ERFP}$  = -0.37 and N<sub>2</sub>O,  $\Delta_{N2O}$  /  $\Delta_{ERFP}$  = -0.05 383 (Figure 3), result in a constant increase in marginal abatement cost,  $\Delta_{cost} / \Delta_{ERFP}$  = 45.52. In the third group (reduction from 1.20 to 1.23 kg CO<sub>2</sub>eq / kg CWE), mitigation 384 385 is considerably more expensive ( $\Delta_{cost}$  /  $\Delta_{ERFP}$  = 1465.56) mainly due to the use of more

costly ingredients – replacing the maize silage (Figure 4) a considerably cheap
 ingredient. The cost-effectiveness grouping of the solution frontier is typical of MO
 models and is related to the intensity of divergence of the conflicting objectives.

389 Our model offers a more nuanced analysis of the environmental and economic 390 trade-offs in feedlots by combining emissions factors with a maximum profit objective. 391 Figure 3 shows that although the feedstuff LCA makes the largest contribution to total 392 emissions, CH<sub>4</sub> and N<sub>2</sub>O together account for about 50% of total emissions. Thus, 393 accounting for the CH<sub>4</sub> and N<sub>2</sub>O emissions from enteric fermentation and manure 394 management in the optimization model has a significant impact on the CO<sub>2</sub>eq 395 assessment, and thus, abatement levels. Furthermore, Figure 4 indicates a possibility 396 to reduce environmental impacts by intensifying the production system, i.e., increasing 397 SWG. These results show that both the choice of ingredients with lower impact 398 footprint and less gaseous emissions yield, and shortening of the animal life cycle are 399 a combined strategy in reducing CO<sub>2</sub>eq and other environmental impacts. This is 400 notable in the minimum-impact solution, which is 38 days shorter than the maximum-401 profit solution (supplementary material). Reducing emissions by increasing animal 402 performance can only be captured in the analysis by the use of the NLPMD rather than 403 the typical least-cost model. Our results show that – other things being equal – an 404 increase in animal efficiency alone can reduce 17% of the total GHG emissions 405 intensity in the maximum-profit solution in the feedlot phase.

406 In the French feedlot context our work shows that significant GHG intensity 407 abatement (about 8% from total emission intensity, from Figure 2) can be achieved 408 solely in the feedlot growing phase while simultaneously reducing other environmental 409 impacts. The reduction in GHG emissions intensity - aligned with proposed 410 sustainable intensification of agriculture (Tilman et al., 2011) - shows that beef 411 production levels can be maintained while reducing total emissions. Hence, we can 412 infer that net mitigation in beef feedlot systems is possible, although a quantitative 413 result would require a thorough analysis considering different beef demand projections. 414 Moreover, the reduction in GHG emissions in Figure 1a, are shown to be achieved 415 alongside the reduction of other impacts, i.e. without causing environmental impact 416 transference. The maximum theoretical GHG emission abatement of 44.7% is 417 guaranteed to occur in the RCS. At this point, the RCS indicates a degree of impact 418 transference – with a conspicuous slight decrease of GHG emissions at the expense

of increasing NRE emissions - however without having any EI surpassing the 419 420 reference values of the EIREF-ub solution. However, with the RCS we can assess the 421 GHG mitigation gap required to avoid transference. The difference between the 422 theoretical maximum reduction (RCS) and the BIS reduction on the feedlot growing phase is only 8.3%. Moreover, the maximum reduction in the BIS is achieved at similar 423 424 costs in the RCS, as observed in Figure 2. Ultimately, our results show that cost-425 effective GHG mitigation in beef feedlot can imply in overall environmental impact 426 reduction, i.e. indirectly reducing land occupation, soil eutrophication, i.a. Hence, the 427 reduction on CH<sub>4</sub> and N<sub>2</sub>O direct and indirect emissions does not necessarily requires 428 the usage of feedstuff that carries heavy environmental footprint, e.g. wheat DDGS or 429 molasses, which accumulate great land occupation LCA.

430 The sensitivity analysis in Figure 5 shows that the objective of minimizing 431 CO<sub>2</sub>eq emissions is consistent with reduction in most impacts, although antagonistic 432 with NRE. This result suggests the existence of correlation between NRE and CC LCA 433 impacts in the ingredients. However, a thorough analysis of feedstuff production 434 processes and LCA would be required to prove this hypothesis. Overall, the sensitivity 435 analysis indicates that the complex dynamics between impacts will most certainly 436 produce impact transference with extreme choices of the parameters  $\beta$  and  $\lambda$ , i.e. 437 minimizing solely one impact. Moreover, comparing the sensitivity analysis with the 438 results from Figure 1, we see that for intermediate solutions in the efficient frontier (0 439  $< \lambda \leq 1$ ), all impacts can be reduced simultaneously with minimal transference among 440 them. Thus, an arbitrary – and relatively balanced – choice of weights  $\beta$  does not affect 441 significantly the solutions of MO model within a certain range of  $\lambda$ , i.e., balancing profit 442 and impacts. However, caution is required in the case of extreme solutions (such as 443 the RCS at  $\lambda = 0$ , minimizing only CC), as those are much more likely to cause impact 444 transference.

Model limitations derive mainly from our choice of data and uncertainties in the ruminant nutrition system. Improving accuracy in enteric fermentation and manure management estimates is crucial to improve GHG mitigation analysis. Accordingly, the model incorporates uncertainties from the systems and equations used in estimating N<sub>2</sub>O and CH<sub>4</sub> emissions, and global warming potential (GWP) factors for CH<sub>4</sub> and N<sub>2</sub>O (IPCC, 2013). Moreover, these results neglect stochasticity both in animal and ingredient prices. By introducing stochasticity, one can derive more precise estimates of the expected GHG reduction under alternative policy and possible carbon tax assumptions. Future research can also explore the inclusion of agro-industrial byproducts in the animal diet as a strategy to reduce emissions. Figures 1 - 4 suggests that the inclusion of by-products – which usually carry lower LCA footprint – in the animal diet may further decrease all environmental impacts, as suggested by literature (Oishi et al., 2011). This is corroborated by Figure 3, which shows that the main source of CO<sub>2</sub>eq is LCA footprint.

459 This work could be expanded to a broader, i.e., regional, analysis of feedlots 460 with different operational conditions, providing more accurate predictions of abatement 461 potential at a regional scale similar to that presented by Toorn et al. (2021). A complete 462 analysis of beef systems would require multiple MO models representing each feeding 463 phase to assess the optimal lifecycle strategy from growing to finishing. A significant 464 proportion of the total GHGs arise from the grazing phase. Thus, optimal mitigation 465 strategies would ideally combine the grazing phase (e.g., on-pasture supplementation) 466 with feedlot finishing measures. Combining this work with other models, such as De 467 Oliveira Silva et al. (2018), would help to address GHG impact mitigation potential of 468 mixed systems. Evaluating complete systems is a complex task that would still need 469 to couple the calf-cow interaction, and to coherently assess the footprint of each 470 animal. Methodologically, this model could theoretically be formulated by the means 471 of dynamic programming coupled with this model. However, computational tractability 472 is a challenge and will considerably increase the number of optimizations required.

#### 473 6 Conclusion

This paper demonstrates the advantages of a multiobjective model to evaluate the full complexity of the environmental and economic trade-offs involved in cattle feeding decisions. Our methodology can efficiently solve the nonlinear profit-maximizing diet model in regard of CH<sub>4</sub> and N<sub>2</sub>O emissions calculations, diet LCA and other environmental impacts. Results suggest that optimal mitigation is a combination of well-known strategies applied concurrently and that it is possible to avoid significant environmental impact transference.

In the French feedlot context, significant CO<sub>2</sub>eq abatement can be obtained
solely from changing feeding practices, i.e., increasing animal performance, reducing
diet life cycle, and reducing CH<sub>4</sub> and N<sub>2</sub>O production from enteric fermentation and

484 manure decomposition. This CO<sub>2</sub>eq abatement can be obtained simultaneously with 485 overall lower environmental impacts. This share of abatement in French feedlots is 486 seemingly consistent with government proposals in the SNBC to reduce agricultural 487 GHG emissions by 18% by 2030. It is salient, however, that an in-depth analysis along 488 the whole animal lifecycle must be conducted to determine the full extent to which 489 environmental impacts, and especially CO<sub>2</sub>eq emissions, can be reduced through 490 feeding strategies. Our model is the basis of a decision support system to guide 491 farmers and policymakers towards more accurate metrics for evaluating the impacts 492 of different feeding strategies on GHG emissions mitigation.

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- 499 **Declaration of interest**
- 500 None.
- 501 Ethics statement
- 502 Not applicable.
- 503 Software and data repository resources
- 504 https://github.com/BlackNellore/GreenFeeding

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