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Citation for published version:
Marques, G, De Oliveira Silva, R, Gustavo Barioni, L, Hall, JAJ, Fossaert, C, Tedeschi, LO, Garcia-launay, F & Moran, D 2021, 'Evaluating environmental and economic trade-offs in cattle feed strategies using multiobjective optimization', *Agricultural systems*, vol. 195, 103308. https://doi.org/10.1016/j.agsy.2021.103308

Digital Object Identifier (DOI):
10.1016/j.agsy.2021.103308

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Agricultural systems

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

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1 Introduction

Beef production systems have been implicated as the source of a significant proportion of global agricultural greenhouse gas (GHG) emissions, with methane (CH_4) from ruminant enteric fermentation as the principal source (Gerssen-Gondelach et al., 2017). However, net emissions vary greatly depending on the production system and levels of intensification, e.g., low input (extensive) versus feedlot finishing with high energy-dense diets. The rhetoric around sustainable intensification of agriculture has highlighted the advantages of feedlot systems to shorten the animal production cycle and increasing animal growth efficiency (Tilman et al., 2011). Feedlot systems and on-pasture supplementation can also reduce net CH_4 emission per kilogram of beef (de Oliveira Silva et al., 2015). In some regions, feedlots might decrease GHG emissions intensity by 25% compared with extensive pasture-based systems (Cortez-Arriola et al., 2016). In such systems, feed ingredients and diet formulation contribute significantly to GHG emissions (Tilman et al., 2011). However, the extent of any potential GHG reduction depends both on the impact of feed composition – on CH_4 emissions – and of manure decomposition – on CH_4 and N_2O emissions – from different management practices, and the environmental life cycle impacts of individual ingredients.

A potential cost-effective emissions mitigation strategy is to use proper diet formulation balancing economic and environmental objectives. The economic optimization of feed formulation is typically achieved through a least-cost linear programming diet model (Soto and Reinoso, 2012), which formulates the optimal diet minimizing feeding cost subject to a set of nutritional constraints. The environmental objective in feed formulation varies considerably across species with CH_4 production from ruminants a more significant target compared to relatively negligible emissions from monogastrics. In this context, Jean dit Bailleul et al. (2001) developed a multiobjective model based on an least-cost model focusing solely on nitrogen (N) excretion in pigs. Similarly, Hadrich et al. (2005) and Pomar et al. (2007) examined reducing phosphorus (P) excretion based on an least-cost model using multiobjective optimization, focusing on cattle and pigs, respectively. Later models minimizing both nitrogen (N) and P production were introduced by Kikuhara et al. (2009) for dairy cattle, and by Dubeau et al. (2011) for pigs. Moraes et al. (2012) represented carbon cost equivalent from N and CH_4 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_4 emissions, improving the representation of economic and environmental impact trade-offs.

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

However, in the case of ruminants, and more specifically cattle, the Garcia-Launay et al. (2018) methodology has two drawbacks. First, it does not account for emissions from enteric fermentation (CH_4) and manure decomposition (N_2O), which are significant in ruminants. Second, it does not tackle profit maximization in the feed formulation, a reasonable objective. One possible reason is that these factors can imply a hard-to-solve nonlinear programming model, which has recently been addressed by Marques et al. (2020) in relation to optimal cattle diet formulation. The latter highlighted significant differences between the use of a nonlinear profit-maximizing diet (NLPMD) model versus least-cost for feed formulation. The NLPMD model can be efficiently solved through parametric linear programming, i.e., by optimizing the least-cost model for the range of feasible shrunk weight gain (SWG), i.e., animal weight gain in terms of shrunk bodyweight, approximately 96% of live weight. By integrating the contributions from Marques et al. (2020) and Garcia-Launay et al. (2018) and computing CH_4 and N_2O 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.

This paper uses a multiobjective method based on a nonlinear profit-maximizing diet model to assess the economic and environmental trade-offs in diet formulation for feedlots in France. The analysis combines data from ingredients LCA – from the ECOALIM database (Wilfart et al., 2016) – and Tier 2 equations for direct cattle emissions derived by Escobar-Bahamondes et al. (2017) and the IPCC (2006). We also analyze the impacts of using a profit-maximizing objective function in contrast to using the least-cost diet, and the implications of weighting different environmental impacts in the multiobjective function. The model context (outlined in section 2) is an exploration of the emissions mitigation potential from French livestock production and its contribution to national mitigation ambitions. Section 3 details the methodology, comprising the multiobjective technique utilized to generate an efficiency frontier considering: (i) feedstuff costs, (ii) revenue associated with animal SWG, (iii) environmental impacts measured by LCAs for each ingredient, (iv) CH_4 emissions from enteric fermentation, and (v) N_2O emissions from manure decomposition. In section 4, using a typical feedlot, we derive the efficiency frontier, the marginal GHG abatement cost curve, the emission intensity per kg of carcass, the diet composition, and animal performance. In section 5, we discuss the results, the environmental (impact) mitigation potential, and the farm-level economic implications within the French production context. We conclude our findings in section 6.

2 Background and policy context

Livestock is of significant importance in the European economy, accounting for roughly 21.5% of the total € 41.6 billion in exports in 2019 (EUROSTAT, 2020a). European beef production has been constant, ranging from 86 to 89 million heads per year since 2011 (EUROSTAT, 2020b). However, the average carcass weight has been increasing, e.g. additional 24 kg/head between 2000 and 2015, increasing total meat production over time (Hocquette et al., 2018). France is Europe's largest beef producer and exporter, producing over 18 million head of cattle in 2019, which accounts for a little over 20% of Europe's total (EUROSTAT, 2020a). Developments in the sector are being influenced by several factors, including shifting consumer behaviours, changing meat consumption per capita, and emerging environmental constraints (Hocquette et al., 2018). A significant driver of change is the growing concern over the livestock contribution to climate change. Many countries are therefore examining total GHG emissions mitigation strategies within more or less (sustainably) intensive systems i.e., seeking to reduce emissions per kg of product without compromising economic performance, what would lead to reducing total emissions for the same demand level of a baseline scenario. Ruminant emissions are particularly implicated in mitigation strategies, accounting for a significant share of sector emissions and around 31% of those arising from global food production (Ritchie, 2019), a contribution that varies between countries (Tedeschi and Fox, 2020, Chapter 3.1). Many mitigation measures have been proposed, with significant effort made to identify those that are cost-effective (Pellerin et al., 2017). Less attention has been paid to the emerging ancillary effects of measures implemented alone or in combination and the issue of environmental impact transference, i.e. reducing one impact metric causes increase in other metrics.

In its National Low-Carbon Strategy (SNBC), France has set a target to reduce agricultural sector emissions by 18% by 2030 compared to a 2015 baseline (MTES, 2020). Among other strategies, the SNBC highlights N_2O and CH_4 emission reduction by "*reducing excess protein intake in animal diets*" and "*limiting enteric fermentation through adjustments to animal feed…"* (MTES, 2020). Given this ambition, our model aims to assess the emissions reduction potential (expressed in CO_2 equivalent - CO_2eq) from cattle feedlots while accounting for potential environmental impact transference and any trade-offs with productivity and profit.

3 Material and methods

We developed an ε-constrained multiobjective (MO) model – solved through ε-constrained technique – defining two objectives in diet formulation: profit maximization and environmental impact minimization. The ε-constrained is a MO technique, which overcomes convexity issues in nonlinear programming, in contrast to the weighted sum technique (Bérubé et al., 2009). We use the nonlinear profit-maximizing diet model proposed by Marques et al. (2020), which is based on the predictive equations of nutrient requirements from NASEM (2016) and Tedeschi and Fox (2020). Using the 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.

3.1 Feedstuff properties

We obtained the nutritional properties of feedstuffs from NASEM (2016), which has a library with over 200 feeding ingredients. The mathematical model developed by Marques et al., (2020) requires the following properties to evaluate the nutritional requirements: metabolizable protein (MP), physically effective neutral detergent fiber (peNDF), fat content (FAT), ruminally degradable protein (RDP), crude protein (CP), net energy for maintenance and gain (CNEm and CNEg), and dry matter (DM) to “as fed” (AF) conversion for each ingredient. We obtained LCA information of each ingredient from the ECOALIM database (Wilfart et al., 2016). Analogous to Garcia-Launay et al. (2018), we considered the following environmental impacts: phosphorus demand (PD, in kg P/kg of ingredient DM), non-renewable energy (NRE, MJ/kg of ingredient DM), climate change potential (CC, in kg CO_2eq/kg of ingredient DM), acidification potential (AC, in mol H^+-eq/kg of ingredient DM), eutrophication potential (EU, in kg PO_4^{3-}eq/kg of ingredient DM) and land occupation (LO, m^2 year/kg of ingredient DM).

The CH_4 emission from enteric fermentation is calculated using a linear-equivalent equation from Escobar-Bahamondes et al. (2017) and that from manure management uses the IPCC Tier 2 (IPCC, 2006). Both equations can be split into the contribution of each ingredient *j*, considering their partial nutritional composition, thus being integrated linearly into the model. For simplification, the CH_4 equation had its fat factor adjusted to utilize the first rather than the third power, with $R^2 \leq 0.99$. Moreover, we consider the constraint that the feedlot-fed cattle diet typically has less than 65% DM forage content. We used the conversion factor of 34 kg CO_2eq / kg CH_4 (IPCC, 2013). For the N_2O emissions, we use the IPCC Tier 2, which also does not affect the structure of the mathematical model; i.e., it can still be solved using the same technique. For N_2O, we consider the animal’s final weight in a dry lot system (0.02 kg N_2O / kg Nitrogen excreted), $N_{retention\_frac}$ of 7% and conversion rates of 298 kg CO_2eq

/ kg N_2O (IPCC, 2013), and 1.57 kg N_2O-N / kg N_2O (IPCC, 2006). The equations are shown in appendix Equations A.1.

3.2 Multiobjective approach

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

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

We can assemble the objective function of the six environmental impacts $k \in K$={PD, NRE, CC, AC, EU, LO} into a single environmental impact metric (EI) as shown in (2). The LCA_{jk} for each feed $j \in J$ and environmental impact $k \in K$ is weighted by a coefficient β_k, such that $\sum_{k \in K} \beta_k = 1$. This coefficient balances the relative "importance" of each LCA in the objective function. In practice, the weights must be chosen in a way that avoids environmental impact transference. That is, the propensity for reducing one impact at the cost of increasing others. The first part of equation (2) is identical to Garcia-Launay et al., (2018). The second includes the CH_4 and N_2O emission contribution from each ingredient converted to (kg CO_2eq/kg of ingredient DM). Both are subject to the exact weighting for climate change potential (β_{CC}). For mathematical purposes, we use normalized LCA values in (2) and convert them back to marginal values to present the results. This approach does not change the optimal solution in the model.

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

The multiobjective function is the convex combination of functions (1) and (2): MO(λ, SWG, **x**) = λ × Z(SGW, **x**) - (1 - λ) × EI(**x**), such as $\lambda \in [0; 1]$. When λ = 1, we are maximizing only the profit function, for which we can compute the reference (maximum) environmental impact $EI_{REF\text{-}ub}$, using (2). Conversely, for λ = 0, we can find the minimum environmental impact $EI_{REF\text{-}lb}$. The functions (1) and (2) can have the time parameter T replaced by a target weight, and be written as a function of SWG, as T = (SBW_f - SBW_0) / SWG. We used the ε-constrained method instead of the weighted sum since the latter can skip solution points in the solution frontier of nonlinear problems (Bérubé et al., 2009). With the combined function, we can generate the complete solution frontier for the nonlinear MO problem using the ε-constrained method. In **Algorithm 1** we show how to obtain the efficient frontier defined by the nutritional constraints in the NLPMD. In Algorithm 1, line 2, by solving the NLPMD model we calculate the upper bound environmental impacts ($EI_{REF\text{-}ub}$), i.e., the impacts when the objective is only to maximize profit. Alternatively, replacing the objective function of the NLPMD by minimizing (2), we compute the minimum possible environmental impact ($EI_{REF\text{-}lb}$), i.e., the lower bound, in line 3. To generate a frontier with *N* points, in line 4 we compute the step value ε = ($EI_{REF\text{-}ub}$ - $EI_{REF\text{-}lb}$)/*N*, and then solve the nonlinear model (NLPMD) *N* times with the additional constraint EI(x) = $EI_{REF\text{-}lb}$ + ε × 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.

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

$EI_{REF\text{-}ub} \leftarrow EI(\mathbf{x^*} \mid \{Max: MO(\lambda = 1, SWG, \mathbf{x})\})$

$EI_{REF\text{-}lb} \leftarrow EI(\mathbf{x^*} \mid \{Max: MO(\lambda = 0, SWG, \mathbf{x})\})$

$\varepsilon = (EI_{REF\text{-}ub} - EI_{REF\text{-}lb})/N$

for s = 0 **to** N **do**

  solve NLPMD:{ Max: MO(λ = 1, SWG, **x**),

   s.t.: $EI(x) \leq EI_{REF\text{-}lb} + \varepsilon \times s$}

end for

3.3 Analysis and scenarios

We use one typical feedlot input in the French production system: Charolais steers fattened from 350 kg to 620 kg (live weight) with body condition score 5, sold at €3.73 (2015 reference) per kilogram of carcass weight equivalent (CWE), or €2.46 per kg SWG (IDELE, 2016) – note that CWE is approximate 0.66 × SWG (Tedeschi and Fox, 2020a, 2020b). We use typical ingredients available in France to compose the diet, presented in Table 1. The table contains ingredient cost, minimum and maximum inclusion levels in the diet, and their respective LCA. Such values are the same as those used by Garcia-Launay et al. (2018), allowing us to compare the results. We extracted the properties of the ingredients used in the mathematical model from the RNS model (Tedeschi and Fox, 2020a, 2020b), generating the RData file used to run the model. The model and respective data used are available in Marques (2021). We estimate animal full-cycle GHGs and assume in both the scenarios that the animals bring an overhead emission (i.e. emissions accumulated prior to the current process of interest) of 14.3 kg CO_2eq / kg LW (12.24 kg CO_2eq / kg CWE, at the final live weight of 620kg) from birth and raise before being moved to the feedlot growing phase (Desjardins et al., 2012).

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

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

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 ($EI_{REF\text{-}ub}$). At this point, the absolute environmental impact is the same for both scenarios since their objective function is essentially equal, given by equation (1). In contrast, EI_{REF-lb} is given by equation (2); thus, the objective functions BIS and RCS differ in direction due to the differing weights of coefficient β_k. The x-axis is expressed as a percentage reduction of the maximum profit of €1139.00 (GHG reduction = 0%), the minimum weighted environmental impact is obtained for the BIS and RCS on the right-hand side of the graph at (a) €992.05 (GHG reduction = 44.7%, equivalent to 483 kg CO_2eq) and (b) €1024.34 (GHG reduction = 36.4%, equivalent to 392 kg CO_2eq), respectively. In the BIS the minimum impact scenario is not the minimum CO_2eq emissions solution. Furthermore, the global minimum CO_2eq solution is only found on the RCS for a high reduction in profit.

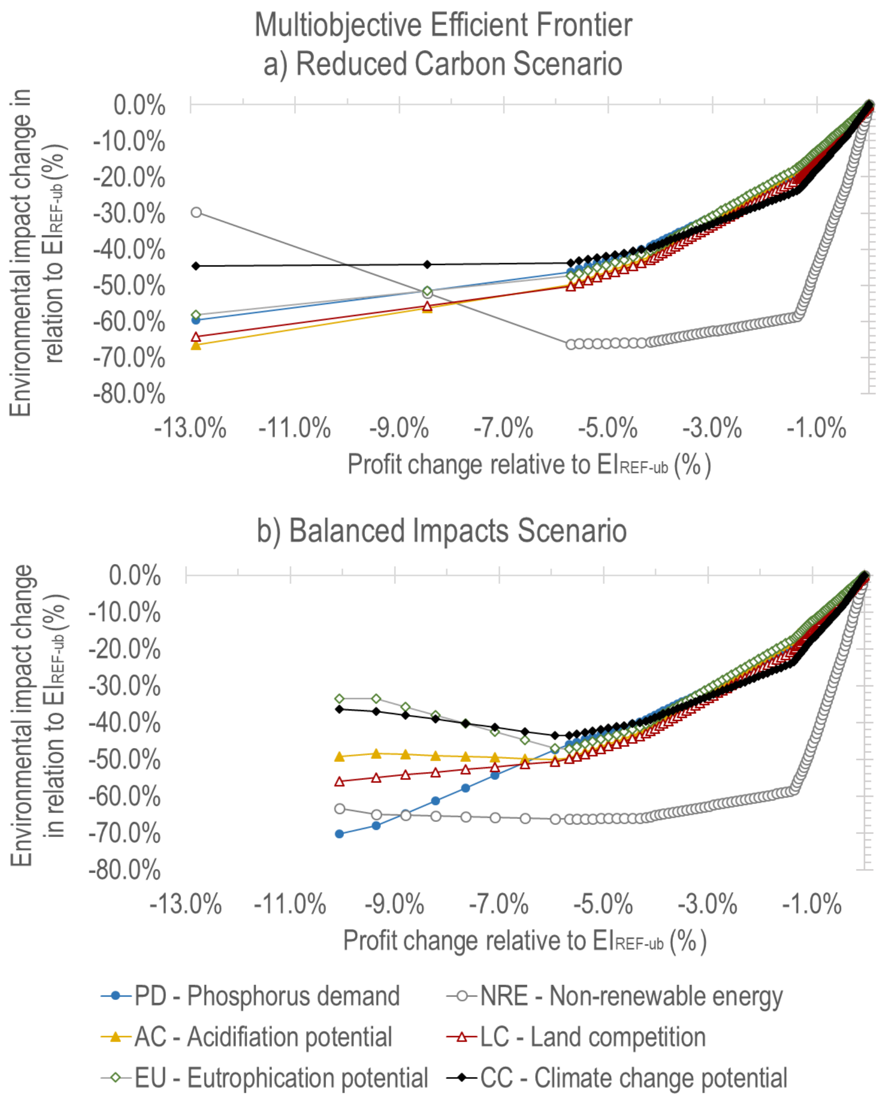

Figure 1 – Efficient solution frontier for (a) reduced carbon scenario and (b) balanced impacts scenario. Each solution (mark) is associated with a decrease in profit (x-axis) and was plotted with its associated percentage change in each of the environmental impacts (y-axis) calculated in relation to $EI_{REF\text{-}ub}$, 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.

Figure 2 shows the marginal GHG abatement cost (€ / kg CO_2eq / 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_2eq / kg LW, at 350 kg LW) plus feedlot phase GHGs – vary from the maximum 14.99 kg CO_2eq / kg CWE, in both scenarios, to a minimum of 13.98 kg CO_2eq / kg CWE for the BIS, and 13.76 kg CO_2eq / kg CWE in the RCS. The marginal abatement cost computes, in relation to the baseline ($EI_{REF\text{-}ub}$), the marginal profit loss per unit reduction in CO_2eq 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_2eq / 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_2eq / kg CWE, achieved with a profit reduction of 5.7%.

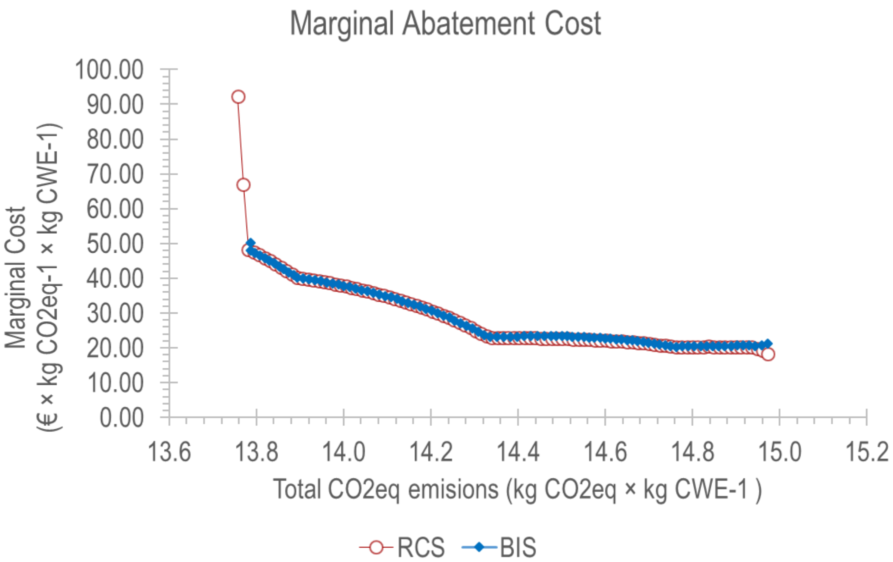

Figure 2 – The marginal abatement cost and its respective total emissions in the animal life cycle (including initial footprint) are shown for the RCS (reduced carbon scenario) and BIS (balanced impact scenario). Total emissions include overhead before the feedlot-optimized phase of 12.74 kg CO_2eq / kg CWE.

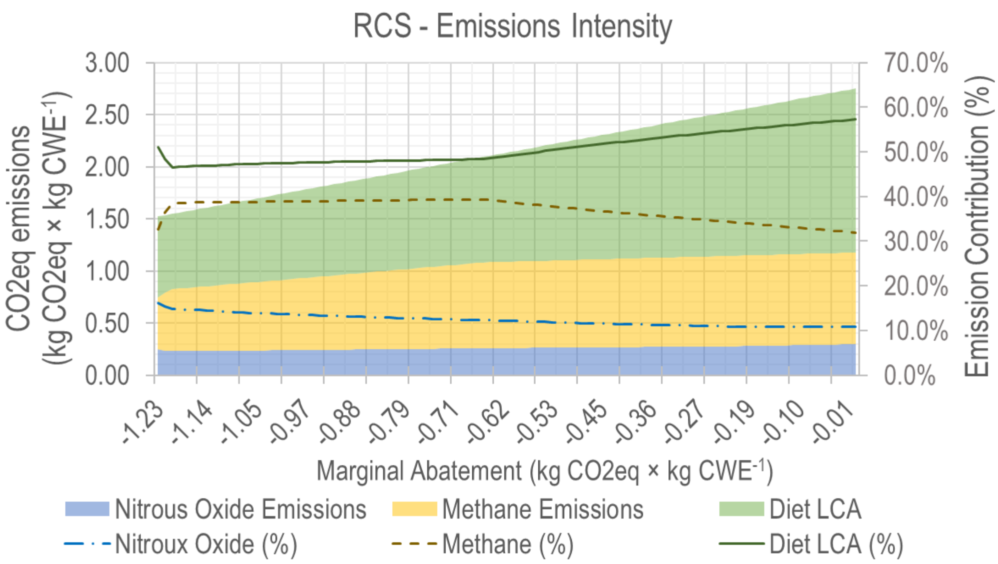

Figure 3 – Solution frontier of the climate change emission sources in the diet for the RCS (reduced carbon scenario). Along with the marginal contribution of each source (area graph), we also present the respective fraction of each source (lines) that contributes the total feedlot emission. The x-axis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

The contribution of each climate change factor, i.e., indirect emissions (diet LCA), and direct animal emissions (CH_4 and N_2O) are shown in Figure 3 for the RCS (BIS results are included in supplementary material). Figure 3 shows that diet LCA, CH4, and N2O represent, 58%, 32%, and 11% of the total carbon footprint in the maximum profit solution. The RCS emissions start at a maximum of 1.57, 0.88, and 0.30 kg CO_2eq / kg CWE, for diet, CH_4, and N_2O contributions, respectively. In the minimum emissions solution, these values fall to 0.78, 0.50, and 0.25 kg CO_2eq / kg CWE (reductions of 54%, 32%, and 17%, respectively). The sum of these individual contributions adds to the initial carbon footprint of 12.74 kg CO_2eq / kg CWE, representing the emissions decrease shown in Figure 2. Hence, these values and behavior represent only the feedlot feeding phase.

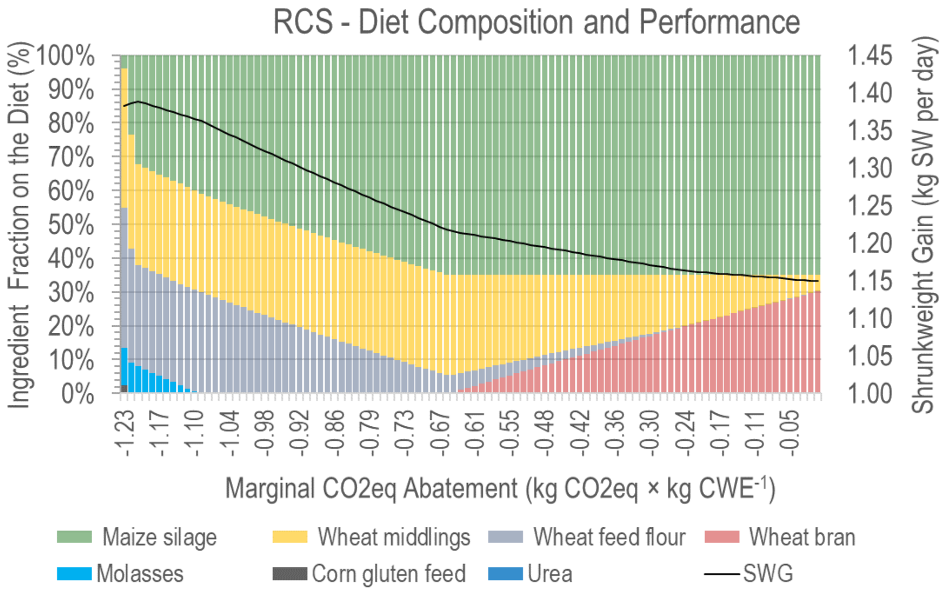

Figure 4 – Diet composition for each multiobjective model solution for the balanced impact scenario (BIS), showing solution respective shrunk weight gain (SWG) on the secondary axis (right-hand side). Each optimal diet composition in the multiobjective solution space is presented in relation to its consequential marginal CO_2eq abatement. Only ingredients with inclusion greater than 0% in at least one multiobjective solution are displayed.

Figure 4 presents the optimal diet composition for the efficient solution frontier. Each optimal solution in the figure is characterized by the respective profit reduction and marginal CO_2eq abatement, which can be related to the results presented in Figure 3. The feedstuff not shown in Figure 4 (included in Appendix Table A2) have entry-level equals to zero throughout the whole MO solution space. Thus from the 19 ingredients available, only 7 are used in at least one optimal solution of the efficient frontier. The maximum and minimum values for SWG are 1.38 kg SW per day (at 1.23 kg CO_2eq / kg CWE abatements) and 1.15 kg SW per day (at zero abatements), respectively. This change in daily weight gain is reflected on the feeding days until the animal is finished, lowering from 225 days in the maximum profit solution to a minimum of 187 days in the minimum GHG emissions solution. The resulting tables used to create all the graphs are included in the supplementary materials.

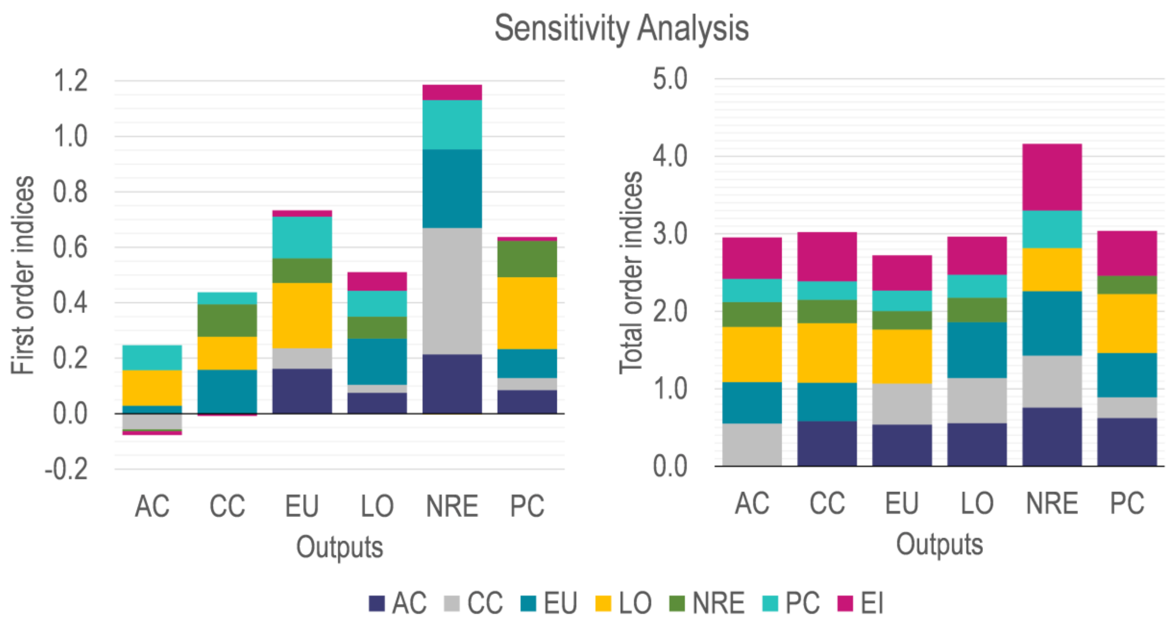

Figure 5 – Sobol sensitivity analysis of the environmental impacts outputs as a function of the multiobjective function weights. While the outputs are the measurements of the total impact in the solutions, the legend represents the weights β_k, for $k \in K$ = {PD, NRE, CC, AC, EU, LO}, and the multiobjective weight *(1 – λ)* 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.

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

5 Discussion

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

Our results indicate that the optimal GHG mitigation strategy for the growing feedlot phase (350 kg LW to 620 kg LW) is a combination of three sub-strategies: (i) reducing diet footprint, (ii) reducing animal CH_4 and N_2O emissions, and (iii) increasing animal performance. For the RCS, Figure 1a shows that the mitigation strategy can be divided into three different groups, defined by the cost-effectiveness and maximum CO_2eq reduction achievable. In the first group, high emission reduction is achieved (up to 0.62 kg CO_2eq / kg CWE, for the RCS) mostly by reducing the diet LCA footprint, as seem in Figure 3. This is combined with a steady increase in animal performance, from 1.15 kg SW per day to 1.21 kg SW per day, shown in Figure 4. Note that this initial mitigation strategy is the cheapest, with a roughly constant cost of 22 € / (kg CO_2eq / kg CWE), shown in Figure 2. This 24% emission reduction in the feedlot feeding phase – i.e. not accounting for overhead – in relation to the maximum profit baseline is consistent with the results of Garcia-Launay et al. (2018). However, to achieve higher marginal mitigation per kg CWE, the optimal solution is a combination of the sub-strategies, defining an intermediate group with emissions from 0.62 to 1.20 kg CO_2eq / kg CWE. Here, considering the CO_2eq emissions reduction in the feeding phase (Δ_{ERFP}), the increase of animal performance, Δ_{SWG} / Δ_{ERFP} = 0.27 (Figure 4), and constant reductions of CH_4, Δ_{CH4} / Δ_{ERFP} = -0.37 and N_2O, Δ_{N2O} / Δ_{ERFP} = -0.05 (Figure 3), result in a constant increase in marginal abatement cost, Δ_{cost} / Δ_{ERFP} = 45.52. In the third group (reduction from 1.20 to 1.23 kg CO_2eq / kg CWE), mitigation is considerably more expensive (Δ_{cost} / Δ_{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.

Our model offers a more nuanced analysis of the environmental and economic trade-offs in feedlots by combining emissions factors with a maximum profit objective. Figure 3 shows that although the feedstuff LCA makes the largest contribution to total emissions, CH_4 and N_2O together account for about 50% of total emissions. Thus, accounting for the CH_4 and N_2O emissions from enteric fermentation and manure management in the optimization model has a significant impact on the CO_2eq assessment, and thus, abatement levels. Furthermore, Figure 4 indicates a possibility to reduce environmental impacts by intensifying the production system, i.e., increasing SWG. These results show that both the choice of ingredients with lower impact footprint and less gaseous emissions yield, and shortening of the animal life cycle are a combined strategy in reducing CO_2eq and other environmental impacts. This is notable in the minimum-impact solution, which is 38 days shorter than the maximum-profit solution (supplementary material). Reducing emissions by increasing animal performance can only be captured in the analysis by the use of the NLPMD rather than the typical least-cost model. Our results show that – other things being equal – an increase in animal efficiency alone can reduce 17% of the total GHG emissions intensity in the maximum-profit solution in the feedlot phase.

In the French feedlot context our work shows that significant GHG intensity abatement (about 8% from total emission intensity, from Figure 2) can be achieved solely in the feedlot growing phase while simultaneously reducing other environmental impacts. The reduction in GHG emissions intensity – aligned with proposed sustainable intensification of agriculture (Tilman et al., 2011) – shows that beef production levels can be maintained while reducing total emissions. Hence, we can infer that net mitigation in beef feedlot systems is possible, although a quantitative result would require a thorough analysis considering different beef demand projections. Moreover, the reduction in GHG emissions in Figure 1a, are shown to be achieved alongside the reduction of other impacts, i.e. without causing environmental impact transference. The maximum theoretical GHG emission abatement of 44.7% is guaranteed to occur in the RCS. At this point, the RCS indicates a degree of impact transference – with a conspicuous slight decrease of GHG emissions at the expense of increasing NRE emissions – however without having any EI surpassing the reference values of the EI_{REF-ub} solution. However, with the RCS we can assess the GHG mitigation gap required to avoid transference. The difference between the 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 costs in the RCS, as observed in Figure 2. Ultimately, our results show that cost-effective GHG mitigation in beef feedlot can imply in overall environmental impact reduction, i.e. indirectly reducing land occupation, soil eutrophication, i.a. Hence, the reduction on CH_4 and N_2O direct and indirect emissions does not necessarily requires the usage of feedstuff that carries heavy environmental footprint, e.g. wheat DDGS or molasses, which accumulate great land occupation LCA.

The sensitivity analysis in Figure 5 shows that the objective of minimizing CO_2eq emissions is consistent with reduction in most impacts, although antagonistic with NRE. This result suggests the existence of correlation between NRE and CC LCA impacts in the ingredients. However, a thorough analysis of feedstuff production processes and LCA would be required to prove this hypothesis. Overall, the sensitivity analysis indicates that the complex dynamics between impacts will most certainly produce impact transference with extreme choices of the parameters β and λ, i.e. minimizing solely one impact. Moreover, comparing the sensitivity analysis with the results from Figure 1, we see that for intermediate solutions in the efficient frontier ($0 < \lambda \leq 1$), all impacts can be reduced simultaneously with minimal transference among them. Thus, an arbitrary – and relatively balanced – choice of weights β does not affect significantly the solutions of MO model within a certain range of λ, i.e., balancing profit and impacts. However, caution is required in the case of extreme solutions (such as the RCS at $\lambda = 0$, minimizing only CC), as those are much more likely to cause impact 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_2O and CH_4 emissions, and global warming potential (GWP) factors for CH_4 and N_2O (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 by-products 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_2eq is LCA footprint.

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

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_4 and N_2O 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_2eq abatement can be obtained solely from changing feeding practices, i.e., increasing animal performance, reducing diet life cycle, and reducing CH_4 and N_2O production from enteric fermentation and manure decomposition. This CO_2eq abatement can be obtained simultaneously with overall lower environmental impacts. This share of abatement in French feedlots is seemingly consistent with government proposals in the SNBC to reduce agricultural GHG emissions by 18% by 2030. It is salient, however, that an in-depth analysis along the whole animal lifecycle must be conducted to determine the full extent to which environmental impacts, and especially CO_2eq emissions, can be reduced through feeding strategies. Our model is the basis of a decision support system to guide farmers and policymakers towards more accurate metrics for evaluating the impacts of different feeding strategies on GHG emissions mitigation.

Acknowledgments

RdOS acknowledges the support of a University of Edinburgh Chancellors Fellowship funded by the Data Driven Innovation initiative as part of the Edinburgh and South East of Scotland City Region Deal and CAPES Foundation for the scholarship no. 10180/13-3. DM acknowledges UKRI support under grant number BB/T004436/1. DM, RdOS and LB acknowledge support under UKRI grant ES/N013255/2.

Declaration of interest

None.

Ethics statement

Not applicable.

Software and data repository resources

https://github.com/BlackNellore/GreenFeeding

References

Bérubé, J.F., Gendreau, M., Potvin, J.Y., 2009. An exact ε-constraint method for bi-objective combinatorial optimization problems: Application to the Traveling Salesman Problem with Profits. Eur. J. Oper. Res. 194, 39–50. https://doi.org/10.1016/j.ejor.2007.12.014

Cortez-Arriola, J., Groot, J.C.J., Rossing, W.A.H., Scholberg, J.M.S., Améndola Massiotti, R.D., Tittonell, P., 2016. Alternative options for sustainable intensification of smallholder dairy farms in North-West Michoacán, Mexico. Agric.

Syst. 144, 22–32. https://doi.org/10.1016/j.agsy.2016.02.001

de Oliveira Silva, R., Barioni, L.G., Albertini, T.Z., Eory, V., Topp, C.F.E., Fernandes, F.A., Moran, D., 2015. Developing a nationally appropriate mitigation measure from the greenhouse gas GHG abatement potential from livestock production in the Brazilian Cerrado. Agric. Syst. 140, 48–55. https://doi.org/10.1016/j.agsy.2015.08.011

De Oliveira Silva, R., Barioni, L.G., Queiroz Pellegrino, G., Moran, D., 2018. The role of agricultural intensification in Brazil's Nationally Determined Contribution on emissions mitigation. Agric. Syst. 161, 102–112. https://doi.org/10.1016/j.agsy.2018.01.003

Desjardins, R., Worth, D., Vergé, X., Maxime, D., Dyer, J., Cerkowniak, D., 2012. Carbon Footprint of Beef Cattle. Sustainability 4, 3279–3301. https://doi.org/10.3390/su4123279

Dubeau, F., Julien, P.O., Pomar, C., 2011. Formulating diets for growing pigs: Economic and environmental considerations. Ann. Oper. Res. 190, 239–269. https://doi.org/10.1007/s10479-009-0633-1

Escobar-Bahamondes, P., Oba, M., Beauchemin, K.A., 2017. Universally applicable methane prediction equations for beef cattle fed high- or low-forage diets. Can. J. Anim. Sci. 97, 83–94. https://doi.org/10.1139/cjas-2016-0042

EUROSTAT, 2020a. Agriculture, forestry and fishery statistics — 2020 edition. Luxemburgh. https://doi.org/10.2785/496803

EUROSTAT, 2020b. Bovine population - annual data.

Garcia-Launay, F., Dusart, L., Espagnol, S., Laisse-Redoux, S., Gaudré, D., Méda, B., Wilfart, A., 2018. Multiobjective formulation is an effective method to reduce environmental impacts of livestock feeds. Br. J. Nutr. 120, 1298–1309. https://doi.org/10.1017/S0007114518002672

Gerssen-Gondelach, S.J., Lauwerijssen, R.B.G., Havlík, P., Herrero, M., Valin, H., Faaij, A.P.C., Wicke, B., 2017. Intensification pathways for beef and dairy cattle production systems: Impacts on GHG emissions, land occupation and land use change. Agric. Ecosyst. Environ. 240, 135–147. https://doi.org/10.1016/j.agee.2017.02.012

Hadrich, J.C., Wolf, C.A., Harsh, S.B., 2005. Optimal livestock diet formulation with farm environmental compliance consequences, in: American Agricultural Economics Association Annual Meeting. Providence, RI, USA, p. 15. https://doi.org/http://dx.doi.org/10.22004/ag.econ.19427

Hocquette, J.-F., Ellies-Oury, M.-P., Lherm, M., Pineau, C., Deblitz, C., Farmer, L., 2018. Current situation and future prospects for beef production in Europe — A review. Asian-Australasian J. Anim. Sci. 31, 1017–1035. https://doi.org/10.5713/ajas.18.0196

IDELE, 2016. Poids et prix de vente des animaux Charolais en 2015. France.

IDELE, 2011. Production de jeunes bovins de races à viande et de races laitières. France.

IPCC, 2013. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovern-mental Panel on Climate Change. Cambridge, United Kingdom and New York, NY, USA.

IPCC, 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Directrices para los inventarios nacionales GEI. Institute for Global Environmental Strategies, Hayama, Japan.

Jean dit Bailleul, P., Rivest, J., Dubeau, F., Pomar, C., 2001. Reducing nitrogen excretion in pigs by modifying the traditional least-cost formulation algorithm. Livest. Prod. Sci. 72, 199–211. https://doi.org/10.1016/S0301-6226(01)00224-X

Kikuhara, K., Kumagai, H., Hirooka, H., 2009. Development and evaluation of a simulation model for dairy cattle production systems integrated with forage crop production. Asian-Australasian J. Anim. Sci. 22, 57–71. https://doi.org/10.5713/ajas.2009.80098

Koscheck, J.F.W., Romanzini, E.P., Barbero, R.P., Delevatti, L.M., Ferrari, A.C., Mulliniks, J.T., Mousquer, C.J., Berchielli, T.T., Reis, R.A., 2020. How do animal performance and methane emissions vary with forage management intensification and supplementation? Anim. Prod. Sci. 60, 1201. https://doi.org/10.1071/AN18712

Mackenzie, S.G., Leinonen, I., Ferguson, N., Kyriazakis, I., 2016. Towards a methodology to formulate sustainable diets for livestock: Accounting for environmental impact in diet formulation. Br. J. Nutr. 115, 1860–1874. https://doi.org/10.1017/S0007114516000763

Marques, J.G.O., 2021. GreenFeeding [WWW Document]. URL https://github.com/BlackNellore/GreenFeeding (accessed 3.2.21).

Marques, J.G.O., de O. Silva, R., Barioni, L.G., Hall, J.A.J., Tedeschi, L.O., Moran, D., 2020. An improved algorithm for solving profit-maximizing cattle diet problems. Animal 14, s257–s266. https://doi.org/10.1017/S1751731120001433

Moraes, L.E., Fadel, J.G., Castillo, A.R., Casper, D.P., Tricarico, J.M., Kebreab, E., 2015. Modeling the trade-off between diet costs and methane emissions: A goal programming approach. J. Dairy Sci. 98, 5557–5571. https://doi.org/10.3168/jds.2014-9138

Moraes, L.E., Wilen, J.E., Robinson, P.H., Fadel, J.G., 2012. A linear programming model to optimize diets in environmental policy scenarios. J. Dairy Sci. 95, 1267–1282. https://doi.org/10.3168/jds.2011-4651

MTES, 2020. Stratégie Nationale Bas-Carbone. France.

NASEM, 2016. Nutrient Requirements of Beef Cattle, 8th Revised Edition, 8th ed, Nutrient Requirements of Beef Cattle, 8th Revised Edition. National Academies Press, Washington, D.C. https://doi.org/10.17226/19014

Oishi, K., Kumagai, H., Hirooka, H., 2011. Application of the modified feed formulation to optimize economic and environmental criteria in beef cattle fattening systems with food by-products. Anim. Feed Sci. Technol. 165, 38–50. https://doi.org/10.1016/j.anifeedsci.2011.02.015

Pashaei Kamali, F., van der Linden, A., Meuwissen, M.P.M., Malafaia, G.C., Oude Lansink, A.G.J.M., de Boer, I.J.M., 2016. Environmental and economic performance of beef farming systems with different feeding strategies in southern Brazil. Agric. Syst. 146, 70–79. https://doi.org/10.1016/j.agsy.2016.04.003

Pellerin, S., Bamière, L., Angers, D., Béline, F., Benoit, M., Butault, J.P., Chenu, C., Colnenne-David, C., De Cara, S., Delame, N., Doreau, M., Dupraz, P., Faverdin, P., Garcia-Launay, F., Hassouna, M., Hénault, C., Jeuffroy, M.H., Klumpp, K., Metay, A., Moran, D., Recous, S., Samson, E., Savini, I., Pardon, L., Chemineau, P., 2017. Identifying cost-competitive greenhouse gas mitigation potential of

French agriculture. Environ. Sci. Policy 77, 130–139. https://doi.org/10.1016/j.envsci.2017.08.003

Pomar, C., Dubeau, F., Létourneau-montminy, M., Boucher, C., Julien, P., 2007. Reducing phosphorus concentration in pig diets by adding an environmental objective to the traditional feed formulation algorithm 111, 16–27. https://doi.org/10.1016/j.livsci.2006.11.011

Ritchie, H., 2019. Food production is responsible for one-quarter of the world's greenhouse gas emissions - Our World in Data [WWW Document]. OurWorldInData.org. URL https://ourworldindata.org/food-ghg-emissions (accessed 3.15.21).

Soto, C., Reinoso, V., 2012. Modelo de formulación de raciones al mínimo costo para ganado de carne basado en el sistema NRC 2000. Arch. Zootec. 61, 255–266. https://doi.org/10.4321/S0004-05922012000200010

Tedeschi, L.O., Fox, D.G., 2020a. The Ruminant Nutrition System, Volume I – An Applied Model for Predicting Nutrient Requirement and Feed Utilization in Ruminants, 3rd ed. XanDu Publishing, Inc., Ann Harbor, MI, USA.

Tedeschi, L.O., Fox, D.G., 2020b. The Ruminant Nutrition System: Volume II - Tables of Equations and Coding. XanEdu, Ann Harbor, MI, USA.

Tilman, D., Balzer, C., Hill, J., Befort, B.L., 2011. Global food demand and the sustainable intensification of agriculture. Proc. Natl. Acad. Sci. 108, 20260–20264. https://doi.org/10.1073/pnas.1116437108

Toorn, S.I. aan den, Worrell, E., van den Broek, M.A., 2021. How much can combinations of measures reduce methane and nitrous oxide emissions from European livestock husbandry and feed cultivation? J. Clean. Prod. 127138. https://doi.org/10.1016/j.jclepro.2021.127138

Wilfart, A., Dusart, L., Méda, B., Gac, A., Espagnol, S., Morin, L., Dronne, Y., Garcia-Launay, F., 2019. Réduire les impacts environnementaux des aliments pour les animaux d'élevage. INRA Prod. Anim. 31, 289–306. https://doi.org/10.20870/productions-animales.2018.31.2.2285

Wilfart, A., Espagnol, S., Dauguet, S., Tailleur, A., Gac, A., Garcia-Launay, F., 2016. ECOALIM: A Dataset of Environmental Impacts of Feed Ingredients Used in

French Animal Production. PLoS One 11, e0167343. https://doi.org/10.1371/journal.pone.0167343