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MOO-GAPS: A multi-objective optimization model for global animal production and sustainability

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ABSTRACT

Agricultural and livestock production involves significant trade-offs between multiple sustainable development goals, including reducing hunger and poverty, and reducing emissions of greenhouse gasses. Here we describe a multi-objective optimization tool for livestock production to evaluate trade-offs among environmental and economic objectives with high spatial granularity and the capability to be aggregated to national or global scales. We illustrate the use of this tool analysing how and where to produce beef to optimize the weighted sum of environmental and economic objectives, in this case minimizing greenhouse gas emissions and minimizing costs of production. We present how the outputs of this model can inform a sustainable transition of the industry and policy decisions, with a focus on inherent trade-offs. By comparing optimal production with current production, we highlight the potential environmental and economic efficiencies that can be made by changing the location or methods of production. As such, this tool provides a platform to identify trade-offs and synergies among multiple diverse sustainability goals, critical in the livestock and agricultural sectors.

1. Introduction

Agriculture and livestock production has had substantial impacts on the environment, including occupying nearly 50% of habitable land on the planet (Ellis et al., 2010), contributing to 26% of total anthropogenic greenhouse gas (GHG) emissions (Poore and Nemecek, 2018) and accounting for 70% of global freshwater withdrawals through irrigation of feed crops (Rosegrant et al., 2009). At the same time, over a quarter of the global population is employed within the agricultural sector (World Bank, 2019). Therefore, environmental and socio-economic impacts from the agricultural industry represent significant trade-offs between Sustainable Development Goals of reducing hunger, fighting poverty, mitigating climate change, and reducing the loss of natural habitats and biodiversity (Clark and Wu, 2016). With a rising global population and increasing food demand in most countries (van Dijk et al., 2021), environmental impacts from agricultural activities are expected to increase (Smith et al., 2019). As such, there is a growing need to better understand the linkages between agricultural land and livestock management, and the trade-offs between socio-economic and environmental outcomes.

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We present in this paper a novel approach, MOO-GAPS (Multi-Objective Optimization model of Global Animal Production and Sustainability), a high-resolution spatial optimization algorithm that enables the evaluation of multidimensional trade-offs and synergies between sustainability objectives from the production of animal-source food. Here we illustrate the approach and utility of MOO-GAPS by applying it to beef production and evaluating trade-offs between economic and emissions mitigation goals. The application of the tool to beef production follows the need to inform complex sustainable land management decisions in this agricultural sector. Indeed, the global beef industry is the largest contributor to greenhouse gas emissions (~33% of total agricultural emissions; FAO (2018)), but also a considerable agri-economic powerhouse with an estimated value of 220 billion USD in annual revenues worldwide (FAOSTAT, 2021), and provides livelihood and nutrition security, especially of the poor (Thornton, 2010).

Previous work has been conducted to explore multidimensional trade-offs from land-use change to a large extent with a focus on ecosystem services (Aryal et al., 2022; Bryan et al., 2015; Groot et al., 2018; Kragt and Robertson, 2014; Ma and Wen, 2021). However, few models have attempted to examine how to optimize land use for environmental and economic goals in livestock production, particularly using land information at fine spatial resolution and at a scale that supports national-level policy decisions. Indeed, while Accatino et al. (2019) and Domingues et al. (2019) examined trade-offs and synergies between multiple ecosystem services in livestock production in France, their analysis did not include the economics of land-use change nor a spatial resolution adequate for in-depth analysis of land-use change. Similarly, another study assessed the environmental (feed ingredient life cycles, methane, nitrous oxide emissions from enteric fermentation and manure decomposition) and economic (profits) trade-offs in cattle feed strategies in feedlots also in France (Marques et al., 2022). Again, however, the optimization did not include the spatial dimension of land use and only provided national level outputs. Contrary to the above, Wang et al. (2022) analysed trade-offs between ecosystem services associated with animal husbandry in a municipality in China, at an informative land use resolution but did not consider socio-economic costs or benefits from livestock production critical to the industry. Using a case study of England and Wales, Chatterton et al. (2015) developed a linear programming model to find most suitable areas to maximize multiple ecosystem services from the livestock sector. However, the study did not assess the trade-offs between ecosystem services or present the land-use changes needed to improve efficiency of production.

At a larger scale, integrated assessment models (IAMs) of land use and agriculture (e.g., Dietrich et al., 2019; Havlík et al., 2014) are well suited to capture global patterns and trends in economic and environmental impacts of agriculture over time. Such models have been developed to examine shocks on the economic and agricultural sectors by simulating market equilibrium (Havlík et al., 2014) or minimizing production costs (Lotze-Campen et al., 2008) and identifying optimal land uses for different regions. With MOO-GAPS, we have opted for a different approach to allow for the explicit optimization of multiple objectives rather than using an economic optimization. Furthermore, IAMs investigating livestock production have generally been applied at a spatial resolution, e.g., ~200 km resolution grid cells (Havlík et al., 2014), that may limit model applications for land management decisions at a finer spatial scale. Another study conducted at the global scale by Petz et al. (2014) investigated the trade-offs between environmental services (biodiversity, carbon sequestration, erosion prevention and forage utilization) for different grazing intensities at 50 km resolution. However, the study did not examine the potential efficiency improvements that could be achieved from land-use change and the resulting trade-offs with economic goals. As such, there have been limited studies investigating trade-offs between environmental and economic sustainability goals in livestock production at national scale, while presenting how can land-use change improve efficiency at fine spatial resolution.

The MOO-GAPS beef example presented here aims to identify, at 10 km resolution, the most efficient feeds and locations to produce cattle feed at the national scale to minimize greenhouse gas emissions and economic costs of production. We assessed the aggregated costs and emissions of optimal production for different preferences using a weighted sum optimization. This tool allows us to achieve four outcomes that had not been achieved previously: (1) to explicitly assess and illustrate the trade-offs between environmental and economic objectives, (2) to quantify the potential improvements for environmental and/or economic costs from current beef production by increasing the efficiency of feed and/or changing its location, (3) to provide information on the land-use change needed to increase efficiency of production at fine spatial resolution, and (4) to examine the robustness of efficient production strategies by assessing the level of uncertainty of results considering variability in input parameters.

2. Methods

2.1. Optimization framework

We developed a multi-objective optimization framework to assess the efficiency of different feed options in different locations to produce beef and explore the trade-offs between two objectives: minimizing economic costs of production and minimizing GHG emissions (Fig. 1). The simulation units are grid cells at a resolution of 5 arcminutes (~10 km at the equator). MOO-GAPS was coded using the Python programming language version 3 and is freely available on a GitHub repository (https://github.com/accastonguay/MOOGAPS).

To calculate optimal production, we first assessed suitable and available areas to grow feed on each grid cell (sections 2.2 and 2.3). We then simulated the potential beef production (section 2.5) on each grid cell for the different feed options described in section 2.4. Based on biomass consumed and meat production, we calculated the resulting economic costs (section 2.6) and GHG emissions (section 2.7). Once meat production, economic costs and GHG emissions have been calculated for each feed option and each cell, the optimal feed option for each grid cell was selected using a weighted sum optimization (section 2.8.1). Finally, the grid cells with the lowest weighted sum that meet beef demand were selected to produce beef (section 2.8.2). All parameters used as input in this application of the tool are described in Appendix Table 3 and all state variables calculated within the model are described in Appendix Table 4. The detailed methodology with all equations, variable names and units for sections 2.2 to 2.7 are included in the Appendix.

2.2. Suitable area

We first determined the suitability of each grid cell to produce cattle feed considering the current land cover. We calculated the fraction of each land cover, for instance forest, cropland, grassland, etc. (Appendix Table 1), within each of the 5 arcminutes grid cell i using the 2015 European Space Agency's Climate Change Initiative (ESA-CCI) Land Cover map at 300 m resolution (ESA, 2017). Land cover categories of water bodies, urban areas and permanent snow and ice were excluded. Next, we determined the suitable area on each grid cell by multiplying cell area and the total fraction of suitable land cover, i.e., all land covers except water bodies, urban areas and permanent snow and ice.

2.3. Available area

From the suitable area on a grid cell, we also excluded areas that are producing crops for other uses than cattle feed so that other agricultural activities are not dislodged by the production of new cattle feed. Thus, the area on a cell that is considered available for conversion to feed production is the difference between the total area used for producing current crops from Monfreda et al. (2008) and the current area used for

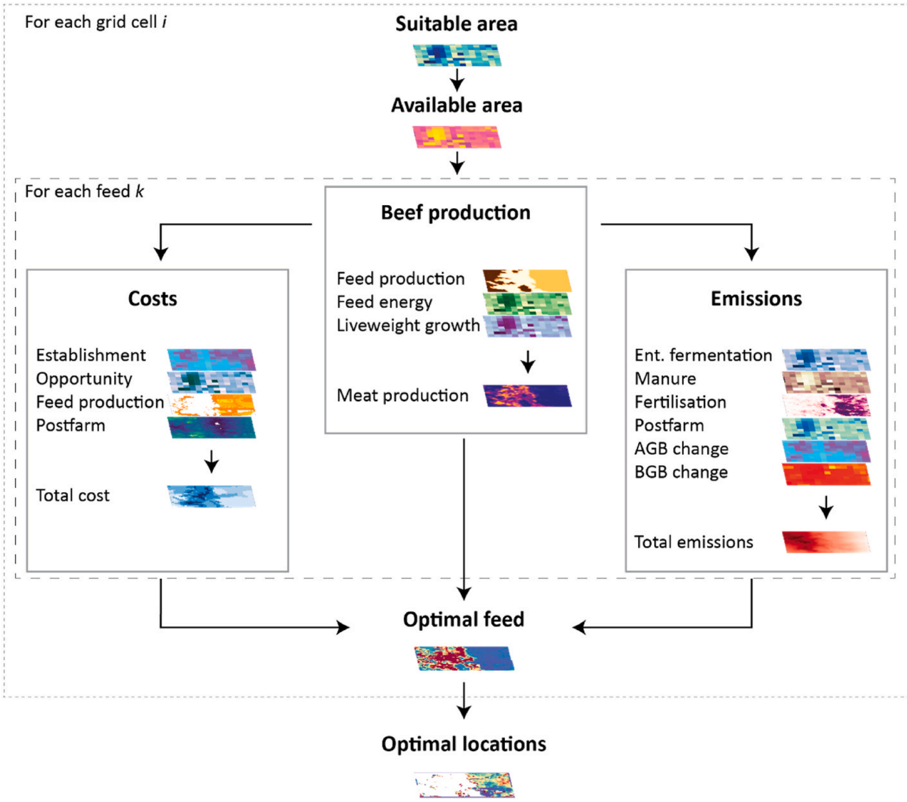

Fig. 1. Framework of the optimization. Suitable area (section 2.2) and available area (section 2.3.) are evaluated for each grid cell (i) whereas beef production (section 2.5), production costs (section 2.6) and GHG emissions (section 2.7) are simulated for each grid cell and feed option (k). The optimal feed is then selected for each grid cell (section 2.8.1) and optimal grid cells are selected for each country (section 2.8.2). AGB change and BGB change refer to above- and below-ground biomass change, respectively.

Table 1
Beef cattle feed options (k) considered in the model on each grid cell i.

Description of feed options	Code (k)
Grass with grazing intensity of 25% and N application 0 kg ha^{-1}	1
Grass with grazing intensity of 37.5% and N application 0 kg ha^{-1}	2
Grass with grazing intensity of 50% and N application 0 kg ha^{-1}	3
Grass with grazing intensity of 25% and N application 50 kg ha^{-1}	4
Grass with grazing intensity of 37.5% and N application 50 kg ha^{-1}	5
Grass with grazing intensity of 50% and N application 50 kg ha^{-1}	6
Grass with grazing intensity of 25% and N application 200 kg ha^{-1}	7
Grass with grazing intensity of 37.5% and N application 200 kg ha^{-1}	8
Grass with grazing intensity of 50% and N application 200 kg ha^{-1}	9
Mix of grass and grain	10
Mix of grass and stover	11
Mix of grain and stover	12
Current diet based on Herrero et al. (2013b)	13

the production of beef cattle fodder crops (see Appendix section 1.4.2. for more detail).

2.4. Feed options

We included different types and combinations of feeds to capture a range of cattle diets. In this optimization, feed option (k) can be one of the following:

- Grazing: Grass composes 100% of the diet and all the available area on a cell i described in section 2.3 is converted to grazing. We included nine different grazing management levels from three grazing intensities and three levels of nitrogen (N) fertilizer application rates (see Table 1 for more details).
- Grain and grazing: The available area is converted to fodder crops but grain consumption is limited to a maximum percentage of total feed composition and must be completed with roughage to avoid rumen acidosis (Blackwood and Clayton, 2007). We considered seven major grains and oil crops (hereafter designated as grain for simplicity) used as fodder: barley, maize, rapeseed, rice, sorghum, soybean and wheat.
- Grazing and stover: All the available area is converted to grazing but the feed ration can be supplemented by crop residues from current crop produced for other uses than cattle feed. Crop residues are limited to a given fraction of the diet according to current feed composition that varies depending on world regions (Herrero et al., 2013b).
- Grain and stover: All the available area is converted to grain and the diet is supplemented by crop residues from current crop produced for other uses and from fodder crops. Again, crop residues should not exceed a given fraction of the diet based on current feed composition depending on world regions (Herrero et al., 2013b).
- Current feed: An additional option is to maintain the land use and diet of the current production. In this case, all properties of the current beef production, e.g., quantity of meat produced, total emissions, total costs, etc. remain the same. For this feed option, current biomass consumption, meat production, and emissions from enteric fermentation and manure management were retrieved directly from Herrero et al. (2013b) rather than simulated in this model.

2.5. Beef production

We estimated potential beef production for each feed option listed in Table 1 from the quantity consumed and energy content in the different types of biomass, i.e., grass, grain and/or crop residues. We then converted energy consumed to liveweight gain and meat production using a conversion factor of energy to meat and a dressing percentage, i.e., the percentage of the live animal weight that becomes the carcass weight at slaughter.

2.5.1. Potential feed production

Three types of biomass are considered for cattle feed: grass, feed crops and crop residues. Grazed biomass on a grid cell was obtained from ORCHIDEE-GM simulations (Chang et al., 2016) given the ability of this model to simulate grazing biomass under a variety of grazing management strategies. We used three grazing intensities or pasture utilization rates (25, 37.5 and 50% of total aboveground biomass consumed) and three nitrogen (N) application rates (0, 50, 200 kg/ha/yr), for a total of nine combinations of grazing managements (Appendix Fig. 1).

Potential feed crop biomass production was estimated with the available area on a grid cell where crops can be grown, the average fraction of grid cell area currently used for each crop in the country (Monfreda et al., 2008), yield ceilings (Gerber In prep) and the average yield gap fraction in the country for each of the seven major feed crops (barley, maize, rapeseed, rice, sorghum, soybean and wheat) (Mueller et al., 2012).

Biomass from crop residues available for cattle consumption can come from the production of current crops grown for other uses or from new fodder crops produced in one of the feed options (including new grain crops) (Table 1). The availability of residues for different crops was determined from the residue-to-product ratio for each crop, based on Scarlat et al. (2010) and Gao et al. (2016). To make sure that some crop residues remain on the field and that soil quality is not negatively impacted, we assumed that only 40% of crop residues can be used as feed based on Scarlat et al. (2010) and Lal (2005).

Some diets may be unhealthy or insufficient to maintain animal growth. For feed options that include grain, the proportion of grain in the total diet is limited to 80% to avoid rumen problems such as acidosis (Blackwood and Clayton, 2007). Crop residues can be a good source of roughage but may be insufficient to maintain liveweight gain. As such, the proportion of crop residues in the diet is limited based on regional diet compositions (Herrero et al., 2013b).

2.5.2. Feed energy

Once biomass consumption has been calculated for all feed options and all grid cells, we converted biomass consumption to metabolizable energy (ME) consumption, using energy content in different feeds. ME content in feed crops and crop residues was collated from Heuzé et al. (2013) (Appendix Fig. 3a), whereas ME content in grass was categorized by climate zones and regions according to Herrero et al. 2013) (Appendix Fig. 3b).

2.5.3. Liveweight growth

Liveweight gain was simulated by multiplying ME consumed with a conversion factor of liveweight gain, that varies according to world regions, climate zones (arid, humid or temperate) and production systems (mixed or grazing) (Herrero et al., 2013b) shown in Appendix Fig. 4. Animal growth can be negatively affected by environmental factors. For example, cold stress leads to increased feed and energy intake for heat production (Tarr, 2015). We therefore included the impact of effective temperature (Environment Canada, 2001) on additional biomass requirement (Tarr, 2015).

2.5.4. Meat production

Once liveweight growth has been simulated for each feed option and each grid cell, meat production was estimated by applying a dressing percentage from FAO (2018), i.e., the percentage of live animal weight that becomes carcass weight at slaughter. Meat production for the current system on each grid cell was retrieved directly from Herrero et al. (2013b).

2.6. Costs of production

The total economic cost of producing cattle meat on each cell for each potential feed option was calculated by aggregating establishment, opportunity, production and postfarm (transport and export) costs.

2.6.1. Establishment cost

Establishment cost, or the cost of converting the current land cover to a land use that supports one of the feed options k, was estimated by aggregating the cost of converting a land cover to cropland or pastureland, which only occurs where the current land cover is not categorized as pasture or crop. Thus, we assumed areas already under cropland or pastureland according to ESA-CCI land cover ESA (2017) do not incur cost of land conversion and preparation. The costs per area of establishing a new pasture or new feed crops were estimated from Kreidenweis et al. (2018). This cost occurs only once and therefore needs to be annualized to be aggregated with annual costs. Annualization of establishment cost was realized using national lending rates from World bank data (World Bank, 2022) and a time horizon of 30 years, a common practice in agricultural investments (Wang et al., 2016).

In addition to the cost of establishing a new pasture or feed crops, we estimate that feedlot operations need additional infrastructure and machinery if the production of grain-fed beef is increased. We defined the cost of expanding or creating a new feedlot based on the increase in the number of heads on a cell where cattle is grain-fed and a cost of lot improvement, machinery and buildings in feedlots per head based on Duncan et al. (1997).

The cost of clearing current vegetation can vary widely since costs can be recouped if the vegetation has market value. Further, land clearing through fire to make place for cattle ranching is common practice in several countries (DeFries et al., 2008). Due to the lack of information on country-specific economic costs of land clearing, this cost was not considered.

2.6.2. Opportunity cost

Opportunity cost represents the profit forgone for producing beef cattle feed instead of other agricultural activities. Opportunity cost of potential feed options was estimated from the available area used for feed production, the total returns from crop production from Gerber (In prep) and a profit margin for agricultural commodities. Profit margins in agriculture have been shown to increase with farm size (Hoppe, 2014). Due to the current lack of information on profit margin in every country, we created a new spatial layer to estimate profit margins as a function of field size (Fritz et al., 2015) (see Appendix Fig. 5).

2.6.3. Feed production cost

For grazing biomass, we calculated the cost of production based on the application of N, P and K fertilizers. The application rate for N was based on the grazing management scenarios, i.e., 0, 50 or 200 kg ha^{-1} (see Table 1). If a grassland is considered to receive N fertilizer (i.e., grazing with N application rates of 50 or 200 kg ha^{-1}), we also approximated application of P and K based on the nutrient requirements averaged over 16 grass species (Oldham, 2011) and nutrient availability in soil from IIASA/FAO (2022) (see Appendix Table 2). Due to the lack of global databases providing prices of fertilizers, we derived prices from aggregated traded quantity and value for each fertilizer and each country (UN Comtrade, 2021). The total cost of producing grass biomass was then aggregated over all fertilizers.

To calculate the cost of producing fodder crops, we used producer prices of each grain in each country from FAOSTAT (2021) combined with feed crop biomass consumed calculated in section 2.5.1. For crop residues, we assumed that the cost of production would be included in the producer prices of feed crops and therefore no costs of production are associated with crop residues. Production costs for all types of biomass were aggregated for each feed option on each grid cell.

2.6.4. Postfarm costs

To estimate postfarm costs in the supply chain, we considered the cost of transporting cattle to the consumers and cost of exporting beef to importing countries. The transportation cost depends on whether beef is

Table 2
Parameters sampled for uncertainty assessment, with their units, the scale of resampling and the source used in this case to generate ranges for resampling.

Parameter	Unit	Sampling scale	Source
Crop residue removal	%	global	Lal (2005)
Maximum grain in diet	%	global	Blackwood and Clayton (2007)
Fertilizer prices	USD/t	country	UN Comtrade (2021)
Producer prices of crops	USD/t	country	FAOSTAT (2021)
Relative change in soil carbon	%	land use	Guo and Gifford (2002)
Liveweight growth	t/GJ	region-climate	Herrero et al. (2013b)
Emission factor for enteric fermentation	t CO_2 eq/t DM	region-climate	Herrero et al. (2013b)
Emission factor for manure emissions	t CO_2 eq/t DM	region-climate	Herrero et al. (2013b)
Total crop return	USD/ha	Grid cell	(Gerber, In prep); IIASA/FAO (2022)

consumed locally or exported. In the optimization process described in section 2.8.2, if meat production in a country is lower than the country's domestic demand, beef is assumed to be transported to the nearest city for domestic consumption, otherwise, beef is assumed to be transported to the nearest port to be traded to the country's beef export destinations. In both cases, transport cost of meat is based on liveweight transported (calculated in section 2.5.3), payload capacity (Delgado et al., 2016), travel time to nearest city or port (Weiss et al., 2018), fuel efficiency of road transport (Delgado et al., 2016), price of diesel (GIZ, 2019) and hourly wage (International Labour Organization, 2019). If beef production in the country has exceeded domestic demand, the meat produced on a cell is assumed to be traded and an export cost is added to postfarm costs. In this case, the export cost is estimated for each beef trade partner of the exporting country based on FAO trade matrices (FAOSTAT, 2021), the shipping distance between the exporting country and each trade partner (Bertoli et al., 2016), and a trade margin based on the quantity of beef traded and sea distances between countries (Nuno-Ledesma and Villoria, 2019).

2.6.5. Total cost

Total cost ($C_{i,k}$) for each feed option k and grid cell i is then calculated by aggregating all annual costs. Establishment costs were included in total costs of potential production but not for the current production, as sunk costs are outside of the scope of this assessment.

2.7. GHG emissions

The total greenhouse gas emissions of producing cattle meat on cell i for each feed option k was calculated by aggregating non-CO_2 emissions from enteric fermentation (CH_4), manure management (CH_4 and N_2O) and fertilizer emissions (N_2O), and CO_2 emissions from above- and below-ground biomass change resulting from land-use change, and postfarm emissions (transport, exports and meat processing and packaging). The non-CO_2 emissions were converted to CO_2 equivalent (CO_2 eq) using the 100-year Global Warming Potential (Smith et al., 2021).

2.7.1. Enteric fermentation

Methane emissions from enteric fermentation were calculated from biomass consumed calculated in section 2.5.1 and an emission factor from Herrero et al. (2013b) that varies by region, climate zone and production system (grazing vs mixed). Emissions from enteric fermentation of the current beef production on each grid cell were retrieved directly from Herrero et al. (2013b).

2.7.2. Emissions from manure

Similarly to emissions from enteric fermentation, CH_4 and N_2O emissions from manure management were calculated from biomass consumed and an emission factor varying by region, climate zone and production system. Again, we used manure management data directly from Herrero et al. (2013b) to estimate manure emissions of the current beef production.

2.7.3. Emissions from fertilization

Nitrous oxide emissions resulting from fertilizer application were estimated from the quantity of nitrogen fertilizer applied described in section 2.5.1, and a crop-specific N-N_2O conversion factor determined by Gerber et al. (2016). Emissions from fertilization were calculated using the same method for potential feed options and current beef production for consistency.

2.7.4. Postfarm emissions

Postfarm emissions include transport emissions depending on whether meat is transported for domestic consumption or exported. If production in a country has not met the country's demand, we assume that cattle is transported to the nearest city for slaughter, otherwise if a country's production exceeds its demand, we assume that cattle is transported to the nearest port to be exported to the country's trade partners. Annual emissions for transporting meat to consumers were estimated based on transported cattle liveweight (section 2.5.3), travel time to nearest city or port (Weiss et al., 2018), speed (Delgado et al., 2016), fuel efficiency (Delgado et al., 2016) and emission factor of road transport (Waldron et al., 2006). Export emissions were only calculated if domestic beef production already reached domestic beef demand. In such case, export emissions were calculated based on the mean sea distance between exporting country and each of its beef trade partner country (Bertoli et al., 2016) and an emission factor of deep-sea container transportation (Cefic, 2011).

In addition to transport and export costs, we considered the emissions generated from processing and packaging meat as a source of postfarm emissions. Emissions from processing and packaging were calculated based on energy use (FAO, 2018) and emission intensity of energy (t CO_2 eq/GJ) that varies by country (FAO, 2018). Postfarm emissions were then estimated by aggregating transport, export and processing and packaging emissions.

2.7.5. Changes in above-ground biomass

If feed is produced in a new area, i.e., where cattle feed is not currently produced, we assume that the vegetation in this area will be cleared to produce the new feed. To calculate the emissions due to the removal of above-ground biomass, we used the product of the current carbon stock density (Spawn et al., 2020) and the area converted to cattle feed on a grid cell. For feed options that include grass in diet, we considered the remaining standing biomass after grazing, which varies according to grazing intensity of land use k (Table 1). For a feed option that includes grain, we assumed no standing biomass remains on the area used to produce the feed crops. The change in above-ground biomass was then estimated as the difference between the loss of carbon stock from vegetation clearing and remaining standing biomass after grazing. As this emission occurs only once, it is annualized over a 30-year time horizon consistent with annualized initial establishment costs described in section 2.6.1. We assumed there is no change in above-ground biomass for the current production as past emissions for beef production are beyond the scope of this optimization.

2.7.6. Changes in below-ground biomass

We calculated the change in soil carbon as a percentage change of current soil carbon based on land use conversion. The current below-ground biomass carbon density was obtained from Spawn et al. (2020) and the relative change in soil carbon from land use conversion (e.g., from forest to grassland) was collated from Guo and Gifford (2002). To estimate the area of each land use converted to a feed option, we used the current land cover on each grid cell from ESA (2017), grouped into broad classes consistent with categories used by Guo and Gifford (2002) (see Appendix Table 1) before the conversion to a new feed option. We then calculated the change in soil carbon for areas that are converted to cropland and grassland within a grid cell. The sum of soil carbon change from pasture and cropland is then annualized over the 30-year time horizon. We assumed there is no change in below-ground biomass for the current production.

2.7.7. Total emissions

The change in GHG emissions over time on each grid cell and feed option was calculated as the sum of annual emissions from enteric fermentation, manure management, fertilizer application, postfarm emissions and change in above- and below-ground biomass. For total emissions of the current feed option, only emissions from enteric fermentation, manure management, fertilizer application and postfarm emissions were considered, as past changes in above- and below-ground biomass were not included in this application of the model.

2.8. Optimization

Once meat production, production costs and GHG emissions have been calculated for all grid cells i and feed options k, we found the optimal feed option k with a weighted sum optimization. Optimal locations were then identified by selecting all grid cells with the lowest weighted sum that produce a given beef demand, thus minimizing the total impact from beef production.

2.8.1. Selection of optimal feed combination

For each grid cell i and feed option k, a score ($Z_{i,k}$) was obtained by calculating the weighted sum of economic and environmental costs using a weight on economic costs (w_{cost}) attributed to the per unit production costs ($C_{i,k}/B_{i,k}$, USD/tonne (t) beef meat produced) of each feed option on each grid cell, and a weight on emissions (w_{GHG}) attributed to emission intensities for beef meat production ($G_{i,k}/B_{i,k}$, t CO_2 eq/t beef meat produced), where the sum of weights w_{cost} and w_{GHG} equals 1:

$$Z_{i,k} = w_{cost}\frac{C_{i,k}}{B_{i,k}} + w_{GHG}\frac{G_{i,k}}{B_{i,k}}, w_{cost} + w_{GHG} = 1$$

We then minimized the score across all feed options to find the optimal score (Z^*_i) and feed option on each grid cell:

$$Z_i^* = \min_k Z_{i,k}$$

2.8.2. Selection of optimal locations

Once the lowest score has been calculated and the optimal feed option selected for each grid cell, we identified optimal grid cells to achieve the current beef production. Grid cells were ordered by increasing weighted sum score (Z_i^*) and selected for beef production iteratively until the production target is met, in this case, the current production in each country (FAOSTAT, 2021).

2.9. Creation of pareto frontier

To generate a Pareto efficiency frontier or trade-off curve, the optimization can be run with multiple combinations of weights w_{cost} and w_{GHG}. The more combinations of weights are simulated, the smoother the Pareto frontier will be. For each combination of weights, the costs of production and GHG emissions of optimal grid cells that produce total beef demand are aggregated and compared with the total costs and emissions of the current production.

2.10. Uncertainty analysis

Due to the large number of model inputs and variables, we conducted uncertainty assessment by sampling from a range of values using uniform distributions for selected parameters shown in Table 2. For spatially-explicit parameters, e.g., crop returns used to calculate opportunity cost (section 2.6.2), the range of value for sampling was determined for each grid cell based on the minimum and maximum value on each cell from two spatial layers (Gerber, In prep; IIASA/FAO, 2022). For liveweight conversion (section 2.5.3), enteric fermentation (section 2.7.1) and manure management emission factors (section 2.7.2), we used the lowest and highest values across climates for each region and production system (see Appendix Fig. 4) to define the sampling range. For country-level parameters (e.g., producer prices of crops), the range was defined by using the lowest and highest values from each global region. For the relative change in soil carbon, we used ranges provided by Guo and Gifford (2002) for each land use transition. A Pareto-frontier was generated with the same set of parameters from Tables 2,i.e., parameters were sampled once for all weight combinations used to generate a single frontier. We assessed robustness by analysing the range of total costs and emissions for each optimal solution, i.e., where 50% and 90% of results from multiple simulations, in this case 100 simulations, for a given combination of weights.

Finally, we assessed the robustness of feed strategies by looking at how frequently an optimal feed was selected on a grid cell. For this purpose, we reduced the categories of feed options to four: (1) unimproved grasslands (without N inputs), (2) improved grasslands (with N inputs), (2) a diet composed of a mix of grass and crop residues, and (4) a diet including grains. Over the 100 simulation runs, we recorded the frequency of each of these feed categories on each grid cell and investigated the robustness of feed on a cell by taking the maximum of the four frequencies.

3. Results

The MOO-GAPS model produces the following results 1) Pareto curves representing trade-offs between economic and environmental objectives for a country, 2) optimal spatial allocation of feed based on sets of weights on objectives and production constraints, and 3) detailed expression of the costs, feed types and emissions for an optimal spatial allocation of feed. Further, results can be compared to the current system with the associated simulated costs and emissions. All results have a spatial resolution of 5 arc minutes and can be produced for any area on the globe for which information is available. Here we provided outcomes at a national scale to highlight the outputs of MOO-GAPS using two of the five largest beef producing countries (FAOSTAT, 2021) with contrasting production systems, the United States (USA) with a significant proportion of cattle fed with grain-based diets, and Argentina (ARG) with a large proportion of rangelands.

3.1. Trade-offs between multiple objectives

Trade-offs in MOO-GAPS are articulated through a Pareto efficiency frontier linking the set of optimal solutions with different combinations of weights on objectives, here for costs and emissions. In this example, optimal solutions were obtained with 10 combinations of weights w_{GHG} and w_{cost}. Comparing aggregated costs and emissions from production at each Pareto solution enables the assessment of trade-offs between objectives. For instance, Fig. 2 shows the economic and emissions trade-offs for beef production in USA and Argentina. The extremes of the curve represent extreme preferences where either cost or emissions reduction is prioritized. The steepness of the curves represents the degree of the trade-off as preferences change (illustrated by arrows in Fig. 2). In the case of the USA, the trade-off curve is very steep and substantial emission reductions can be achieved at a very low cost, translated to nearly 1256 kg CO_2eq reduction for a dollar increase (solution a to solution b in Fig. 2) where the objective of cost reduction is prioritized. As the weight on emission reduction (w_{GHG}) increases, solutions move along the curve to the lower right part of the Pareto frontier and each unit reduction in emissions becomes increasingly expensive on the production side, a translation of 1.5 kg CO_2eq

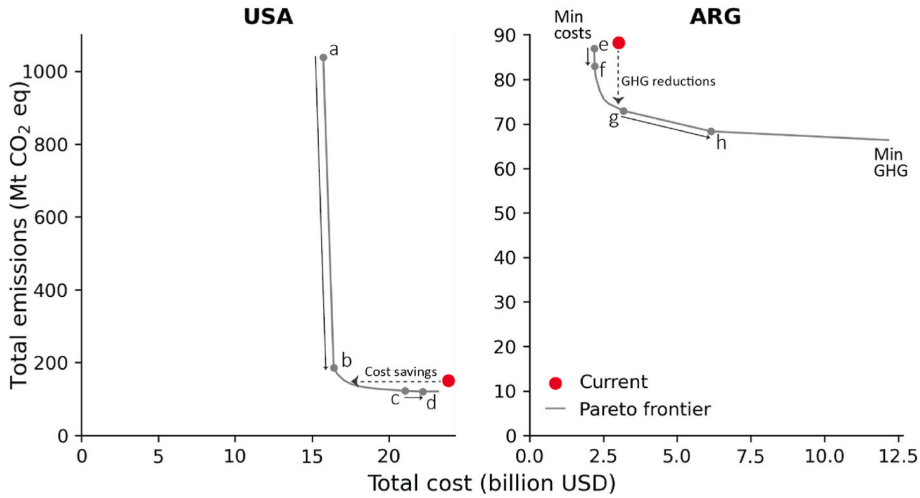

Fig. 2. Pareto efficiency frontier with examples of trade-offs between GHG emission reduction and cost savings between different solutions of the frontiers in the USA and Argentina (ARG). Arrows represent the trade-off between economic and environmental objectives between optimal solutions of beef production. Dashed lines with arrows indicate cost savings and GHG reduction possible at current emission and cost levels.

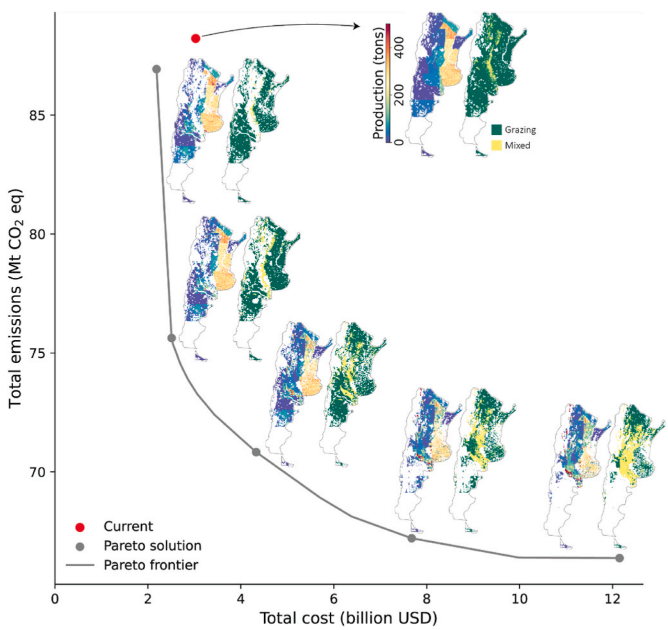

Fig. 3. Maps of beef production and production systems (grazing if only grass is consumed or mixed if diets include grain or crop residues) associated with different solutions along the Pareto efficiency frontier and with the simulated current beef production in Argentina.

reduction for a dollar cost increase (solution *c* to solution *d* in Fig. 2). In comparison, the Pareto frontier in Argentina displays less significant trade-offs where cost reductions are prioritized, as a dollar increase yields a reduction of 223 kg CO_2eq (solution *e* to solution *f*).

By comparing the current production costs and emissions (red dots, Fig. 2) within each nation to the Pareto efficiency curve, we can observe the potential cost savings and emissions mitigation that could be achieved even with the same level of production. As such, the model can highlight the current inefficiency in the production system and assess the potential gains at the current level of emissions or costs. For instance, 68% of total potential emissions reductions (i.e., reductions achievable if only GHG emissions are minimized), could be achieved in Argentina for the same cost as the current production, compared to 100% in the USA. This indicates that increasing costs beyond the current level can yield more emissions reductions in Argentina, as evidenced by the steeper slope of the trade-off (solutions *g* and *h* in Fig. 4), whereas the trade-off between the same set of preferences in the USA only allows for negligible emission reductions per cost increase (solutions *c* to *d* in Fig. 2).

3.2. *Achieving goals through optimal production*

MOO-GAPS optimization provides the best types of feed and locations for the production of feed for different weight combinations of the objectives considered. That is, each Pareto efficient solution (grey dots, Fig. 3) corresponds to a spatial distribution of beef production at 5 arcminutes (left maps, Fig. 3), as well as different feed combinations shown in the Argentinian example here (right maps, Fig. 3). Feed combinations are presented here as broad classes including grazing (where the feed option is entirely composed of grass) or mixed systems (where the feed option includes grain or crop residues) but can be represented at the level of detail described in section 2.4. As well as potentially informing production management, these visualizations highlight spatial shifts in production as preferences move towards, in this case, emissions or costs reduction. Overall patterns here for Argentina show that grass diets dominate when costs are minimized, while a greater fraction of grain and crop residues in feed is observed for emissions reductions. Moreover, spatial shifts potentially required from current production to improve efficacy towards our objectives can be observed (map at red dot, Fig. 3).

This breakdown of feed production can be further examined within the MOO-GAPS framework by exploring the overall fraction of feeds utilized to optimize our objectives (Fig. 4). While a large proportional shift in cattle diets is observed to minimize emissions in Argentina (Fig. 4b), this shift is less significant in the USA (Fig. 4a), given the relatively large proportion of grain in current cattle diets (Herrero et al., 2013b).

This pattern, shifting towards cattle diets with a greater fraction of grains, has been observed in previous studies (e.g., Havlík et al., 2014) and likely results from the higher methane efficiency in mixed systems (i.e., less methane emissions per unit of biomass consumed; Appendix Fig. 4) and the higher metabolizable energy in grains (Appendix Fig. 3a), thus requiring less biomass to produce the same amount of meat. Feed crops also tend to have higher yields than grasslands which reduces the land requirement and limit the need for land expansion and deforestation.

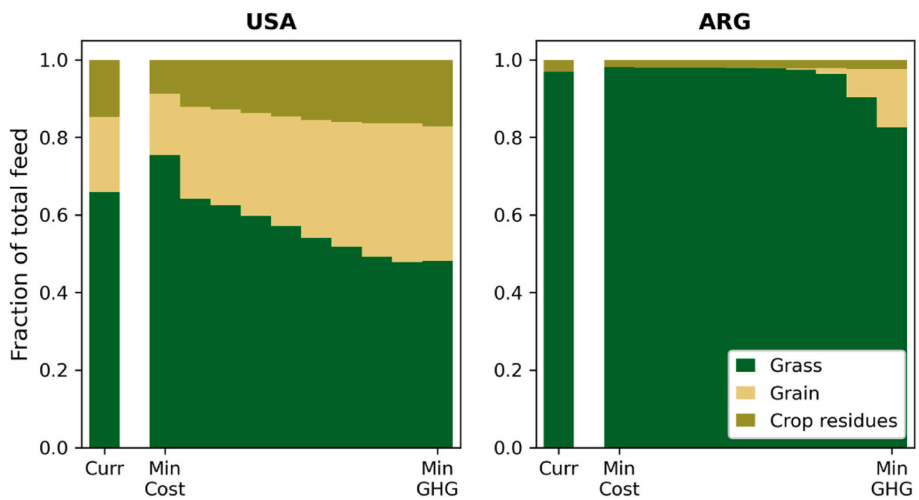

Fig. 4. Feed breakdown as fraction of total feed ration for the United States (USA) and Argentina (ARG) for current and pareto efficient production under different preferences.

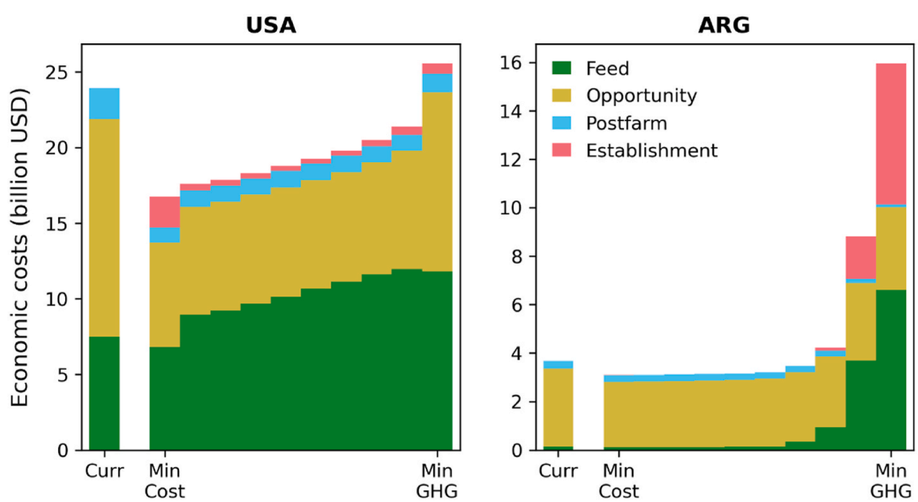

Fig. 5. Cost breakdown for current and optimal production for the USA and Argentina.

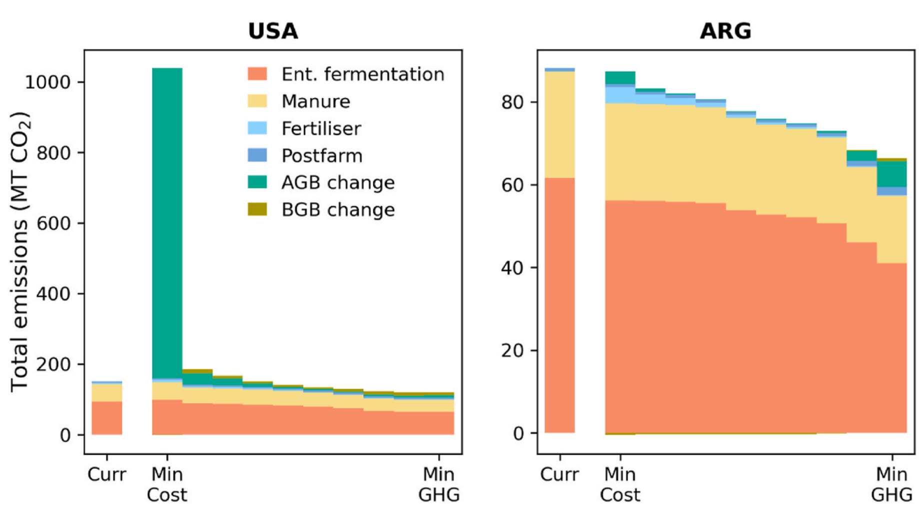

Fig. 6. Emission breakdown for current and optimal production for the USA and Argentina. Ent. fermentation stands for enteric fermentation, and AGB change and BGB change stand for above- and below-ground biomass change, respectively.

3.3. Exploring the cost and emission breakdown of shifts in production

For different weight combinations of the objectives considered, total costs and emissions can be broken down into their component parts. Here we compare different sources of costs and emissions associated with the current beef production and optimal solutions for the two countries used as examples (Figs. 5 and 6). Opportunity cost represent the major cost for the current production in the two countries. Feed production can also represent an important share of total costs, however it can be reduced to negligible amounts if a large fraction of the production comes from rangeland, for instance in Argentina, and if costs are minimized (Fig. 5). Feed production costs can increase significantly if GHG emissions are minimized, as the proportion of grain in feed composition increases (Fig. 5). As noted in section 2.6.5, establishment costs are only considered for potential production and tend to be negligible but can increase substantially if new feedlots need to be constructed due to an increase in grain-fed production, for instance in Argentina, where a large proportion of the current production is grass-fed. Postfarm costs, including transport and export costs, represent a low fraction of total costs for both current and optimal production solutions.

Enteric fermentation currently represents the largest source of direct emissions from cattle, followed by emissions from manure management (FAOSTAT, 2021). Both sources of emissions can be reduced if GHG emissions are minimized but only to a limited extent (Fig. 6). On the other hand, change in above-ground biomass from land-use change can vary significantly and impact total emissions when only production costs are minimized, for instance in the United States. Change in below-ground biomass can represent negative emissions, particularly where croplands are converted to grasslands, thus increasing soil carbon. Changes in above- and below-ground biomass were only considered for potential production, i.e., past deforestation associated with the current production was not considered here. Other sources of emissions, such as emissions from fertilizer application and postfarm emissions have a minor contribution to total emissions, as observed in previous studies (e.g., Poore and Nemecek, 2018). Critically, within MOO-GAPS, we can explicitly explore where the changes in costs and/or emissions are coming from, and concomitantly assess opportunities and limitations to further reductions.

3.4. Uncertainty assessment within MOO-GAPS

Within the examples shown at the national scale there is uncertainty in several parameters. MOO-GAPS allows for exploration of the impact of uncertainty and the robustness of solutions to this uncertainty. We present here intervals where 90 (light grey shaded area, Fig. 7) and 50 (dark grey shaded area) percent of the uncertainty simulations lie within (Fig. 7). In our USA and Argentina examples, we observe that 90% of simulations still provide substantial reductions in production costs and GHG emissions. These results only show relatively large uncertainties at the extremes of the Pareto fronts where only one objective is being optimized. For instance, large variation in emissions can be observed in the USA if only costs are minimized (left panel, Fig. 7). Similarly, large cost variations can be observed for Argentina if only emissions reductions are valued (right panel, Fig. 7). In addition to the uncertainty in cost savings and emission reduction, the tool allows to quantify the variability in trade-offs among objectives between two given Pareto solutions. For instance, arrows in Fig. 7 show the difference between trade-offs for two solutions along the Pareto frontiers in the USA for the 5% lower curve (points *a* and *b*) and the 95% upper curve (points *c* and *d*), where an increase in one dollar would yield a reduction of 465 kg CO_2 eq and 1286 kg CO_2 eq, respectively.

The MOO-GAPS tool also allows us to explore spatial uncertainty. Here, we measured spatial variation of beef production using the coefficient of variation after 100 simulations with the example of Argentina (Fig. 8). The solution where costs are minimized shows a greater variation in production in the northern part of the country. This variation is likely due to the uncertainty in the opportunity cost parameter, given its large contribution to total economic costs when only costs are minimized, and its parameter value sampling at grid cell level for uncertainty analysis (Table 2). Furthermore, for the solution where costs are minimized, feed production costs are negligible in the case of Argentina (Fig. 5) as most of the feed consumed is composed of grass (Fig. 4) and therefore variation in fertilizer and producer price have little impacts on optimal locations to produce beef. On the other hand, emission intensity of enteric fermentation and manure management vary based on production system and climate, and soil carbon vary based on land-use change. Exploring these further, could help inform the importance of uncertainty in specific variables to land use decisions, enabling informed data gathering.

A critical aspect of uncertainty for decision-making is understanding how robust an optimal solution is to parameter uncertainty. The MOO-GAPS tool allows users to assess the robustness of feed options. For instance, Fig. 9 displays how frequently an optimal land use is selected to grow beef cattle feed. Most areas show robust feed options that are repeatedly selected across simulations (blue areas) irrespective of the parameters utilized. However, the model also identifies areas with more uncertain optimal feed, for instance the northern part of the country

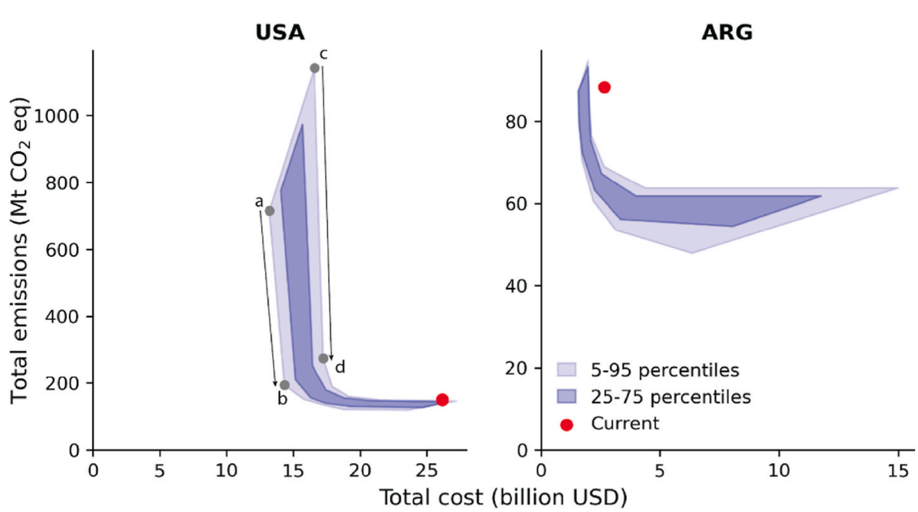

Fig. 7. Uncertainty range in Pareto frontiers after 100 simulations for the United States and Argentina. Arrows demonstrate the degree of trade-offs between cost savings and emission reductions between different solutions on the Pareto frontier.

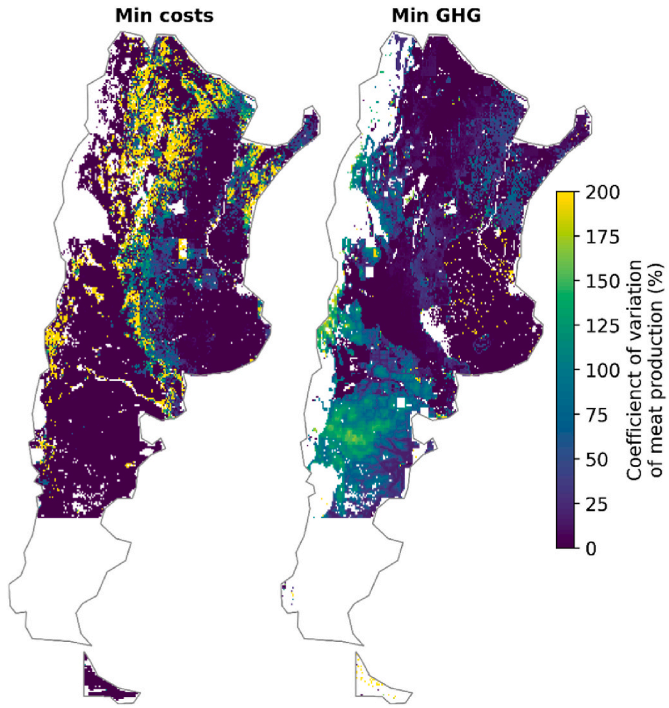

Fig. 8. Spatial variation of meat production after 100 simulations with the example of Argentina.

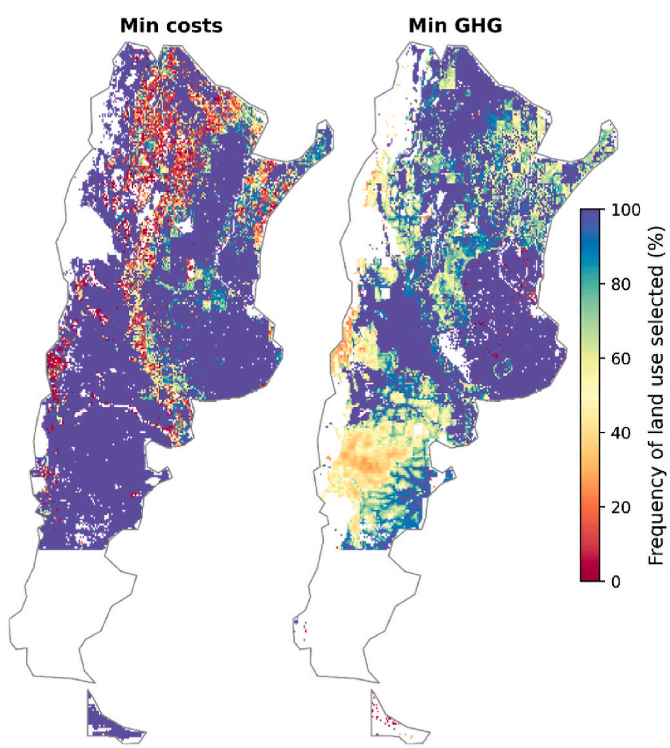

Fig. 9. Robustness of feed options illustrated by the frequency of the most common feed option selected after 100 simulations, with the example of Argentina.

where costs are minimized and southern region in the solution where GHG emissions are minimized, leading to larger uncertainties in meat production (Fig. 8). As such, the tool enables the identification of areas more likely to be suitable for a given optimal feed even considering uncertainty in model parameters, and other areas and feeds that may be optimal but more sensitive to the variability in parameter values. This information can assist decision-makers in identifying areas where further data collection could enable reduced uncertainty in optimal feed types.

4. Discussion

4.1. Opportunities and limitations

4.1.1. Implications for policy recommendation

The optimization illustrates how to achieve the best possible outcomes for a weighted sum of economic and environmental objectives by choosing where and how beef should be produced. The approach allows decision-makers to explore a range of possibilities to make the beef sector cleaner and more sustainable and provides insights into how to achieve desired and feasible outcomes. The tool also allows the identification of areas and feed options that are more likely to yield the better results even with uncertainty in parameters. Comparing current patterns of production with optimal patterns highlights what kinds of changes in beef production would be beneficial. The next question is then how to move beef production towards the efficiency frontier. Different policy tools could be used to help the beef industry transition towards more desirable outcomes. For example, the MOO-GAPS tool could be used in more detailed case studies to assess the effectiveness of land-use zoning regulation that prescribes where production of feed or grazing can occur (Qiu et al., 2020) or to protect specific ecosystem services (Li et al., 2021). Payments for ecosystem services (PES) can also be used to foster change in land use and achieving multiple benefits. PES can be an effective instrument to improve environmental outcomes while offsetting loss of income or increases in costs to cattle farmers (Calle, 2020). The model can incorporate PES by integrating payments into financial returns and can then be used to show how PES changes the optimal location and feed composition of beef production, with resulting changes in ecosystem services and economic returns associated with beef production. But critically the approach is also flexible, allowing areas to be locked in and highlighting improvements that could be achieved by modifying only how beef is produced within the beef sector.

To improve the usability of the tool and uptake by decision-makers, a web application could be developed to explore results interactively, without the need to obtain all input datasets and run the optimization. Potential savings, the land-use changes needed to achieve these savings and uncertainty quantification could be visualised for a selected set of preferences. The modelling framework could also be used along with a prioritization framework using expert elicitation, for instance analytical hierarchy process (Saaty, 1977), to first identify preferences of stakeholders for different sustainability objectives before identifying efficient production locations and feeds, and the resulting benefits.

4.1.2. Data quality

As with other complex models of livestock production (e.g., FAO, 2018; Havlík et al., 2014), several datasets are needed as inputs to the model. The optimization was set up to evaluate optimal production in any country, so that we included globally available data, but higher quality data will likely be available for some locations. For some variables, there is large uncertainty, such as with land value or opportunity cost data, for which no global data layer is readily available. In the application of the optimization presented in this paper, this opportunity cost was estimated based on the total returns from agricultural commodities, field size and profit margin (section 2.6.2). However, the optimization is flexible and could be run on a smaller scale or specific area where higher resolution and higher quality input data are available. For instance, if the scope of the model was restricted to the USA, observed land value information at higher resolution (Nolte, 2020) could be used in place of opportunity cost of agricultural production, thus reducing uncertainty related to land value.

4.2. Future work and scenarios

4.2.1. Additional sustainability objectives

As shown in Fig. 4, the fraction of grain in total cattle feed tends to increase as solutions move along the Pareto frontier toward minimizing GHG emissions. This can be explained by the higher yields and energy content in grains compared to grasses and therefore the lower area requirement and resulting deforestation. Mixed systems generally have a higher conversion of metabolizable energy into liveweight gain than grazing systems and therefore emit less emissions from enteric fermentation and manure per kilogram of meat produced (Herrero et al., 2013b). However, this intensification, although beneficial for emissions reduction, can come with other impacts. For instance, different types of production systems can have substantial impacts on water footprint (Heinke et al., 2020), nitrogen pollution and ammonia emissions (Uwizeye et al., 2020) and biodiversity loss through land-use change and intensity (Alkemade et al., 2013). Additionally, animal husbandry can provide cultural and social benefits such as employment throughout the supply chain (Herrero et al., 2013a), and can affect human health at different stages of production (Tomley and Shirley, 2009) and from consumption (Bouvard et al., 2015). Such social and health impacts should also be considered when assessing how and where to sustainably produce animal-source food. The MOO-GAPS model can be expanded to capture these extra dimensions and allow a more holistic trade-off analysis for sustainability.

4.2.2. Expanded scope

The MOO-GAPS tool we presented here focused on beef production. However, beef is not the only agricultural sector with significant contribution to agricultural GHG emissions nor the only sector striving to reduce its emissions. Dairy production and small ruminants also have high emission intensity (Poore and Nemecek, 2018) and could be explored using this model. Furthermore, preferences may favour certain types of livestock products depending on the sustainability objectives. For instance, chicken and pork may be preferred in some regions if minimizing GHG emissions is the dominant objective (Kesse-Guyot et al., 2021). Besides livestock, the model could be applied to any type of agricultural production if inputs on productivity and sustainability outcomes are available.

We have shown that the optimization is able to identify potential gains from beef production in comparison with the current production systems. Further innovations not considered here could yield additional gains (Herrero et al., 2020). For example, closing crop yield gaps and sustainable grazing intensification would contribute to decreasing the area requirement to produce cattle feed and therefore reduce the need for new land and deforestation (Herrero et al., 2010). Closing the “beef yield gap”, or improving emission intensity of beef, could help to produce more meat with lower emissions per quantity of biomass consumed (Chang et al., 2021), therefore decreasing costs and emissions simultaneously. Novel feeds (Ridoutt et al., 2022) and feed additives (Honan et al., 2022) have the potential to substantially reduce emissions from enteric fermentation and land requirements. Beside feed selection, manure management can also be improved by optimizing the utilization of manure N as fertilizer while limiting GHG emissions (van der Meer, 2008) and organic liquid fertilizer can provide a cost-effective way of increasing feed crop yields (Shah et al., 2013; Turan et al., 2022). Further, ecosystem restoration could be examined where current production is found to be sub-optimal in the optimization or inform higher value options for landholders such as revegetation to enhance carbon sequestration (Castonguay et al., 2023) and biodiversity restoration (e.g., Strassburg et al., 2020). This alternative land use option can be evaluated in the model to offset some of the emissions from cattle production, but also to provide income opportunities from carbon trading. All these innovations may incur an additional production cost but gains in GHG emissions reduction may outweigh the cost increase depending on the importance given to both objectives, a result that can be investigated using the MOO-GAPS tool.

5. Conclusions

In this paper, we introduced MOO-GAPS, a model that takes a supply-based approach to identify potential gains in efficiency in animal production and minimize trade-offs between economic and environmental outcomes for a given level of production in each country. With the example of beef production in two key producing countries, we demonstrated the ability of the tool to (1) estimate economic costs and GHG emissions of efficient production according to preferences for the two objectives, (2) analyse the trade-offs between economic and environmental outcomes of beef production, (3) compare simulated efficient and current production to assess efficiency improvements in costs and emissions for a given beef production in different countries, and (4) assess the robustness of the model to spatially identify optimal beef production systems.

The paper provides a first step to analyse multidimensional trade-offs at large spatial scale based on high resolution information that can inform decisions to foster cleaner and more sustainable agricultural land management. Such a flexible tool can be built upon to explore a larger array of competing environmental, social or economic objectives in the food system, such as the Sustainable Development Goals, as trade-offs between these objectives will likely become more pronounced with a growing food demand, competing demand for land and increasing climate change impacts on agricultural productivity.

CRediT authorship contribution statement

Adam C. Castonguay: Writing – original draft, Conceptualization, Software, Formal analysis, Methodology, Visualization. **Stephen Polasky:** Writing – review & editing, Methodology, Conceptualization, Supervision. **Matthew Holden:** Writing – review & editing, Methodology, Conceptualization. **Mario Herrero:** Writing – review & editing, Resources, Conceptualization. **Jinfeng Chang:** Writing – review & editing, Resources. **Daniel Mason-D’Croz:** Writing – review & editing, Conceptualization. **Cecile Godde:** Writing – review & editing. **Katie Lee:** Writing – review & editing. **Brett Bryan:** Writing – review & editing, Conceptualization. **James Gerber:** Resources. **Edward T. Game:** Conceptualization, Writing – review & editing. **Eve McDonald-Madden:** Funding acquisition, Writing – review & editing, Methodology, Conceptualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.136440

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