

Balancing farm profit and greenhouse gas emissions along the dairy production chain through breeding indices

Journal of Cleaner Production

Shi, Rui; Wang, Yue; van Middelaar, Corina E.; Ducro, Bart; Oosting, Simon J. et al

<https://doi.org/10.1016/j.jclepro.2024.142099>

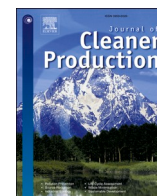
This publication is made publicly available in the institutional repository of Wageningen University and Research, under the terms of article 25fa of the Dutch Copyright Act, also known as the Amendment Taverne.

Article 25fa states that the author of a short scientific work funded either wholly or partially by Dutch public funds is entitled to make that work publicly available for no consideration following a reasonable period of time after the work was first published, provided that clear reference is made to the source of the first publication of the work.

This publication is distributed using the principles as determined in the Association of Universities in the Netherlands (VSNU) 'Article 25fa implementation' project. According to these principles research outputs of researchers employed by Dutch Universities that comply with the legal requirements of Article 25fa of the Dutch Copyright Act are distributed online and free of cost or other barriers in institutional repositories. Research outputs are distributed six months after their first online publication in the original published version and with proper attribution to the source of the original publication.

You are permitted to download and use the publication for personal purposes. All rights remain with the author(s) and / or copyright owner(s) of this work. Any use of the publication or parts of it other than authorised under article 25fa of the Dutch Copyright act is prohibited. Wageningen University & Research and the author(s) of this publication shall not be held responsible or liable for any damages resulting from your (re)use of this publication.

For questions regarding the public availability of this publication please contact openaccess.library@wur.nl



Balancing farm profit and greenhouse gas emissions along the dairy production chain through breeding indices

Rui Shi^{a,b,c,1}, Yue Wang^{b,1}, Corina E. van Middelaar^b, Bart Ducro^c, Simon J. Oosting^b, Yong Hou^{d,**}, Yachun Wang^{a,*}, Aart van der Linden^b

^a National Engineering Laboratory for Animal Breeding, Key Laboratory of Animal Genetics, Breeding and Reproduction, MARA, College of Animal Science and Technology, China. Agricultural University, State Key Laboratory of Animal Biotech Breeding, 100193, Beijing, PR China

^b Animal Production Systems Group, Wageningen University & Research, P.O. Box 338, 6700 AH, Wageningen, the Netherlands

^c Animal Breeding and Genomics Group, Wageningen University & Research, P.O. Box 338, 6700 AH, Wageningen, the Netherlands

^d State Key Laboratory of Nutrient Use and Management, College of Resources and Environmental Sciences, China Agricultural University, 100193, Beijing, PR China

ARTICLE INFO

Handling editor: Biagio Giannetti

Keywords:

Dairy cow
Breeding index
Genetic traits
Greenhouse gas emissions
Farm profit
Life cycle assessment (LCA)

ABSTRACT

Breeding is a promising greenhouse gas (GHG) mitigation option for the dairy sector that offers potential permanent and cumulative effects. However, there is limited understanding of how genetic traits affect GHG emissions from the dairy production chain and how breeding indices could be used to find a balance between GHG emissions and farm profit. Using a typical Chinese dairy farm as a case study, we developed a novel method to address these gaps. The farm comprised of 1523 Holstein-Friesian dairy cows and 1429 young stock. The average milk yield at the farm was 11,533 kg per cow per year. Life cycle assessment was combined with an existing bio-economic model to determine the emission intensity values (IV) of six genetic traits: milk yield, protein yield, fat yield, calving interval, productive life, and incidence of clinical mastitis. The IVs and economic values of the traits were used to form different breeding indices, of which the economic and environmental consequences were assessed. Results showed that for the next generation, breeding animals with optimal indices could reduce carbon dioxide equivalents per ton of fat-and-protein-corrected milk by six to 10 kg, while increasing profitability by 822 to 1355 Chinese Yuan per cow unit. Different indices can balance farm profit and GHG emissions to different degrees. However, the indices with higher profit showed less potential in reducing GHG emissions. This study provides insights into how breeding strategies could contribute to GHG mitigation in the dairy sector.

1. Introduction

Dairy farming is responsible for approximately 20% of the greenhouse gas (GHG) emissions caused by all global livestock (Gerber et al., 2013). These GHG emissions exacerbate the occurrence of extreme weather events, such as severe heat and drought (IPCC et al., 2022; Donnelly et al., 2024). Dairy production contributes to GHG emissions along the chain through several processes, which include feed production, enteric fermentation, manure management, and energy use (Van Middelaar et al., 2014). Major GHGs, i.e., carbon dioxide (CO₂), methane (CH₄) and nitrous oxide (N₂O), are released during these processes, and GHG emission intensity (EI), which is defined as emissions

per unit of milk produced, is usually used to express the climate impact of dairy production.

To reduce GHG emissions from dairy production, several potential mitigation options have been proposed, such as dietary adjustments and manure management strategies (Hou et al., 2015; York et al., 2018; Vogel and Beber, 2022). However, the effects of most of these strategies are not cumulative in successive generations of dairy cows and require continuous efforts. Breeding, instead, is considered permanent and cumulative. Although it may take several generations to evaluate the effectiveness of selective breeding, incorporating GHG emissions into breeding programmes is seen as a promising tool to reduce the climate impacts from dairy cattle in the long run (González-Recio et al., 2020; De

* Corresponding author.

** Corresponding author.

E-mail addresses: yonghou@cau.edu.cn (Y. Hou), wangyachun@cau.edu.cn (Y. Wang).

¹ Rui Shi and Yue Wang contributed equally to this work.

Haas et al., 2021).

Breeding programmes for cattle require a clearly defined breeding goal that determines the desired direction of change over generations and a breeding index that weights multiple genetic traits in its overall score (Hazel, 1943). Genetic traits refer to the heritable characteristics that are genetically transferred from one generation to another, such as milk yield and longevity. In practice, maximizing farm profit is often defined as the key breeding goal. In accordance with this, the relative importance of each trait (the weighting factor) in the breeding index is determined by its economic value (EV), i.e., the marginal profit change caused by the change of trait. The farm profit of the breeding index can be predicted for future generations. Pursuing high farm profit is a priority in the breeding industry (Cole et al., 2021). However, the potential importance of GHG mitigation through selective breeding is now acknowledged due to the pressing environmental problems and there are more and more attempts to explore this potential (Van Middelaar et al., 2014; Richardson et al., 2021).

Two approaches so far have been used for incorporating the reduction of GHG emissions into breeding programs. The first extends the breeding index by introducing enteric CH₄ emissions as a new trait and adding an economic weight to it. In this way, selective breeding could reduce CH₄ production in future generations (González-Recio et al., 2020; De Haas et al., 2021). However, this approach is hampered by difficulties in recording animal-specific emissions, in determining genetic correlations between enteric CH₄ emissions and other traits, and in estimating the EV of CH₄ emissions (De Haas et al., 2021; Hossein-Zadeh, 2022). In the second approach, the impacts of conventional genetic traits on GHG emissions are estimated, and environmentally favourable trait combinations (breeding index) have been developed without update of new traits (like enteric CH₄) (Van Middelaar et al., 2014; Richardson et al., 2021). Instead of EV, this approach determines the intensity value (IV) of GHG emissions for conventional traits, which is defined as the marginal change of EI with change of the trait.

However, most previous studies that have been conducted using the above approaches only considered the enteric CH₄ emissions from dairy cattle (e.g., Amer et al., 2018; De Haas et al., 2021; Richardson et al., 2021). From the perspective of the entire dairy value chain, there are GHG emissions from other processes, such as feed production and manure management. Not accounting for these emissions may lead to bias on the assessment of mitigation options (Van Middelaar et al., 2014). To date, there has only been one study conducted (Van Middelaar et al., 2014) that has investigated the IVs of genetic traits of dairy cattle by incorporating changes in GHG emissions along the entire production chain. Moreover, to date, no studies have incorporated both chain-level IVs and EVs into breeding indices, to the best of our knowledge. For this, the combination of bio-economic model and LCA analysis could provide a valuable tool, which could enable exploration of the maximum GHG mitigation potential of breeding indices, as well as to balance their economic and environmental consequences.

As one of the major countries that contributes to global GHG emissions, China is committed to achieving peak carbon emissions before 2030 and carbon neutrality before 2060 (SCPRC, 2021). Despite serious concern about the environmental impact of the growing dairy sector in China, little attention has been given to the role of breeding in GHG mitigation so far (Wang et al., 2016; Bai et al., 2018; Huang et al., 2021). The objective of this study, therefore, is to introduce a novel method to assess the economic- and environmental consequences of different breeding indices, using Chinese dairy farming as a case study.

The IVs of important genetic traits of dairy cows were determined by combining an existing bio-economic model and a life cycle assessment (LCA) for a typical Chinese dairy farm. Following this, different breeding indices were developed based upon different breeding goals. The farm profit and EI of those indices were compared, and the indices that can balance farm profit and EI were identified. This study provides insight into how breeding indices could be used as a tool to achieve environmental and economic objectives. The whole framework and results

could be useful for breeding organizations worldwide that want to contribute to a more environmentally friendly dairy sector.

2. Materials and methods

2.1. A typical Chinese dairy farm

This study was modelled on data from a typical commercial Holstein dairy farm in Beijing, China (39.6° N, 116.2° E, within a warm temperate zone, with a half moist continental monsoon climate; Fig. S1). The data were collected in 2020. The farm was managed by Sunlon Livestock Development Co. Ltd. On this landless dairy farm with zero grazing, cows were housed in ventilated barns with a free stall design. The milk yield was 11,533 kg per cow per year, which was higher than the national average (7800 kg per cow per year) (Dou et al., 2020). Other important characteristics of the study farm are summarized in Table 1.

Any diseased cows were transferred to an isolated group, and their milk was retained if antibiotic treatments were required (e.g., in the incidence of clinical mastitis). Oestrous synchronization strategies and artificial insemination were applied at this farm. Production data were collected via equipped Affifarm software (<https://www.afifarm.com/afifarm/>), which automatically records milking, reproductive information (e.g., birth, calving, and insemination), and health events (e.g., type of disease, and the number of days of milk retained) of each cow. Economic data were collected through consultation with the accountants of the farm and details can be found in Shi et al. (2024).

As for most intensive farms in China, the farm had no cropland area, and all feedstuffs had to be purchased. A total mixed ration was supplied, three times a day, and the animals were provided with *ad libitum* access to this ration and water. Data about feed composition consumed by animals in different age categories was collected from the farm (Table S1). The major feed ingredients fed to dairy cows were maize silage, maize, soybean meal, alfalfa hay, and by-products from crops and from food processing. The amount of feed consumed by different age categories was calculated based on the energy requirement of the animals and ration composition (NRC, 2001). Manure was collected daily from the solid floor and separated into solid- and liquid parts. Afterwards, solid manure was stored in the open air while liquid manure was stored in an open lagoon until being sold to either nearby crop farms or manure processors.

2.2. Calculating greenhouse gas emissions

An LCA was used to calculate the emissions of CO₂, CH₄ and N₂O, along the dairy production chain ‘from cradle to farm-gate’. Sources of GHG emissions included: fertilizer manufacturing, field operations, processing and transportation of crops and concentrates, enteric fermentation from animals, manure management, and the production and combustion of energy.

The emissions from fertilizer manufacturing were calculated based on the fertilizer application rate for each feed crop and the emission factors per unit of fertilizer. It was assumed that no animal manure was applied due to the decoupling of livestock and crop production and the low recycling rate of animal manure in China (Jin et al., 2020). The

Table 1
Characteristics of the study farm in Beijing, China.

Item	Unit	Value
Number of cows	head	1523
Number of youngstock	head	1429
Milk yield	kg/cow/year	11,533
Protein content of milk	%	3.3
Fat content of milk	%	4.5
Age at first calving	month	26
Replacement rate	% per year	33.5

amount of artificial fertilizer used for each feed crop, i.e., nitrogen (N), phosphorus pentoxide, and potassium oxide, was derived from peer-reviewed articles (Table S2). The GHG emission factors for the production of one unit of artificial fertilizer were derived from Zhang et al. (2013) and the Ecoinvent 3.8 database. Emission factors for (direct and indirect) N₂O emissions from the application of artificial N fertilizer are provided in Table S2. The parameters of CO₂ emissions for the use of fossil fuels during field operations were derived from the Global Livestock Environmental Assessment Model (GLEAM) (FAO, 2022). Economic allocation was used to assign the GHG emissions related to feed products that have been derived from multiple output processes. The economic allocation factors for the feed products are shown in Table S3. Emissions from feed processing originated mainly from energy consumed in activities such as milling, crushing and heating of the feed crops and from blending concentrate feed. The emission factors of these processes were taken from the GLEAM model (FAO, 2022). The emissions from feed transportation were estimated based on the transport distance, transport means (e.g., by ship or truck), and emission factors for transportation. More details can be found in Supplementary Note 1.

For enteric CH₄ fermentation from dairy cows, feed-specific emission factors were adopted from Vellinga et al. (2013) and Šebek et al. (2016) (Table S3). For enteric CH₄ emissions from young stock, the IPCC Tier 2 approach was used, in which emissions were calculated based on gross energy intake and a CH₄ conversion factor (IPCC et al., 2019). The emissions of CH₄ and N₂O from manure management (i.e., housing and storage) in the farm were calculated following the IPCC Tier 2 method. The data on the total amount of annual on-farm energy use (i.e., diesel and electricity) were provided by the farm. The GHG emission factors of production and transport of energy were adopted from IPCC et al. (2019), and that of the combustion of fuel from Jiang et al. (2013) (Table S4). More details can be found in Supplementary Note 1.

The emissions of different GHGs were converted to CO₂ equivalents (CO₂-eq) based on their global warming potential over 100 years, i.e., 1 for CO₂, 27.2 for biological CH₄, 29.8 for fossil CH₄, and 273 for N₂O (IPCC et al., 2022). Economic allocation was used to separate GHG emissions between milk and meat. This was found to be 87% for milk at the baseline (current) situation for this type of farm. For this farm, the price of milk was set to be 3.8 CNY per kg of milk and the price of sold animals was from 4000 to 14,500 CNY per head, depending upon the life stage and weight of the animals. Emissions were expressed per ton of fat- and protein-corrected milk (FPCM) (4.46 % fat and 3.33 % protein), which can be referred to as the emission intensity (EI) or the carbon footprint of milk.

2.3. Derivation of emission intensity values for genetic traits

A total of six genetic traits were selected for analysis in this study; annual milk yield (MY, kg per cow per year), annual protein yield (PY, kg per cow per year), annual fat yield (FY, kg per cow per year), calving interval (CI, d), productive life (PL, d), and incidence of clinical mastitis (MAS, % of cows with at least one mastitis case per lactation). The first three traits describe the production level of cows, while the last three are indicators of reproduction, longevity and cow health, respectively. These six traits are economically important for dairy farms and are, therefore, usually included in breeding programmes in different countries (Miglior et al., 2017).

The EVs of those traits, defined as the marginal farm profit change per cow unit per year from a 1-unit change in the trait, were directly derived from the bio-economic model that was developed with data from the same dairy farm. A cow unit comprises of one dairy cow and the young stock kept to eventually replace this dairy cow. Two modules were incorporated in the bio-economic model, in which the biophysical module determines the effect of the traits on farm performance, and the economic module sums up revenues and costs. More details about the model and the set-up of the calculations of EVs could be found in Shi et al. (2024).

The IVs, i.e., marginal GHG emission change per ton of FPCM from a 1-unit change in the trait, were calculated in this study (Equation [1]). For each trait, the biophysical module of the bio-economic model was initially used to determine how the change of trait would affect farm performance in e.g., herd structure and production level. Subsequently, the results were combined with the LCA model to calculate the marginal effect of the change of the trait on EI.

$$IV_i = \frac{\Delta EI_i}{x_i} \quad [1]$$

where IV_i is the IV for the trait i , ΔEI_i is the marginal GHG emission change per ton of FPCM from a unit change of the trait i , and x_i is 1-unit change of the trait i .

For production traits (MY, PY and FY), the marginal effect in GHG emissions was mainly reflected by the change of energy requirements of cows, which subsequently results in a change in feed intake and relevant emissions. For CI, a one-unit increase will affect GHG emissions along the chain by decreasing annual calving rate, changing herd composition, and decreasing MY. For PL, a one-unit increase will also affect the herd structure and increase MY. For both CI and PL, the marginal change of herd structure will affect the feed intake of the animals in different ages, and result in further changes in GHG emissions. For MAS, an 1% increase will result in reductions of MY, including discarded milk due to usage of antibiotics, and potential milk loss due to a lower milk yield after treatment. It was assumed that the feed intake of cows is not affected by disease due to lack of data on this.

2.4. Breeding goals and results of breeding indices

The EVs or IVs of the traits calculated above were used to develop different indices under different goals. A breeding index is a linear combination of EV or IV and genetic gain in each trait, which can be obtained through Equation [2], where v is the vector of EV or IV, and R_{trait} is the genetic gain of each trait (6×1 vector). The R_{trait} was calculated using Equation [3], where P^{-1} is the inverse matrix of phenotypic variance-covariance matrix for the target traits, G is the genetic variance-covariance matrix for the target traits. The information of P^{-1} and G can be found in Fig. S2.

$$\text{Breeding index} = v' R_{trait} \quad [2]$$

$$R_{trait} = \frac{(P^{-1}Gv)'G}{\sqrt{(P^{-1}Gv)'Gv}} \quad [3]$$

Two breeding goals were set in this study, namely, maximizing profit (based on EV) and minimizing EI (based on IV), following Van Middelaar et al. (2014). The index maximizing profit was referred to as the most profitable index (MPI) and the index minimizing GHG emission was referred to as least emissions index (LEI).

The farm profit and EI of MPI and LEI were calculated using Equation [4]. Moreover, the relative weight (w) of the trait was determined using Equation [5], where σ_a is the vector of genetic standard deviation of six target traits, $\sigma_{a-trait}$ is the genetic standard deviation of individual trait (Table S5), v_{trait} is the EV (or IV) of the target trait. The theory assumes equal predicting accuracies for the studied traits, which is commonly applied in animal breeding (Kumar et al., 2022; Richardson et al., 2022a).

$$\text{Profit or EI} = \frac{(P^{-1}Gv)'Gv}{\sqrt{(P^{-1}Gv)'P(P^{-1}Gv)}} \quad [4]$$

$$w = \left[\frac{\sigma_{a-MY} \times v_{MY}}{\sigma_a'v}, \dots, \frac{\sigma_{a-MAS} \times v_{MAS}}{\sigma_a'v} \right]' \quad [5]$$

2.5. Selection of breeding indices

Solely aiming for maximum profit or minimum EI can result in undesired responses in traits. For example, an increase in clinical mastitis cases. In addition, it may be of significance to find a balance between economic and environmental objectives rather than maximizing one or the other. To avoid undesired responses in traits and provide a range of options that represent a compromise between environmental and economic objectives, the following steps were conducted: (1) a large set of potential indices was created by manually changing the EVs that determine the relative importance of the traits (Brascamp et al., 1985). For each trait, ten values were uniformly selected from a range of $-5 \times \text{EV}$ to $5 \times \text{EV}$ (including the calculated EV) to construct more potential indices. This resulted in a total of one million indices based on the six target traits. The same process was also applied to IVs. Meanwhile, the relative weight and genetic gain of each trait, as well as the profit and EI of all the indices, were calculated using Equations [2–5]; (2) Constrained indices were selected from the potential indices by constraining the genetic gain of each trait in only the desired direction, i.e., the R_{trait} of MY, PY, FY and PL had to be positive, while that of CI and MAS had to be negative; (3) Optional indices on the frontier line between farm profit and EI were identified from the constrained indices. For a given farm profit, this line indicates the optional index with the lowest EI. Likewise, for a given EI, this line indicates the optional index with the highest farm profit; (4) A score ($\text{Score}_{\text{index}}$) was developed to rank all the optional indices on the frontier line using Equations [6–8]. Score_{EI} was defined as the ratio between the EI of the assessed index and the lowest EI on the frontier line. Likewise, $\text{Score}_{\text{profit}}$ was defined as the ratio between the profit of the assessed index and the highest profit on the frontier line. $\text{Weight}_{\text{EI}}$ and $\text{Weight}_{\text{profit}}$ indicate the relative importance of EI and profit. For demonstration, $\text{Weight}_{\text{EI}}$ and $\text{Weight}_{\text{profit}}$ were settled as 0/100, 50/50, 100/0, respectively. The corresponding indices with the highest score were referred to as optimal indices (OI), i.e., $\text{OI}_{\text{profit}}$, $\text{OI}_{\text{balance}}$ and $\text{OI}_{\text{emission}}$, respectively. $\text{OI}_{\text{profit}}$ indicates the optimization for (maximum) profit. $\text{OI}_{\text{emission}}$ indicates the optimization for (minimum) EI. $\text{OI}_{\text{balance}}$ indicates the optimization for both profit and EI (equally weighted). Note that the $\text{OI}_{\text{balance}}$ were selected based on EV and IV, respectively.

$$\text{Score}_{\text{index}} = \text{Score}_{\text{EI}} * \text{Weight}_{\text{EI}} + \text{Score}_{\text{profit}} * \text{Weight}_{\text{profit}} \quad [6]$$

$$\text{Score}_{\text{EI}} = \frac{\text{EI of index}}{\text{Lowest EI on the frontier line}} \quad [7]$$

$$\text{Score}_{\text{profit}} = \frac{\text{Profit of index}}{\text{Highest profit on the frontier line}} \quad [8]$$

2.6. Software and data accessibility

The procedures of calculating genetic gains and optimizing of breeding goals were realized in Python 3.7, with packages NumPy and Pandas (Van Rossum and Drake, 2009; McKinney, 2010; Harris et al., 2020). Figures were created by matplotlib (Caswell et al., 2021) and Plotly (Plotly Technologies Inc. <https://plotly.com>). The model and calculation steps of IVs were stored in the Excel sheets of Supplementary materials, the calculations of the IV of MY have been provided as an example.

3. Results and discussion

3.1. Greenhouse gas emissions of the typical farm

Total GHG emissions per ton of FPCM under current circumstances were 1317 and 1141 kg CO₂-eq, without and with economic allocation between milk and meat respectively. This result is comparable to some previous work, in which a value was found of approximately 1300 kg CO₂-eq per ton FPCM in North China (Zhang et al., 2017; Wang et al.,

2018). The values were lower than that of a nationwide study in China with a result of 1950 kg CO₂-eq per ton FPCM (Dong and Wei, 2020), which could be mainly explained by the relatively high milk yield in the farm studied compared to the national average (Dou et al., 2020). Emissions of CH₄, CO₂ and N₂O were responsible for 50%, 37% and 13% of the total emissions, respectively. Feed production and enteric fermentation contributed almost equally to the total GHG emissions, with a respective share of 36% and 33%, followed by manure management (20%) and energy use (11%) (Fig. 1).

3.2. Emission intensity values of genetic traits

The results of this study showed that negative IVs were obtained for all target traits except for MAS (Table 2), which means that increasing target traits results in less GHG emissions per unit of milk in the following generation. Increasing MY by one kg per cow per year, for instance, decreased GHG emissions by 0.045 kg CO₂-eq per ton of FPCM at entire production chain level. This is comparable with results found for Dutch dairy farming, i.e., 0.039–0.071 kg CO₂-eq per ton of FPCM at entire production chain level (Van Middelaar et al., 2014).

Increasing PY, FY, and PL by one unit led to a decrease of 0.322, 0.075, and 0.362 kg CO₂-eq per ton of FPCM at entire production chain level, respectively. These values were found to be larger than the ones found by Amer et al. (2018) for Ireland (i.e., 0.047 for PY and 0.008 for FY). The smaller values found by Amer et al. (2018) can be explained by the fact that only enteric emissions from animals were considered, whereas all major GHG sources along the entire value chain were considered in our study. This indicates that it matters at what level of the production system the mitigation effects of genetic traits are assessed. In the study of Amer et al. (2018), the IV of PY was approximately five times higher than that of FY, which is in line with the results of this study. A Canadian study reported IVs of 0.005 for PY, 0.004 for FY, and 0.012 for PL, respectively (Richardson et al., 2021), with only enteric emissions from animals considered and use of a different functional unit (kg CO₂-eq per kg of protein equivalent). These differences partly explain the differences between reported IVs in Richardson et al. (2021) and this study. Note that the protein-equivalent based unit has been recommended by studies to better support the local milk payment systems, which encourages more milk proteins but penalizes higher milk volume (e.g., Richardson et al., 2022b). Nevertheless, our study used FPCM as the unit because it has been widely used in the carbon footprint analysis of milk production, and can be compared across different contexts (IDF, 2015). In addition, it simultaneously allows increases in MY, FY and PY (Richardson et al., 2022b), which is in line with the milk payment systems of developing countries, such as China (Shi et al., 2024).

Despite differences in the values of IVs, all the above studies showed that increase of these traits (i.e., MY, FY, PY, and PL) were beneficial for GHG emissions. The result of increasing CI on GHG emissions, however, was found to be different from previous studies. Our results show that a 1-d increase in CI lead to a decrease of 0.038 kg CO₂-eq per ton of FPCM, whereas Amer et al. (2018) found that the increase of CI results in more GHG emissions. The increase of CI reduced the annual calving rate of cows and milk production. Based on our assumptions, the decrease of the annual calving rate reduced the number of on-farm young stock, which resulted in a decrease of emissions along the chain from young stock. The reduction of EI from these emission processes outweighed the increase of that from reduced milk yield and resulted in an overall negative IV. It should be noted that all female calves were assumed to be raised on the farm in this study, irrespective of the calving rate and according to the general protocols of dairy farms in China. However, the number of on-farm young stock may remain constant with a 1-d increase in CI in farms where surplus female calves are sold. This would probably result in a positive IV for a 1-d increase in CI, which was solely due to the reduction of milk production (Bell et al., 2013).

The increase in incidence of MAS led to an increase of 0.276 kg CO₂-

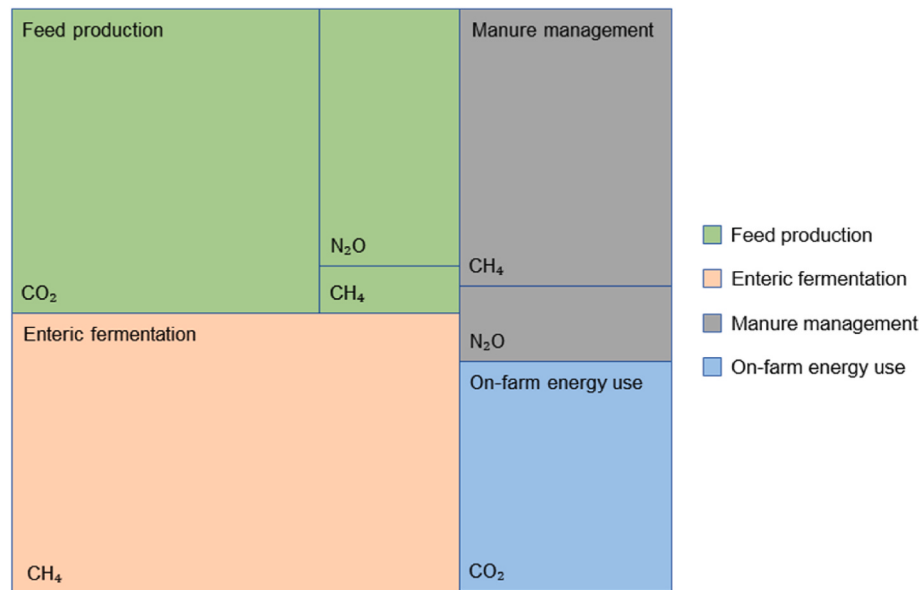


Fig. 1. Relative contribution of different processes to greenhouse gas emissions from the typical dairy farm. Greenhouse gases are expressed in CO₂-eq based on 100-years GWP factors from IPCC AR6. Feed production refers to processes that included fertilizer manufacturing, field operations, processing, and transportation of crops and concentrates. Enteric fermentation refers to methane production during the digestive process of cattle. Manure management refers to on-farm manure excretion and storage. On-farm energy refers to electricity and diesel use on the farm. Note that emissions of CH₄ and N₂O from energy use are not displayed in the figure due to their minor proportions.

Table 2
Emission intensity values (IV) and economic values (EV) for target traits.

Trait	Unit	IV (kg CO ₂ -eq/ton FPCM/ trait unit) ^b	EV ^a (CNY/trait unit) ^c
Annual milk yield	kg/cow/ yr.	-0.045	2.39
Annual protein yield	kg/cow/ yr.	-0.322	89.60
Annual fat yield	kg/cow/ yr.	-0.075	32.85
Calving interval	d	-0.038 ^e	-93.03
Productive life	d	-0.362	4.14
Clinical mastitis	% ^d	0.276	-11.15

^a The results of EVs are derived from Shi et al. (2024).

^b FPCM is fat- and protein-corrected milk.

^c CNY is Chinese Yuan.

^d % is the percentage of cows with at least one mastitis case per lactation.

^e The negative result of calving interval was because that all female calves were assumed to be raised at the farm, irrespective of the calving rate, and according to the general protocols of dairy farms in China. This result may be specific for the Chinese context.

eq per ton of FPCM (Table 2), which is much higher than the result from Richardson et al. (2021) (0.001 kg, enteric emission only). Mostert et al. (2019) considered several contributory factors to the emissions caused by MAS at chain level that include culling (39%), retained milk (38%), milk loss after mastitis (17%), and prolonged CI (6%), and reported a result of 0.480 kg CO₂-eq per ton of FPCM for 1% increase in incidence of MAS. In our study, only the effects of retained milk and milk loss were considered due to the lack of data. Therefore, the IV of MAS (0.275) in our study was around 55% of the reported value (0.480) in Mostert et al. (2019). In general, our results were more comparable to studies that have also adopted an LCA approach than those that have only focused on one or a few emission processes.

The EVs of target traits are also listed in Table 2, from which the direction of the change in both emissions and profitability after genetic selection can be evaluated. As a result, the improvements in all selected traits are contributing to profit and GHG mitigation simultaneously,

except for CI, i.e., reduction of CI (favourable direction) is contributing to higher profit, but also is resulting in more GHG emissions. Nevertheless, this does not imply that CI needs to be excluded from breeding selections. In practice, multiple traits are included in a breeding scheme (Miglior et al., 2017; Shi et al., 2024), and the trade-offs among traits is dealt with by considering correlations in the computations. Still, lining up and comparing IVs and EVs can be helpful for breeders to identify the individual traits that may lead to trade-offs between economic- and environmental consequence, and, if necessary, to further adjust the weighting of the trait in the breeding index.

3.3. The impact of changing genetic traits on greenhouse gas emissions along the chain

Different traits affected chain processes and their emissions in different ways (Fig. 2). For MY and PY (Fig. 2a and b), the EI was reduced mainly due to the dilution effect of increasing FPCM. The reduction of enteric CH₄ and feed N₂O emissions contributed most to the reduction of EI. A distinctive pattern was observed for FY (Fig. 2c), i.e., the reduction of EI was mainly through a reduction in CO₂ emissions from energy use. This could be explained by the dilution of maintenance being especially apparent in emissions from energy used for milking as increased FY increased FPCM but not the absolute milk volumes. In case of feed-related emissions (from feed cultivation, enteric fermentation, manure), however, dilution of maintenance was partly compensated by an increase in feed intake, resulting in increased EIs for these processes. Thus, the final IV of FY is relatively small compared to the IV of PY. The increase of CI affected all the emission processes along the chain through the reduced number of young stock and decreased milk yield (Fig. 2d). With a 1-d increase in PL, relatively more multiparous cows were kept on the farm, and the average milk production was increased due to an increase in the average parity. Thus, the emissions from all processes were diluted by higher FPCM (Fig. 2e). For MAS, the increase of EI was mostly due to retained milk and milk loss after curation (Fig. 2f).

Compared to Van Middelaar et al. (2014) and Richardson et al. (2021), the current approach, which combines a bio-economic model and an LCA, simultaneously traces the emission changes of different GHGs, emission processes along the chain, and their internal

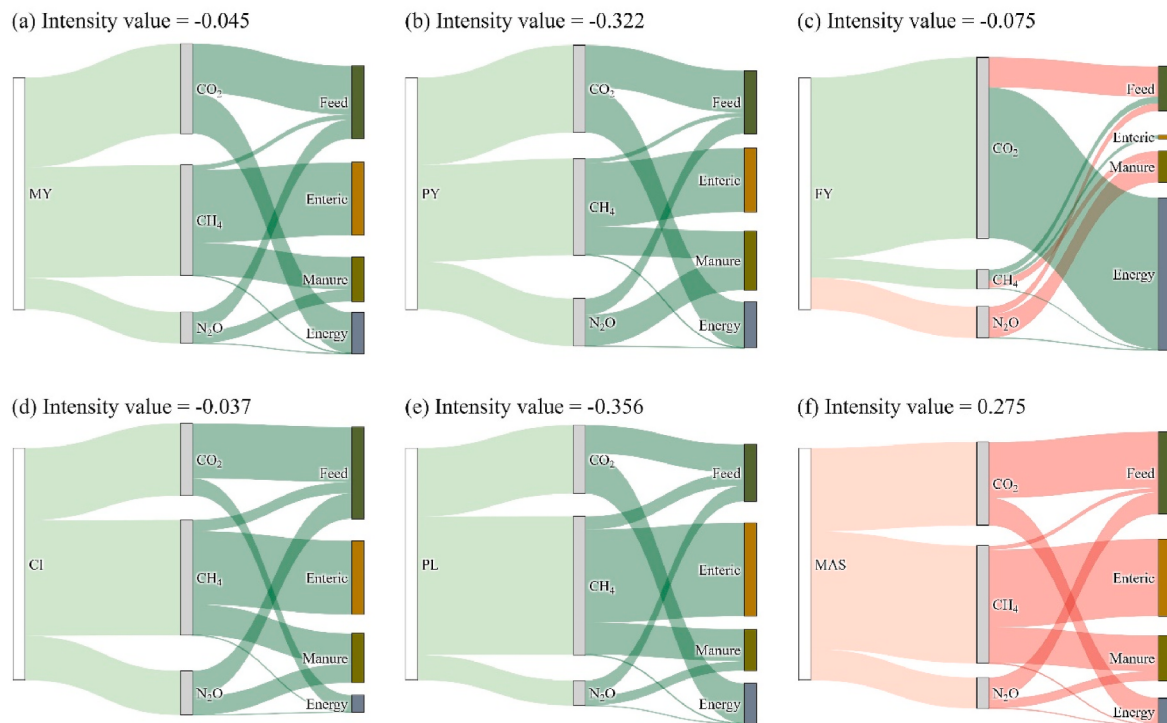


Fig. 2. The impact of a 1-unit increase for each target trait on greenhouse gas emissions along the chain (intensity value) for the next generation. Greenhouse gases are expressed in kg CO₂-eq per ton of fat-and protein-corrected milk. Panel (a) to (f) displayed the results for annual milk yield (MY, kg per cow per year), annual protein yield (PY, kg per cow per year), annual fat yield (FY, kg per cow per year), calving interval (CI, d), productive life (PL, d), and clinical mastitis (MAS, %), respectively. Green indicates a reduction in emissions, while red indicates an increase in emissions. Note that the increase of CI results in lower emissions due to the decrease of emissions from on-farm young stock.

interactions for target traits. Moreover, the current approach is flexible and enables update of environmental parameters or inclusion of more traits. It may, therefore, be possible to implement this approach in farms

with different conditions and different breeding goals.

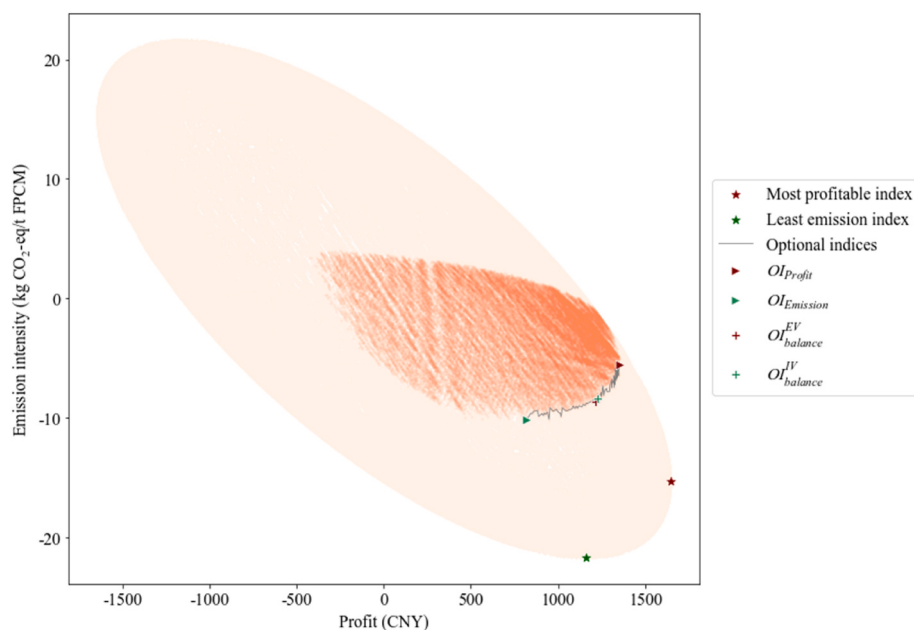


Fig. 3. The economic and environmental consequences of different breeding indices. The light shadowed area represents one million indices under different combinations of EVs or IVs of the traits. The orange cloud indicates all favourable indices with constraints on genetic gain. Optional indices indicate ones that balance economic and environmental consequences to different extents. OI_{Profit} , $OI_{Emission}$, $OI_{EV_balance}^{EV}$, and $OI_{IV_balance}^{IV}$ refer to the optimal indices (OI) that were selected from optional indices, where the subscript refers to different emphasis on emission and profit (See Methods). EV refers to economic values of the traits, and IV refers to emission intensity values (IV) of traits.

3.4. Breeding indices under different objectives or constraints

The profit and EI of the million indices are shown in Fig. 3 (light shadowed area). Broadly, within the area, this shows that for a given amount of farm profit, there were various possibilities of GHG intensity under different indices, and *vice versa*. This indicates a synergy between farm profit and GHG mitigation.

The LEI was observed at the lowest boundary of the shadowed area, which indicates the index with the greatest potential capacity to reduce GHG emissions, i.e., by 22 kg CO₂-eq per ton of FPCM. The MPI was observed at the rightmost boundary of the shadowed area, which indicates the index with the greatest potential capacity to improve farm profitability, i.e., by 1645 CNY per cow unit. However, neither LEI nor MPI were considered practically desirable as they increase CI and MAS (Table S6), which could be explained by the positive correlations with production traits (Fig. S2).

The orange cloud within the shadowed area in Fig. 3 represents all constrained indices that prevent undesired responses in traits. The grey frontier line represents the optional indices that balance profit and GHG emissions to different extents, and provide multiple options for the stakeholders or policymakers. The profitability of the optional indices ranged from 822 to 1355 CNY per cow unit. The reduction of EI of the optional indices ranged from six to 10 kg CO₂-eq per ton of FPCM. The higher the EI of the indices, the lower the GHG reduction potential the indices had. $OI_{balance}^{EV}$ and $OI_{balance}^{IV}$ produced similar results in both profit (about 1200 CNY per cow unit) and EI reduction (about -9 kg CO₂-eq per ton of FPCM). Note that changing the relative importance of profit and EI (in this case 50/50) leads to a different result. It is also obvious that the constraints on genetic gain for the traits limits the space for both improving profit and reducing EI to some extent, which is the basic property of constrained indices (Brascamp et al., 1985). Some discontinuities can be observed in the orange cloud, which is mainly due to the limited number of settings (10 values generated based on EV or IV for each trait). If the number of settings were larger, the cloud would have been fully solid, and the frontier line would have been smoother. However, larger settings would require higher computation loads, but would not alter the main insights of our analysis.

Another approach to integrate economic and environmental assessments is to assume a carbon price on GHG emissions (Mosnier et al., 2019; De Haas et al., 2021). Nevertheless, by summing up farm profit

and GHG emissions into one value, the actual consequences of GHG emissions are still hidden. Thus, to have a clear and detailed understanding about the synergies and trade-offs between economic and environmental consequences, it is important to keep them separate.

The relative weighting of each trait that integrates the (extended) EVs or IVs and genetic potential is shown in Fig. 4. This could be used for investigating the balance among target traits. In general, the summed weights of production traits (MY, PY and FY) accounted for at least half of the indices as a whole, except for that in OI_{profit} (37%). In practice, it is recommended that the weighting of production traits accounts for 40%–60% of the index, while that of other functional traits or body conformation traits comprises 20%–30% (LPI, 2022; NVI, 2023; Sørensen et al., 2018; TPI, 2021; Van Raden et al., 2021). It can be seen that the optimal indices are better aligned with the recommendation compared with LEI and MPI.

For individual traits, LEI put the highest weight on MY (57%), while OI_{profit} put the least (21%). Placing too much emphasis on MY, however, can lead to deterioration of fertility traits in the long-run, which may affect the farm profits negatively due to the negative genetic correlation between MY and fertility traits (Gonzalez-Recio et al., 2004; Liu et al., 2017; Shi et al., 2024). In some national indices (e.g., in Canada), more emphasis has been placed on functional traits or efficiency traits (e.g., feed efficiency) than on MY (LPI, 2022). Nevertheless, MY will take a large part in the breeding index of China, at least in the near future, due to the increasing demand for milk and the potential to increase MY, especially in small-scale farms (Dou et al., 2020; Wang et al., 2022). The share of PY also differed among indices (from 8% in $OI_{balance}^{IV}$ to 25% in MPI), as did FY (from 4% in OI_{profit} to 18% in $OI_{emission}$). It was observed that OI_{profit} put 40% emphasis on CI, whereas $OI_{emission}$ put less than 30% emphasis on CI and PL together. In addition, $OI_{balance}^{EV}$ tended to put more weighting on PL (34%), while $OI_{balance}^{IV}$ tended to put more weight on CI (30%). The weightings of MAS were much lower compared with other traits given a small genetic standard deviation (Table S5).

3.5. Contribution of individual traits in optimal indices

The contributions of individual traits to profits and EI in the optimal indices are shown in Fig. 5. Overall, the profits were mainly from MY, CI and PL (Fig. 5a). The profit of increasing MY for $OI_{emission}$ was higher (507 CNY per cow unit) than that of reducing CI (183 CNY per cow unit),

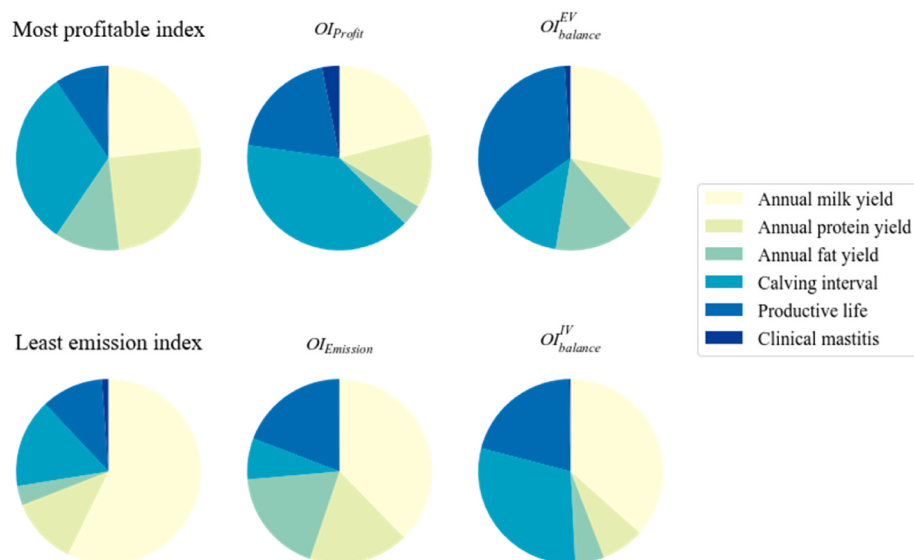


Fig. 4. Relative weight of genetic traits in different indices. OI_{profit} , $OI_{emission}$, $OI_{balance}^{EV}$, and $OI_{balance}^{IV}$ refer to the optimal indices (OI) that were selected from optional indices (See Materials and Methods), where the subscript refers to different emphasis on emission and profit, EV refers to economic values of the traits, and IV refers to emission intensity values (IV) of traits.

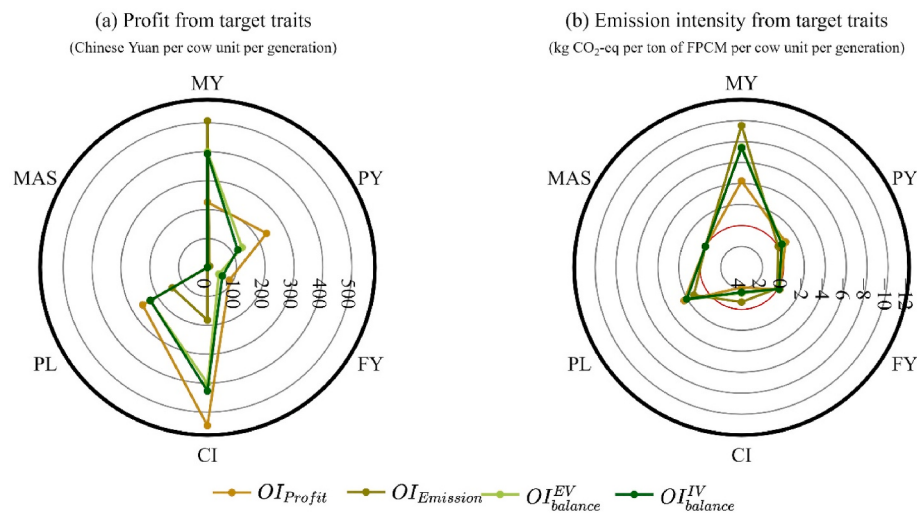


Fig. 5. Economic and environmental contributions from target traits of different optimal indices. Panel (a) displays the profitable contributions of target traits in Chinese yuan per cow unit per generation in different indices, while panel (b) displays the contributions of reducing emission intensity for the traits in optimal indices in kg CO₂-eq per ton of fat- and protein-corrected milk per cow unit per generation. The red ring in panel (b) indicates 0 contributions. The traits included are annual milk yield (MY), annual protein yield (PY), annual fat yield (FY), calving interval (CI), productive life (PL), and clinical mastitis (MAS). OI_{profit} , $OI_{emission}$, $OI_{EV_balance}$, and $OI_{IV_balance}$ refer to the optimal indices (OI) that were selected from optional indices, where the subscript refers to different emphasis on emission and profit, EV refers to economic values of the traits, and IV refers to emission intensity values (IV) of traits. The selection of optimal indices could be found in the Materials and Methods.

while the reverse was observed for OI_{profit} . For $OI_{EV_balance}$ and $OI_{IV_balance}$, the contributions of MY and CI to profits were relatively comparable. Meanwhile, the profits of PY were much higher for OI_{profit} , $OI_{EV_balance}$, and $OI_{IV_balance}$ (236, 138 and 121 CNY per cow unit, respectively) than those for $OI_{emission}$ (9 CNY per cow unit). The variations among indices could be attributed to different weightings for the traits in different indices (Fig. 4), and the correlations among the traits (Fig. S2). In addition, for all the indices, the contributions from FY were less than 100 CNY per cow unit, and the contributions from MAS were less than 1 CNY per cow unit.

Regarding EI, MY contributed to a reduction of around 4.2–9.5 kg CO₂-eq per ton of FPCM across the indices (Fig. 5b). The GHG reductions of PL were from 1.3 to 2.3 kg CO₂-eq per ton of FPCM, while those of PY, FY, and MAS were below 1 kg CO₂-eq per ton of FPCM for all the indices. In contrast, results showed that reducing CI will emit more GHG (from 0.7 to 2.1 kg CO₂-eq per ton of FPCM), although it was always recognized as a more profitable strategy with higher annual calving rate and more MY (Samaraweera et al., 2022; Van Knegsel et al., 2022; Shi et al., 2024). This negative effect in EI, however, can be compensated by the significant positive effect of MY in the index, making the overall EI of the index to decrease.

3.6. Limitations and future work

We see potential in our approach for improvement beyond the results demonstrated in this study. For instance, the diet composition of cows and the milk price were assumed to be unchanged for the next generation. The inclusion of these factors would require an upgrade of the existing bio-economic model through incorporation of more parameters in e.g., animal nutrition and market dynamics, which was beyond the scope of this work. Only six traits were considered in this study in its conceptual development. However, there are more traits (e.g., udder health, lactose, feed efficiency) that could be included (De Haas et al., 2021). In practice, the step of generating and selecting candidate indices in this study could also be simplified if undesired changes are not observed using the calculated EV or IV. In addition, more complex equations could be included to obtain accurate genetic gains. For example, the expected genetic gain in CI may be somewhat smaller when

accounting for the low prediction accuracy of estimated breeding values of CI (Zhang and Amer, 2021). Moreover, regarding the environmental sustainability, this study solely used GHG emissions as an indicator, but there are various other environmental aspects, such as nutrient pollution and food-feed competition, that are relevant for the Chinese dairy sector and that could be incorporated in future studies (Bai et al., 2018; Wang et al., 2022). It is also worth noting that the values of GWPs change over time (updated every seven years), which will affect the results for different generations of dairy cattle. In addition, the analysis was conducted based on one typical dairy farm in North China. Although the approach and general trend may be generalized, the absolute values are subject to farm-specific conditions. Nevertheless, we believe that our method combining bio-economic farm models and LCA could also be applied in other contexts (either at different farm types or in different regions) in future studies.

4. Conclusions

This study has important implications in both scientific methods and practice. Firstly, by linking LCA analysis with a bio-economic model, we provide novel insights into how to determine the IVs for six important traits of dairy cows. GHG emissions along the chain have been taken into consideration (instead of merely enteric CH₄ emissions), which gives a more holistic understanding of how the change of the traits would affect GHG emissions from different processes. Furthermore, a set of optional indices that compromise environmental and economic consequences has been identified. These results provide options for Chinese dairy farms to reduce EI while still maintaining economic benefits. We also believe that the approach we have introduced could be potentially applied or adapted to different contexts, and that our results provide a valuable reference to the dairy sector worldwide.

CRedit authorship contribution statement

Rui Shi: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Yue Wang:** Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Corina E. van Middelaar:** Supervision, Writing – review &

editing. **Bart Ducro:** Supervision, Writing – review & editing. **Simon J. Oosting:** Supervision, Writing – review & editing. **Yong Hou:** Supervision, Writing – review & editing. **Yachun Wang:** Funding acquisition, Supervision, Writing – review & editing. **Aart van der Linden:** Supervision, Writing – review & editing.

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

I have shared the data/code in the supplementary materials.

Acknowledgement

This work was supported by National Key Research and Development Projects (2022YFE0115700), the earmarked fund for China Agriculture Research System (CARS-36), the Sino-Dutch Dairy Development Center of China Agricultural University, the Program for Changjiang Scholar and Innovation Research Team in University (IRT_15R62), the China Scholarship Council (No. 201913043; No. 201906350227), and Hainan University. We would like to thank the members of the Cattle Genetics & Breeding Research Team of the China Agricultural University, who participated in data collection, data management and the discussions around this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jclepro.2024.142099>.

References

- Amer, P.R., Hely, F.S., Quinton, C.D., Cromie, A.R., 2018. A methodology framework for weighting genetic traits that impact greenhouse gas emission intensities in selection indexes. *Anim* 12 (1), 5–11. <https://doi.org/10.1017/S1751731117001549>.
- Bai, Z., Lee, M.R.F., Ma, L., Ledgard, S., Oenema, O., Velthof, G.L., Ma, W., Guo, M., Zhao, Z., Wei, S., Li, S., Liu, X., Havlik, P., Luo, J., Hu, C., Zhang, F., 2018. Global environmental costs of China's thirst for milk. *Global Change Biol.* 24 (5), 2198–2211. <https://doi.org/10.1111/gcb.14047>.
- Bell, M.J., Eckard, R.J., Haile-Mariam, M., Pryce, J.E., 2013. The effect of changing cow production and fitness traits on net income and greenhouse gas emissions from Australian dairy systems. *J. Dairy Sci.* 96 (12), 7918–7931. <https://doi.org/10.3168/jds.2012-6289>.
- Brascamp, E.W., Smith, C., Guy, D.R., 1985. Derivation of economic weights from profit equations. *Anim. Sci.* 40 (1), 175–179. <https://doi.org/10.1017/S0003356100031986>.
- Caswell, T.A., Droettboom, M., Lee, A., Andrade, E. S. de, Hunter, J., Firing, E., Hoffmann, T., Klymak, J., Stansby, D., Varoquaux, N., Nielsen, J.H., Root, B., May, R., Elson, P., Seppänen, J.K., Dale, D., Lee, J.J., McDougall, D., Straw, A., Hobson, P., Gohlke, C., Yu, T.S., Ma, E., Vincent, A.F., Silvester, S., Moad, C., Kniazev, N., Ernest, E., Ivanov, P., 2021. Matplotlib/matplotlib: REL: V3.3.4. <https://doi.org/10.5281/zenodo.4475376>.
- Cole, J.B., Dürr, J.W., Nicolazzi, E.L., 2021. Invited review: the future of selection decisions and breeding programs: what are we breeding for, and who decides? *J. Dairy Sci.* 104, 5111–5124. <https://doi.org/10.3168/jds.2020-19777>.
- De Haas, Y., Veerkamp, R.F., De Jong, G., Aldridge, M.N., 2021. Selective breeding as a mitigation tool for methane emissions from dairy cattle. *Anim* 15, 100294. <https://doi.org/10.1016/j.animal.2021.100294>.
- Dong, H., Wei, S., 2020. Greenhouse gas emissions on Chinese dairy farms and potential for reduction. In: CGIAR Research Program on Climate Change, Agriculture and Food Security. CCAFS), Wageningen, the Netherlands. CCAFS Working Paper no. 384.
- Donnelly, J., Daneshkhan, A., Abolfathi, S., 2024. Forecasting global climate drivers using Gaussian processes and convolutional autoencoders. *Eng. Appl. Artif. Intell.* 128, 107536. <https://doi.org/10.1016/j.engappai.2023.107536>.
- Dou, M., Sun, L., Luo, G., Chen, L., 2020. China Dairy Data Report. Holstein Farmer & Dairy Consultants (in Chinese).
- Ecoinvent version 3.8 database. Software SimaPro 9.4.
- FAO, 2022. Global Livestock Environmental Assessment Model (GLEAM). https://www.fao.org/fileadmin/user_upload/gleam/docs/GLEAM_3.0_Model_description.pdf. (Accessed 20 February 2024).
- Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falucci, A., Tempio, G., 2013. Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities. In: Food and Agriculture Organization of the United Nations: Rome.
- Gonzalez-Recio, O., Pérez-Cabal, M., Alenda, R., 2004. Economic value of female fertility and its relationship with profit in Spanish dairy cattle. *J. Dairy Sci.* 87, 3053–3061. [https://doi.org/10.3168/jds.S0022-0302\(04\)73438-4](https://doi.org/10.3168/jds.S0022-0302(04)73438-4).
- González-Recio, O., López-Paredes, J., Ouatahar, L., Charfeddine, N., Ugarte, E., Alenda, R., Jiménez-Montero, J.A., 2020. Mitigation of greenhouse gases in dairy cattle via genetic selection: 2. Incorporating methane emissions into the breeding goal. *J. Dairy Sci.* 103 (8), 7210–7221. <https://doi.org/10.3168/jds.2019-17598>.
- Harris, C.R., Millman, K.J., Walt, S. J. Van der, Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N.J., Kern, R., Picus, M., Hoyer, S., Kerkwijk, M. H. Van, Brett, M., Haldane, A., Río, J. F. del, Wiebe, M., Peterson, P., Gérard-Marchant, P., Sheppard, K., Reddy, T., Weckesser, W., Abbasi, H., Gohlke, C., Oliphant, T.E., 2020. Array programming with NumPy. *Nature* 585 (7825), 357–362. <https://doi.org/10.1038/s41586-020-2649-2>.
- Hazel, L., 1943. The genetic basis for constructing selection indexes. *Genetics* 28, 476–490.
- Hossein-Zadeh, N.G., 2022. Estimates of the genetic contribution to methane emission in dairy cows: a meta-analysis. *Sci. Rep.* 12, 12352. <https://doi.org/10.1038/s41598-022-16778-z>.
- Hou, Y., Velthof, G.L., Oenema, O., 2015. Mitigation of ammonia, nitrous oxide and methane emissions from manure management chains: a meta-analysis and integrated assessment. *Global Change Biol.* 21 (3), 1293–1312. <https://doi.org/10.1111/gcb.12767>.
- Huang, X., Shi, B., Wang, S., Yin, C., Fang, L., 2021. Mitigating environmental impacts of milk production via integrated maize silage planting and dairy cow breeding system: a case study in China. *J. Clean. Prod.* 309, 127343. <https://doi.org/10.1016/j.jclepro.2021.127343>.
- IDF (International Dairy Federation), 2015. A Common Carbon Footprint Approach for the Dairy Sector- the IDF Guide to Standard Life Cycle Assessment Methodology, pp. 479–2015.
- IPCC, 2019. Refinement to the 2006 IPCC guidelines for national greenhouse gas inventories. In: Calvo Buendia, E., Tanabe, K., Kranjc, A., Baasansuren, J., Fukuda, M., Ngarize, S., Osako, A., Pyrozhenko, Y., Shermanau, P., Federici, S. (Eds.), Published: IPCC. Switzerland.
- IPCC, 2022. Climate change 2022: impacts, adaptation, and vulnerability. Contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change. In: Pörtner, H.-O., Roberts, D.C., Tignor, M., Poloczanska, E.S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., Rama, B. (Eds.), Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA, p. 3056. <https://doi.org/10.1017/9781009325844>.
- Jiang, L., Ou, X., Ma, L., Li, Z., Ni, W., 2013. Life-cycle GHG emission factors of final energy in China. *Energy Proc.* 37, 2848–2855. <https://doi.org/10.1016/j.egypro.2013.06.170>.
- Jin, S., Zhang, B., Wu, B., Han, D., Hu, Y., Ren, C., Zhang, C., Wei, X., Wu, Y., Mol, A.P.J., Reis, S., Gu, B., Chen, J., 2020. Decoupling livestock and crop production at the household level in China. *Nat. Sustain.* 4 (1), 48–55. <https://doi.org/10.1038/s41893-020-00596-0>.
- Kumar, M., Vohra, V., Ratwan, P., Gowane, G.R., Malhotra, R., 2022. Sustainable multi-trait selection index based on production, reproduction, and health traits for genetic improvement of Murrah buffaloes. *Anim. Biotechnol.* 1–9. <https://doi.org/10.1080/10495398.2022.2101117>.
- Lifetime Performance Index (LPI), 2022. <https://www.cdn.ca/document.php?id=443>. (Accessed 20 February 2024).
- Liu, A., Wang, Y., Sahana, G., Zhang, Q., Liu, L., Lund, M.S., Su, G., 2017. Genome-wide association studies for female fertility traits in Chinese and Nordic Holsteins. *Sci. Rep.* 7 (1), 8487. <https://doi.org/10.1038/s41598-017-09170-9>.
- McKinney, W., 2010. Data structures for statistical computing in Python. In: Walt, Van der, S., Millman, J. (Eds.), Proceedings of the 9th Python in Science Conference, pp. 56–61. <https://doi.org/10.25080/Majora-92bf1922-00a>.
- Mosnier, C., Britz, W., Juliere, T., De Cara, S., Jayet, P.A., Halvliik, P., et al., 2019. Greenhouse gas abatement strategies and costs in French dairy production. *J. Clean. Prod.* 236, 117589.
- Mostert, P.F., Bokkers, E.A.M., de Boer, I.J.M., Van Middelaar, C.E., 2019. Estimating the impact of clinical mastitis in dairy cows on greenhouse gas emissions using a dynamic stochastic simulation model: a case study. *Anim* 13 (12), 2913–2921. <https://doi.org/10.1017/S1751731119001393>.
- Miglior, F., Fleming, A., Malchiodi, F., Brito, L.F., Martin, P., Baes, C.F., 2017. A 100-year review: identification and genetic selection of economically important traits in dairy cattle. *J. Dairy Sci.* 100 (12), 10251–10271. <https://doi.org/10.3168/jds.2017-12968>.
- NRC, 2001. Nutrient Requirements of Dairy Cattle: seventh revised edition. National Academies Press, Washington, D.C., p. 9825. <https://doi.org/10.17226/9825>.
- Plotly Technologies Inc. Collaborative data science. <https://plotly.com>.
- Richardson, C.M., Baes, C.F., Amer, P.R., Quinton, C., Hely, F., Osborne, V.R., Pryce, J.E., Hailemariam, D., Miglior, F., 2021. Estimating the environmental impact of dairy cattle breeding programs through emission intensity. *Anim* 15 (1), 100005. <https://doi.org/10.1016/j.animal.2020.100005>.
- Richardson, C.M., Amer, P.R., Quinton, C., Crowley, J., Hely, F.S., Van Den Berg, I., Pryce, J.E., 2022a. Reducing greenhouse gas emissions through genetic selection in the Australian dairy industry. *J. Dairy Sci.* 105, 4272–4288. <https://doi.org/10.3168/jds.2021-21277>.

- Richardson, C.M., Hely, F., Post, M., Nguyen, T.T.T., Nieuwhof, G.J., Amer, P.R., 2022b. Comparing measurements of product output when defining emissions intensity. In: Proceedings of 12th World Congress on Genetics Applied to Livestock Production (WCGALP). Presented at the World Congress on Genetics Applied to Livestock Production. Wageningen Academic Publishers, Rotterdam, the Netherlands, pp. 111–114. https://doi.org/10.3920/978-90-8686-940-4_16, 16.
- Samaraweera, A.M., Van der Werf, J.H.J., Boerner, V., Hermes, S., 2022. Economic values for production, fertility and mastitis traits for temperate dairy cattle breeds in tropical Sri Lanka. *J. Anim. Breed. Genet.* 139 (3), 330–341. <https://doi.org/10.1111/jbg.12667>.
- Sebek, L.B., Mosquera, J., Bannink, A., 2016. Rekenregels voor de enterische methaanemissie op het melkveebedrijf en reductie van de methaanemissie via mest-handling, het handelingsperspectief van het voerspoor inzichtelijk maken met de kringloopwijzer. In: Livestock Research Rapport 976, Lelystad, Wageningen UR. University & Research centre Livestock, Research (in Dutch).
- Selectie-index in de Nederlandse en Vlaamse Melkveehouderij (NVI), 2023. https://www.cooperatie-crv.nl/wp-content/uploads/2023/04/E_20-NVI-April-2023-Engels.pdf. (Accessed 20 February 2024).
- Shi, R., Van der Linden, A., Oosting, S., Wang, Y., Ducro, B., 2024. Derivation of economic values for breeding objective traits of Chinese Holstein dairy cows using a bio-economic model (manuscript submitted for publication).
- Sørensen, L.P., Pedersen, J., Kargo, M., Nielsen, U.S., Fikse, F., Eriksson, J.-Å., Pösö, J., Stephansen, R.S., Aamand, P., 2018. Review of Nordic Total Merit Index Full Report, p. 96. <https://www.nordicebv.info/wp-content/uploads/2018/11/2018.11.06-NTM-2018-report-Full.pdf>. (Accessed 20 February 2024).
- The State Council of the People's Republic of China (SCPRC), 2021. https://www.gov.cn/zhengce/2021-10/24/content_5644613.htm. (in Chinese) (Accessed 20 February 2024).
- Total Performance Index (TPI), 2021. https://www.holsteinusa.com/genetic_evaluations/ss_tpi_formula.html. (Accessed 20 February 2024).
- Van Middelaar, C.E., Berentsen, P.B.M., Dijkstra, J., Van Arendonk, J.A.M., de Boer, I.J.M., 2014. Methods to determine the relative value of genetic traits in dairy cows to reduce greenhouse gas emissions along the chain. *J. Dairy Sci.* 97 (8), 5191–5205. <https://doi.org/10.3168/jds.2013-7413>.
- Van Knegsel, A.T.M., Burgers, E.E.A., Ma, J., Goselink, R.M.A., Kok, A., 2022. Extending lactation length: consequences for cow, calf, and farmer. *J. Anim. Sci.* 100 (10), skac220 <https://doi.org/10.1093/jas/skac220>.
- Van Raden, P.M., Cole, J.B., Neupane, M., Togiani, S., Gaddis, K.L., Tempelman, R.J., 2021. Net merit as a measure of lifetime profit. https://www.ars.usda.gov/ARSUserFiles/80420530/Publications/ARR/nmcalc-2021_ARR-NM8.pdf. (Accessed 20 February 2024).
- Van Rossum, G., Drake, F.L., 2009. Python 3 Reference Manual. CreateSpace, Scotts Valley, CA.
- Vellinga, T.V., Blonk, H., Marinussen, M., 2013. Methodology used in Feedprint: a tool quantifying greenhouse gas emissions of feed production and utilization. *Livestock Research* 674, 121. No. Report.
- Vogel, E., Beber, C.L., 2022. Carbon footprint and mitigation strategies among heterogeneous dairy farms in Paraná, Brazil. *J. Clean. Prod.* 349, 131404 <https://doi.org/10.1016/j.jclepro.2022.131404>.
- Wang, X., Kristensen, T., Mogensen, L., Knudsen, M., Wang, X., 2016. Greenhouse gas emissions and land use from confinement dairy farms in the Guanzhong plain of China – using a life cycle assessment approach. *J. Clean. Prod.* 113, 577–586. <https://doi.org/10.1016/j.jclepro.2015.11.099>.
- Wang, X., Ledgard, S., Luo, J., Guo, Y., Zhao, Z., Guo, L., Liu, S., Zhang, N., Duan, X., Ma, L., 2018. Environmental impacts and resource use of milk production on the North China Plain, based on life cycle assessment. *Sci. Total Environ.* 625, 486–495. <https://doi.org/10.1016/j.scitotenv.2017.12.259>.
- Wang, Y., De Boer, I.J.M., Hou, Y., Van Middelaar, C.E., 2022. Manure as waste and food as feed: environmental challenges on Chinese dairy farms. *Resour. Conserv. Recycl.* 181, 106233 <https://doi.org/10.1016/j.resconrec.2022.106233>.
- York, L., Heffernan, C., Rymer, C., 2018. A systematic review of policy approaches to dairy sector greenhouse gas emission reduction. *J. Clean. Prod.* 172, 2216–2224. <https://doi.org/10.1016/j.jclepro.2017.11.190>.
- Zhang, W., Dou, Z., He, P., Ju, X.-T., Powlson, D., Chadwick, D., Norse, D., Lu, Y.-L., Zhang, Y., Wu, L., Chen, X.P., Cassman, K.G., Zhang, F.S., 2013. New technologies reduce greenhouse gas emissions from nitrogenous fertilizer in China. *Proc. Natl. Acad. Sci. U.S.A.* 110 (21), 8375–8380. <https://doi.org/10.1073/pnas.1210447110>.
- Zhang, N., Bai, Z., Luo, J., Ledgard, S., Wu, Z., Ma, L., 2017. Nutrient losses and greenhouse gas emissions from dairy production in China: lessons learned from historical changes and regional differences. *Sci. Total Environ.* 598, 1095–1105. <https://doi.org/10.1016/j.scitotenv.2017.04.165>.
- Zhang, X., Amer, P., 2021. A new selection index percent emphasis method using subindex weights and genetic evaluation accuracy. *J. Dairy Sci.* 104, 5827–5842. <https://doi.org/10.3168/jds.2020-19547>.